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< Risk and Sustainability: Assessing Fisheries Management Strategies >

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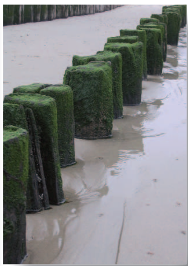

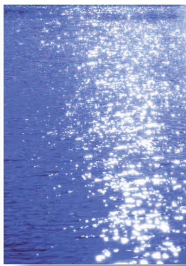


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Risk and Sustainability:
Assessing Fisheries Management Strategies

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Risk and Sustainability: Assessing Fisheries Management Strategies

Abstract

We develop a theoretical framework to assess fisheries management strategies from a sustainability perspective, when the bioeconomic dynamics are marked by uncertainty. Using stochastic viability, management strategies are ranked according to their probability to satisfy economic and ecological constraints over time. This framework is applied to a Chilean fishery case-study, faced with El *Niño* uncertainty. We study the viability of effort and quota strategies, when a minimal catch level and a minimal biomass are required. For realistic sustainability objectives, effort-based management results in a better viability probability than quota-based management.

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

1 Introduction

The analysis in this paper has its origin in some actual concerns regarding the management practices in Chilean fisheries. The Jack-Mackerel Chilean fishery is faced with *El Niño* uncertain cycles, which increase the uncertainty about this resource availability [3], and thus make the management more difficult [14]. 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 an individual (company allocated) quota scheme [24]. The management 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 [31]. Despite this management procedure, the Chilean Jack-Mackerel TAC fell by 76% between 2010 and 2011.[1]

We are here interested in the definition of a framework to address *sustainable* resource management issues under risk,[2] accounting for economic and ecological issues. Optimality in fishery economics is usually defined as the maximization of the total discounted profit of harvesting, or its expected value in a stochastic framework [12, 43, 45]. This approach has the great advantage of defining optimal strategies with respect to a unique criterion, and makes it possible to rank management strategies according to their value

[1]The global annual quota fell from 1,300,000 tons in 2010 to 315,000 tons in 2011.

[2]In the paper, we will use "risk" and "uncertainty" equivalently, with the underlying economic meaning of *risk*, i.e., stochastic events with known probabilities. We do not address the economic issue of *uncertainty*, i.e., unknown or no probabilities.

of discounted expected profit. Discounted expected utility is, however, difficult to apply to sustainable resource management issues, particularly when several sustainability dimensions have to be accounted for. Extending the approach to ecological (or social) issues would require to define a multi-attribute utility function, or to add ecological constraints to the optimization problem (a difficult issue in a stochastic context), jeopardizing the applicability of the approach. Indeed, in practice, management strategies (often defined as simple "rules of thumb") are evaluated in so-called "multicriteria" frameworks [20, 23, 33, 47]. Such methods are based on simulations, and do not necessarily offer the same advantages as discounted expected utility. In particular, they do not make it possible to rank explicitly alternative management strategies as they provide no common metrics for conflicting objectives and risk.

This paper tackles the challenge of providing a framework to define sustainable management strategies and rank alternative management strategies, accounting for conflicting sustainability issues and risk. We address this issue with the so-called viability [2] and especially stochastic viability approach [16]. Given a set of multidimensional "outcome indicators" (either referring to physical or economic variables) and its corresponding set of thresholds representing sustainability bounds (e.g., minimal biomass, minimal profit), we evaluate management strategies by their probability of achieving these objectives jointly and at all times over the planning horizon. The main 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 ranking alternative management strategies according to their viability probability. This allow us to define concepts of optimality and value, and to produce marginal analysis to examine the trade-offs between sustainability issues and risk. This stochastic viability approach is thus closer to economics than the usual multicriteria Management Strategy Evaluation approaches.

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 under *El Niño* uncertainty. In particular, we compare quota and effort-based strategies, relating our results obtained for multiple sustainability objectives to the “price versus quantity” debate in fisheries management [15, 27, 32, 41, 50].

Section 2 presents the literature in fisheries economics on the one hand, and fisheries management on the other hand, and motivates our approach. Section 3 presents our theoretical framework to assess risk and sustainability, and to compare management strategies when sustainability objectives are conflicting. We apply this framework to the Jack-Mackerel Chilean fishery case-study in Section 4, and illustrate our results comparing effort control and quota driven strategies. We conclude with some remarks on the relevance of our results for practical fisheries management in Section 5.

2 Background and settings

Optimality in fishery economics is usually defined as the maximization of the discounted profit of harvest, or its expected value under risk. In the deterministic case, constant harvest and escapement emerges as a possible stationary solution path [11]. Fisheries management issues are, however, highly marked by uncertainty [30], e.g., on stock evaluation, on the recruitment process, as well as on catches [39]. Ignoring uncertainties can lead to excessive harvest and fishery collapse. In the stochastic case, the issue is no longer to define an optimal path but optimal *strategies*, that is, decision rules depending on the information available on-line. The optimal harvest levels may then correspond to very specific management strategies,[3] depending on the stochastic stock level and/or on the uncertain shocks affecting the dynamics [36]. When responding to the uncertain stock fluctuations, optimality may require strong variations of the Total Allowable Catches from year to year, and even fishery closure when the stock size is too low [37]. As fishing industries favor stability of catches [10], optimal management strategies may be hard to apply.[4] In fact, even if economic theory provides a description of optimal strategies that could be used to manage fisheries, the latter are often managed in practice with much simpler tools.[5] Constant effort and constant quotas are two basic management strategies. The former approach, also known as fixed fishing mortality, is based on advice by biologists and results in fluctuating harvest as the stock fluctuates. From an economic point of view, it is linked to a constant use of the capital. The latter approach provides stabilized catch, which is a strategy gaining ground in the industry. The optimal strategy may be neither of these two [27], but these rules of thumb are still discussed as potential management strategies in some fisheries.[6]

[3] For example, a constant-escapement policy may be optimal when the stock is observed before decision-making and the profits are "linear" in the harvest [43]. Linear feedback policies may be optimal for some models [38]. More sophisticated strategies are needed when decision has to be made before knowing stock size, for example adjusting the quota level during the fishing season while the information on the stock size is (costly) available [12]. The presence of multiple uncertainties also makes the optimal policy more complex [45].

[4] Such a willingness to smooth the harvest over time may be related to costly capital adjustment [46] or to risk-aversion [1].

[5] For example, [46] described the Alaskan pacific halibut stock as being managed by setting the yearly harvest as a fixed fraction of the exploitation biomass; this constant harvest rate rule is shown to smooth the catches over time more than the corresponding optimal policy would do it.

[6] *De facto*, Chilean fisheries were managed under a constant effort rule in the 1980s and 1990s (with a frozen maximum effort which was then reached). Since then, a quota system has been in use, with *a posteriori* small changes in the quota levels from year to

In the sustainability context, management objectives are often not limited to profit maximization. For example, resource conservation may be an objective in and of itself, along with obtaining long-term socio-economic benefits from fishing, in an Ecosystem-Based Fishery Management perspective [13, 40]. This increases the number of objectives and stakeholders [22].

Extending the economic optimization approach to several dimensions, for example to account for ecological objectives, raises delicate questions, and different answers are possible. Firstly, the additional ecological objectives could be aggregated with the usual economic objective in a multi-attribute utility function. All the elements of the system that have a value are gathered in the utility function. This latter characterizes the preferences of the " decision-maker." Stake-holders, however, may not want to, or may be unable to agree on a utility function giving all the trade-offs between sustainability issues. Secondly, one can add ecological constraints to the economic optimization problem. In this case, the preferences are characterized by *both* the economic utility function *and* the thresholds of the ecological constraints. This approach is very interesting in the deterministic case, as it provides information on the (marginal) cost of achieving the constraint, or the gain from relaxing it. In the stochastic case, however, it is easy to "translate" the deterministic economic criterion into its expected value, but it is more difficult to "translate" a constraint in stochastic terms.[7] Moreover, this approach

year, with few exceptions, as the case of the 2011 TAC fall in the Chilean Jack-Mackerel fishery.

[7]A strict translation, i.e., requiring that the constraint is satisfied with probability one, yields the robust approach, which usually restricts the decisions so much that the optimization problem loses its interest. Accepting a risk of constraint violation is another possibility. This last approach is related to the Management Strategy Evaluation described below. It requires to consider the performance of the system with respect to the constraint, and provides, additionally to the expected economic performance, a measure of the risk to the resource. We shall see that this approach does no allow to rank management strategies as the performance with respect to the two objectives are not in the same unit, and cannot

clearly puts the priority on the economic objective, the other objectives being side constraints. Some stake-holders may reject this practice.

When one of the ecological, economic or social objective is not met, fisheries are faced with a crisis or a unsustainable situation. Indeed, one of the frequent reasons of management failure in fisheries is the conflict between ecological constraints and social and economic priorities, the latter often having priority over resource conservation [29]. An important issue is thus to determine management procedures[8] that give acceptable results with respect to the sustainability objectives while being robust to uncertainties [10]. Ideally, before defining the MP to be applied, one should compare different potential MPs and rank them with respect to their ability to keep the fishery sustainable in an uncertain environment. Scientific tools are required to support multi-criteria decision making, and evaluate proposed management strategies. A practical challenge is to account for risk, and balance the risk of resource collapse due to excessive exploitation versus the risk of forgone economic benefits if the harvests are lower than necessary.

Various scientific tools have been developed to support sustainable fisheries management [47], including *Management Strategy Evaluation* (MSE) [33] and *Ecological Risk Assessment* (ERA). While the optimality approaches are based on stochastic optimization, and thus defining an optimal management rule, the evaluation of management strategies is mainly done using simulation methods (usually through Monte Carlo simulation), to compare pre-defined strategies which are preferred to stochastic optimization for large models.

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be aggregated.

[8] A Management Procedure (MP) is defined in [9] as a set of rules, which translate data from a fishery into a regulatory mechanism (such as total allowable catches or maximum fishing effort). According to [20], such MPs have been developed (though not always implemented) for a number of fisheries since their development within the International Whaling Commission in the late 1980s.

Management Strategy Evaluation aims at evaluating the performance of management strategies against various objectives [9, 10, 20, 23, 33, 44]. Typically, sustainability objectives consist in maximizing catches while at the same time maximizing industrial stability and limiting biological risks [23]. Risk is usually defined as the probability to fall under a given stock threshold. When comparing alternative Management Procedures, preference goes to smaller risk to the resource, lower variation in TAC over time, and higher average catches [20]. However, these general objectives are usually in conflict, inducing necessary trade-offs. The performance of various management procedures may then be represented in a map of "mean catch – risk to the resource" [47], providing a description of the basic trade-offs to the decision-maker.

For example, following the lead of [8] and [9], Yepes et al. [51] performed a Management Strategy Evaluation of the Chilean Jack-Mackerel fishery. Several strategies were evaluated and represented as points defined by two outcomes – risk to the resource and expected mean annual catches – in a graphic with two axis as in Fig. 1. Risk to the resource was defined as the probability of falling below 20% of the virginal spawning stock biomass over the planning horizon. Average annual catch level was a proxy variable for the economic objective.[9]

"Ideal" management strategies would lie on the South-East part of the map, displaying low risk to the resource and high mean catches. It is, however, not possible to rank the various management procedures from such a graphical representation as there is no "common currency" to aggregate the two objectives (in economic terms, we can say that there is no value func-

[9]Usually, a regulator observes prices, but fishing costs are private information, depending on vessels' specific factors. Profit functions cannot be estimated, unless strong hypotheses are made on fleet homogeneity. Therefore, in practice, the usual approach is to use catches as a proxy for revenue and effort as a proxy for costs.

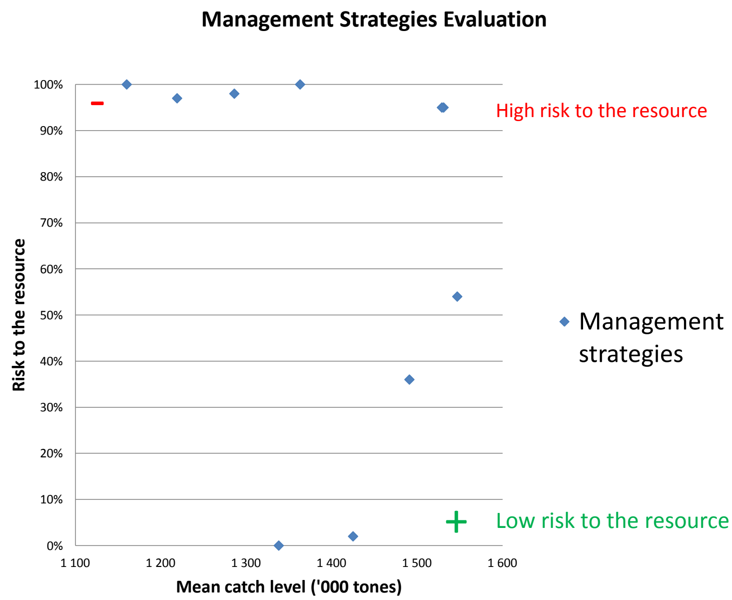

Figure 1: Strategies outcomes. Adapted from [51].

tion). One objective is a mean value (an aggregation of value over time and over uncertainty scenarios) while the other is a probability to overshoot a given ecological threshold. The decision-maker should thus have preferences over value and risk, while the usual approach is to define preferences on value and to aggregate risk by computing the expectation of value.[10] Value and

[10]Though in economic theory we know some types of Utility functions, such as Constant Absolute Risk Aversion (CARA) functions, by means of which a decision maker's preferences about value and risk can be represented in a rather simple way, for instance by means of a linear function of both expected (mean) profits and a simple proxy of risk such as the variance of profits [25, pp. 567 and 713], in policy-making practice it will be hardly feasible to gather proper evidence for assessing the validity of a particular functional form for describing decision makers' preferences, and even more so when there are stakeholders with heterogeneous preferences. Thus, in the face of this complexity, the typical MSE

risk are mixed in a way which is unusual in economics. Moreover, the MSE approach provides no information on the opportunity cost of the constraint, and the marginal gains from relaxing its level (as would optimization under constraint do in the deterministic case).

From our point of view, the limits of this MSE approach, and more generally of the approaches based on optimization under constraints in the stochastic case, come from the fact that the elements of the system that have a value are not treated in a similar way (as it would be the case in a multi-attribute utility function).

The present paper focuses on the assessment of resource management strategies, and formally addresses the issue of sustainable dynamic decision-making under uncertainty, in a multicriteria framework accounting for possibly conflicting issues. Our objective is to compute the likeliness of management strategies to avoiding crises in a fishery. For this purpose, we use the stochastic viability approach. Viability has been advocated to be a relevant framework to address sustainability issues. In the absence of uncertainty, problems of dynamic control under constraints refer to viability [2].[11] Under uncertainty, stochastic viability aims at defining the probability to satisfy these constraints over time [4, 16].

The main ideas consist in the following conceptual and methodological points. Sustainability objectives are defined by constraints on indicators which should be satisfied at all times. Management strategies are evaluated with respect to their probability of success in satisfying the constraints over time. This probability is used as a common currency to evaluate and rank alternative policies (management strategies). In the discounted profit

approach finally "mixes" value and risk in rather ad-hoc ways.

[11]This approach has been applied to sustainable management of fisheries, e.g., in [6, 7, 18, 21, 35].

approach, the common currency is the expected present value. In our approach, the common currency is the probability to achieve all the objectives over time. This probability is also used as a sustainability metrics to exhibit the necessary trade-offs between sustainability objectives and risk. In particular, this allows us to clearly describe the interactions between stock dynamics, sustainability objectives and management strategies, which is emphasized as important by [33]. This is made possible by the fact that our approach treats all the elements of the system that have a value in a similar way, as constraints. Preferences are characterized by the sustainability thresholds, and the objective is to maximize the probability to achieve the sustainability constraints.

As the described framework provides tools to define optimality, value and marginal value, we argue that stochastic viability is a multicriteria framework which is closer to the economic approach than the usual multicriteria approaches such as MSE. In particular, the stochastic viability approach makes it possible to characterize "sustainability" production possibility frontiers that could be the basis of social choice or bargaining process over the various sustainability issues [34].

3 A risk metrics for sustainability objectives

In this section, we describe the theoretical framework proposed to assess resource management strategies. This framework defines optimal viable management strategies under uncertainty, and makes it possible to compare the effectiveness of given (sub-optimal) management strategies. This framework also displays the necessary trade-offs between sustainability objectives.

3.1 Management strategy assessment by stochastic viability

Here, we formalize the decision problem and describe the technical development. The general model and method below are appropriate for setting up any stochastic viability analysis. We provide examples based on the case-study to be addressed in next section.

Dynamical system

We start with a resource harvesting model, which accounts for the dynamics, the uncertainties and the exploitation decisions. For this, let us consider the following discrete-time control dynamical system

$$x(t+1) = G\big(t, x(t), u(t), \omega(t)\big) , \quad t = t_0, \ldots, T-1 , \quad x(t_0) = x_0 , \qquad (1)$$

where

- the *time* index t is discrete, belonging to $\mathbb{T} = \{t_0, \ldots, T\} \subset \mathbb{N}$; the time period $[t, t+1[$ is a year for instance; t_0 is the initial time ; T is the horizon, taken finite here;
- the *state* $x(t)$ is a vector belonging to $\mathbb{X} \subset \mathbb{R}^n$; $x(t) \in \mathbb{R}^n$ may be a vector of abundances at ages for one or for several species;[12]
- the *control* $u(t) \in \mathbb{U} \subset \mathbb{R}^p$ may represent catches or harvesting effort;
- $\omega(t) \in \mathbb{W} \subset \mathbb{R}^q$ denotes an *uncertainty* which affects the dynamics at time t; this may include recruitment or mortality uncertainties in a population dynamic model, climate fluctuations or trends, unknown technical progress, or price uncertainty;

[12]Note that the state vector can also represent abundances at different spatial patches, or include capital stocks (boats or infrastructures) or labor.

- $G : \mathbb{T} \times \mathbb{X} \times \mathbb{U} \times \mathbb{W} \to \mathbb{X}$ 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.

Uncertainty and scenarios

In what follows, the initial state x_0 is supposed to be deterministic and known. 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 for a scenario being

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

Trajectories

The notation $u(\cdot)$ means a *control trajectory*

$$u(\cdot) := \big(u(t_0), \ldots, u(T-1)\big) \tag{4}$$

whereas

$$x(\cdot) = \big(x(t_0), \ldots, x(T-1), x(T)\big) \tag{5}$$

stands for a *state trajectory*.[13]

[13]There is one more state than control because, by (1), there is a final state $x(T)$ produced by an ultimate control $u(T-1)$.

Decision rules and management strategies

When uncertainties affect the dynamics, *closed loop* or *feedback* controls $u(t) = \widehat{u}\big(t, x(t)\big)$ taking the uncertain state evolution $x(t)$ into account display more adaptive properties than open-loop controls $u(t)$ depending only on time. A *(state) feedback* is a mapping $\widehat{u} : \mathbb{T} \times \mathbb{X} \to \mathbb{U}$. A feedback is a *decision rule* which assigns a control $u = \widehat{u}(t, x) \in \mathbb{U}$ to any state x for any time t.[14] From now on, we shall use the term *(management) strategies* to refer to feedback decision rules.

Sustainability objectives described with indicators and thresholds

Consider K real-valued functions[15] $\mathcal{I}_k : \mathbb{T}\times\mathbb{X}\times\mathbb{U} \to \mathbb{R}$, for $k = 1, \ldots, K$, that represent instantaneous *indicators*, having economic or ecological meaning (e.g., profit, annual catches, or spawning stock biomass). Attached to them are thresholds (reference points) $\tau_1 \in \mathbb{R}, \ldots, \tau_K \in \mathbb{R}$, measured in the same unit (e.g., money, tonnes). Sustainability objectives are represented by constraints[16]

$$\mathcal{I}_k\big(t, x(t), u(t)\big) \geq \tau_k \ , \quad \forall k = 1, \ldots, K \ , \quad \forall t = t_0, \ldots, T \ . \tag{6}$$

We aim at identifying bio-economic trajectories $\big(x(\cdot), u(\cdot)\big)$ solutions of (1) and satisfying all the constraints $k = 1, \ldots, K$ at all times $t = t_0, \ldots, T$. For this purpose, we adopt the *viability approach.* A trajectory that does not satisfy one (or more) of the constraints at some time is not viable. In

[14] 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 and/or partial observation of the state is available to the decision-maker.

[15] In fact, at final time T, the indicator $\mathcal{I}_k(T, x, u)$ does not depend on u because, as noticed, there is a final state $x(T)$ but the ultimate control is $u(T-1)$.

[16] We consider sustainability "goods," for which an ad-hoc indicator is defined. This indicator is then constrained to be above a prescribed thresholds. For "bads," such as pollution, one can take their negative value as an indicator (e.g., for CO_2 concentration).

the viability approach, *once the sustainability thresholds are chosen*, there are trade-offs neither between sustainability issues nor between time periods (as it would be the case with discounted utility). At a given time period, the violation of some of the sustainability constraints cannot be compensated by good outcomes in other sustainability dimensions. The violation of the sustainability constraints at some time periods cannot be compensated by good outcomes at other time periods. The requirement to satisfy all the constraints at all times thus reflects the idea that sustainability has to encompass ecological and economic issues, in an intergenerational equity perspective. This approach echoes the "stewardship" approach to sustainability, as discussed in the Stern review [48].

All trade-offs are made when the thresholds are defined [34]. Moreover, in a stochastic framework, the constraints may be violated with some probability. It is thus important to define how to achieve given constraints with a high probability, as well as to describe the trade-offs between sustainability objectives and the risk to fail achieving them.

Viability probability of a management strategy

In an uncertain framework, it is generally impossible to satisfy the constraints for all scenarios $\omega(\cdot)$. Following [16, 19], we adapt the viability approach to the stochastic case, and evaluate strategies.

For any management strategy $\widehat{u}$, initial state x_0, and initial time t_0, let us define the set of *viable scenarios* by:

$$\Omega_{\widehat{u},t_0,x_0} := \left\{ \omega(\cdot) \in \Omega \;\middle|\; \begin{array}{l} x(t_0) = x_0 \\ x(t+1) = G\big(t, x(t), u(t), \omega(t)\big) \\ u(t) = \widehat{u}\big(t, x(t)\big) \\ \mathcal{I}_k\big(t, x(t), u(t)\big) \geq \tau_k \\ k = 1, \ldots, K \\ t = t_0, \ldots, T \end{array} \right\} . \qquad (7)$$

For a given strategy $\widehat{u}$ and a given scenario $\omega(\cdot)$, notice that the dynamics (1) produces a state trajectory $x(\cdot)$ and a control trajectory $u(\cdot)$ once one applies the strategy $u(t) = \widehat{u}(t, x(t))$. Therefore, any viable scenario $\omega(\cdot)$ in $\Omega_{\widehat{u},t_0,x_0}$ is such that the state and control trajectory $\big(x(\cdot), u(\cdot)\big)$ driven by the strategy $\widehat{u}$ satisfies the constraints (6).

A management strategy $\widehat{u}$ is "more viable" 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 of scenarios is equipped with a *probability distribution* $\mathbb{P}$.[17] The notation $\omega(\cdot) = \big(\omega(t_0), \ldots, \omega(T)\big)$ 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 $\big(\omega(t_0), \ldots, \omega(T-1)\big)$ are independent and identically distributed, which defines the probability $\mathbb{P}$, or that they form a Markov chain, or a time series.

We say that $\mathbb{P}[\Omega_{\widehat{u},t_0,x_0}]$ is the *viability probability* associated with the management strategy $\widehat{u}$, the initial time t_0, and the initial state x_0. It is the probability that a sequence of random variables $\big(\omega(t_0), \ldots, \omega(T-1)\big)$ belongs to the set of viable scenarios of the given strategy $\widehat{u}$. This probability is a measure of the likeliness of success of the given strategy for these objectives

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

and the initial state.[18]

3.2 A "value function" for strategies and thresholds

In the stochastic viability framework described above, management strategies can be ranked with respect to their viability probability, for any given set of sustainability thresholds $\tau_1, \ldots, \tau_K$.

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

$$\Pi(\widehat{u}, \tau_1, \ldots, \tau_K) := \mathbb{P}\left\{ \omega(\cdot) \in \Omega \;\middle|\; \begin{array}{l} x(t_0) = x_0 \\ x(t+1) = G\big(t, x(t), u(t), \omega(t)\big) \\ u(t) = \widehat{u}\big(t, x(t)\big) \\ \mathcal{I}_k\big(t, x(t), u(t)\big) \geq \tau_k \\ k = 1, \ldots, K \\ t = t_0, \ldots, T \end{array} \right\} . \quad (8)$$

This viability probability is a common currency to evaluate the consistency of strategies and sustainability objectives. The higher this probability, the lower the risk of violating the sustainability constraints.

[18] From a theoretical point of view, it is possible to determine the strategy that maximizes the viability probability by solving the dynamic programming equation characterizing the viability problem [17], and one can obtain a closed-form solution for some problems (see subsection 3.3). It may, however, be difficult to compute the associated viability probability. From a practical point of view, for a given strategy (the optimal one, or any sub-optimal strategy) it is possible to estimate the viability probability by means of Monte Carlo simulations. A random generator is used to produce scenarios following the distribution $\mathbb{P}$. For each scenario, the given management strategy is applied, and we test if the viability constraints in (7) are respected over the planning horizon. When this is true, we say that the viable scenario is viable for the management strategy. When the number of scenario tested is large, the frequency of viable scenarios can be used as an approximation of viability probability.

When the viability probability function $\Pi(\widehat{u}, \tau_1, \dots, \tau_K)$ smoothly varies w.r.t. thresholds levels (as will generally be the case when the probability distribution $\mathbb{P}$ has a smooth density), the marginal variation of viability probability with respect to the threshold level τ_k is $\frac{\partial}{\partial \tau_k}\Pi(\widehat{u}, \tau_1, \dots, \tau_K)$.

The viability probability provides a tool for

- ranking management strategies with respect to their ability to achieve a set of sustainability objectives represented by constraints on sustainability indicators which have to be satisfied over time,
- evaluating the difficulty of achieving a given objective, with a measure of the marginal value of increasing it.

Note that all the objectives are accounted in their own unit, and that the common currency of the approach is the probability that all the objectives are satisfied over the planing horizon.

Exhibiting trade-offs between objectives

Suppose now that we fix a confidence level $\pi \in [0, 1]$ and that we focus on threshold levels $\tau_1, \dots, \tau_K$ which make it possible to achieve $\Pi(\widehat{u}, \tau_1, \dots, \tau_K) = \pi$. The *marginal rate of substitution* between thresholds τ_i and τ_j is defined by

$$\frac{\partial \Pi(\widehat{u}, \tau_1, \dots, \tau_K)/\partial \tau_i}{\partial \Pi(\widehat{u}, \tau_1, \dots, \tau_K)/\partial \tau_j} = \frac{\partial \tau_j}{\partial \tau_i}_{|\Pi(\widehat{u}, \tau_1, \dots, \tau_K) = \pi} \tag{9}$$

Along an iso-value viability probability curve, this rate measures the necessary trade-offs between sustainability objectives, at a given risk level, i.e., how much one objective must be reduced to increase the other without changing the viability probability.

3.3 Optimal management strategy

In our approach, a management strategy is preferred if it results in a higher viability probability. We define an *optimal strategy* $\widehat{u}^{\star}$ as one which maximizes the viability probability $\Pi(\widehat{u}, \tau_1, \ldots, \tau_K)$ for a given set of economic and ecological sustainability thresholds $\tau_1, \ldots, \tau_K$ over all possible strategies $\widehat{u}$. The *maximal viability probability*

$$\max_{\widehat{u}} \Pi(\widehat{u}, \tau_1, \ldots, \tau_K)$$

is an upper bound for any strategy. Notice that optimal strategies depend on the objective levels $\tau_1, \ldots, \tau_K$.

From a general point of view, determining optimal strategies in dynamical optimization problems under uncertainty is not easy, either for optimal control or for stochastic viability problems. Such strategies are given by a Dynamic Programming equation, but the curse of dimensionality is an obstacle [17]. In specific cases, it is possible to characterize such strategies when the bioeconomic system satisfies some restrictive, but sensible, conditions. For this purpose, we refer to the mathematical result in [19]. We shall here extend the interpretation of the result in [19] to the fisheries management issue. In particular, we interpret the conditions in economic and ecological terms, and we provide an interpretation of the optimal management strategy.

Consider a fishery model, with a dynamics G which is increasing with the state x, i.e., the larger the stock one year (*ceteris paribus*), the larger the stock the following year, as well as decreasing with the control u, i.e., the larger the effort one year (*ceteris paribus*), the lower the stock the following year. Consider also that the control u is scalar and belongs to a closed interval $\mathbb{U} := [u^{\flat}, u^{\sharp}]$.[19]

[19]These assumptions make sense for single species management (or for several species

Consider that the sustainability objectives satisfy the following monotonicity properties.

- One of the indicator is increasing with the state x (i.e., the higher the state, the higher the indicator) and continuous in the control u. This indicator can be considered as "economic."

- The other indicators $\mathcal{I}_2, \ldots, \mathcal{I}_k$ are increasing with the state x (i.e., the higher the state, the higher the indicator), and decreasing with the control u (i.e., the higher the control, the lower the indicator). These indicators, favoring high stocks and low effort, can be considered as "ecological" indicators.

Under these conditions, the mathematical result of Proposition 1 in [19] applies. An optimal strategy for $\max_{\widehat{u}} \Pi(\widehat{u}, \tau_1, \ldots, \tau_K)$ is given by

$$\widehat{u}^{\star}(t,x) := \inf\{u \in [u^{\flat}, u^{\sharp}] \mid \mathcal{I}_1(t,x,u) \geq \tau_1\} \ . \tag{10}$$

In our fishery issue, this management strategy maximizing the viability probability can be interpreted as a "precautionary rule" in the following sense. It consists in maximizing the escapement level, given the satisfaction of the economic objective, e.g., a guaranteed profit for the fishery. Once the economic threshold is reached, harvesting stops. This strategy ensures the satisfaction of the economic objective at present time while maximizing the probability to achieve the economic and ecological objectives in the future.[20]

with economic interactions but no biological interactions), when the recruitment of next year only depends on the current spawning stock biomass. They do not hold for models with several species with biological interactions (such as prey-predator models).

[20]Note that, for many fisheries, the ICES management strategy is based on the somehow opposite strategy: the catch level is set at the highest level compatible with the biological conservation target *at the following year*, given a confidence interval (precautionary fishing mortality value) [18, 33]. By nature, this strategy leads the stock close to the ecological

3.4 Sub-optimal strategies ranking

When it is not possible to identify an optimal strategy (for example, because it cannot be computed), it is of interest to compare given strategies. While we recognize the pitfalls of making such comparisons with an *ad hoc* reduced number of management strategies, our present aim is simply to compare the properties of various in-use policies. This could be useful to support decision-making when given strategies are discussed by stake-holders.

Within our framework, a given strategy performs better than another one for given sustainability thresholds $\tau_1, \ldots, \tau_K$ if its viability probability is larger. The viability probability of the strategies provides a metrics to rank them. Moreover, it is possible to define on which range of sustainability thresholds one strategy performs better than the other in terms of viability probability. Letting sustainability thresholds vary, we can obtain regions where one strategy performs better than the other one.

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

4 A case-study: the Chilean Jack-Mackerel fishery

The Jack-Mackerel fishery is currently the largest in Chile, both in terms of annual catch volume (about 1.5 million tons in 2008, while it peaked at 4.5 million tons in 1995) and economic value generation (US$ 400-500 millions of yearly sales in recent years). Like other small pelagic fisheries, this fishery

constraint, with a risk of fishery closure in the short-medium term if the stock falls below the biological conservation threshold. The strategy presented in this section is conservative and results in keeping the resource stock as "far" as possible from the biological threshold, given the economic objective.

is faced with the recurrent appearance of *El Niño* uncertain cycles. This fishery has been one of the pioneers in Chile in terms of including explicitly biology-related risk indicators within its management strategies. However, this has been mostly done in a very ad-hoc way, using risk indicators as additional information within the policy-decision process, but lacking a formally integrated framework to make choices between risk to the resource and economic return indicators. For instance, in a technical report of SUBPESCA,[21] which is the regulatory body for Chilean fisheries, exogenously defined quota levels are associated with the resulting probabilities of reducing the spawning stock biomass (SSB) available at a future year (2013), relative to its level at year 2004. In [31, p.33-39], such calculations are extended to different time horizons. Nonetheless, none of these analyses include a formal framework for making trade-offs between risk indicators and measures of economic return.

4.1 Bioeconomic model

Biology

We describe the dynamics of the Chilean jack mackerel[22] stock by an age-class model [42, 49] with a Ricker recruitment function.[23]

Time is measured in years, and the time index $t \in \mathbb{T}$ represents the beginning of year t. Let $A = 12$ denote the maximum age group, and $a \in \{1, \dots, A\}$ an age class index, all expressed in years. The vector $N = (N_a)_{a=1,\dots,A} \in \mathbb{R}_+^A$ is made of *abundances* at age: for $a = 1, \dots, A-1$, $N_a(t)$ is the number of individuals of age between $a-1$ and a at the beginning of

[21] Subsecretaria de Pesca, Valparaíso - Chile, SUBPESCA (2004) Cuota Global Anual de Captura de Jurel, Año 2005, p. 26-27.

[22] Computational details, data, and parameters are described in the Appendix.

[23] The Ricker model is frequently used for species with highly fluctuating recruitment, involving high fecundity as well as high natural mortality rates [5]. These two features characterize small pelagic species, such as jack mackerel.

year t; $N_A(t)$ is the number of individuals of age greater than $A-1$.

A dynamics of the form of eq. (1) is detailed in the Appendix (eqs. 19–21–22). The state vector ($A+1$-dimensional) is

$$x(t) = \big(N_1(t), \dots, N_A(t), SSB\big(N(t-1)\big)\big) \ , \tag{11}$$

where the spawning stock biomass (SSB) is defined in the Appendix (eq. 21). The fishing activity is represented by a *fishing effort multiplier* $\lambda(t)$, supposed to be applied continuously during the period t, with the notations of subsection 3.1. The control is thus

$$u(t) = \lambda(t) \ . \tag{12}$$

In what follows, we shall take the initial year $t_0 = 2002$.

Total annual catches Y, measured in million tons, are given by the Baranov catch equation (20) in the appendix.

El Niño cycles model

The *El Niño* phenomenon is the result of a wide and complex system of climatic fluctuations between the ocean and the atmosphere. Nowadays, it is considered to be an important signal of the global weather. However, its frequency and intensity are uncertain.

We simulate the *El Niño* uncertain cycles using a model with a periodic part and an error term, to produce a cycle with random shocks. Details can be found in the Appendix.

Economics

We make the following economic assumptions, which are standard ([11, 12, 43]).

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

- Per unit harvest costs (either in numéraire 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. 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.

For fisheries satisfying these micro-economic assumptions, price and costs do not have a qualitative effect on our results. As quotas are defined in quantity terms in practice, it makes sense to eliminate price and fishing costs from the profit expression, and to concentrate on harvest quantity and fishing effort as proxy of revenue and fishing costs. This assumption is the same as in [12], [43] and [45], in which the expected discounted sum of harvest is maximized instead of the expected discounted sum 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. This implies that there is an upper value for the fishing effort.

4.2 Viability assessment of constant quota and constant effort management strategies

Use the stochastic viability approach, we compare management strategies for the Chilean jack mackerel fishery. We focus on two different types of strategies: constant quota and constant fishing effort[24] both stationary over a fixed period of time ($T = 22$ years). For these classes of strategies, we compute their viability probability associated to two constraints, biological and economical.

Economic and biological constraints

On the one hand, we consider an *economic constraint* on the annual yield

$$Y(N(t), \lambda(t)) \geq y_{\min} , \quad \forall t = t_0, t_0 + 1, ..., T , \tag{13}$$

where the parameter $y_{\min}$ is a minimum level of landings (or annual total catches) to be guaranteed each year. This parameter takes values from 0.7–1.4 million tons, corresponding to relevant catch levels observed in this fishery all along the 2000s. Using the notation of §3.1 and §4.1, the constraint (13) corresponds to the following indicator and threshold:

$$I_2(t, x, u) := Y\big(N, \lambda\big) \text{ and } \tau_2 := y_{\min} . \tag{14}$$

On the other hand, we consider the *biological constraint* on the spawning stock biomass *SSB*

$$\frac{SSB\big(N(t)\big)}{SSB_{\text{virg}}} \geq p , \quad \forall t = t_0, t_0 + 1, ..., T , \tag{15}$$

[24] There are two reasons why we consider these two managements strategies. First, they correspond to policies that have been historically used to regulate this fishery. Second, discussing these strategies will allow us to refer to the "price versus quantity" debate in fisheries economics (see subsection 4.3).

where $SSB_{\text{virg}} = 10.2$ million tons is the *virginal spawning stock biomass* of the fishery, based on Chilean research fishery state institute (IFOP)'s estimations. The parameter p denotes the desired percentage of SSB_{virg} expected to be preserved over time. In our analysis, parameter p takes values from 0.15 to 0.25, which means that $SSB(N(t))$ should be above the values of 15% to 25% of the virginal spawning stock biomass, respectively.[25] Using the notation of §3.1 and §4.1, the constraint (15) corresponds to the following indicator and threshold:

$$I_1(t, x(t), u(t)) := \frac{SSB\big(N(t)\big)}{SSB_{\text{virg}}} \text{ and } \tau_1 := p \, . \tag{16}$$

Viability assessment of constant quota and constant effort strategies

We consider two class of strategies, based respectively on constant efforts and constant quotas.

A *constant effort strategy* (CES) is a constant strategy defined by

$$\widehat{\lambda}(t, N) = \overline{\lambda} \, , \tag{17}$$

yielding the constant effort[26] $\lambda(t) = \overline{\lambda}$.

A *constant quota strategy* (CQS) is a strategy implicitly defined by

$$\widehat{\lambda}(t, N) = \lambda \iff Y\big(N, \lambda\big) = \overline{Y} \, , \tag{18}$$

when possible (else $\widehat{\lambda}(t, N) = 0$).

[25]In the case of South African small pelagic fisheries (sardines and anchovies) in the late 1980s and early 1990s, the fishery regulators considered $p = 0.2$ when applying such biological criteria [8].

[26]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.

We define, within each class of management strategy, the 'optimal' level of the policy instrument for a given set of economic and biological thresholds, i.e., the level which results in the highest viability probability (best constant quota, or best constant effort, to achieve the given sustainability thresholds).

For each couple $(p, y_{\min}) \in [0.15, 0.25] \times [0.7, 1.4]$ of biological and economic thresholds, we compute the highest viability probability for each type of strategy. The viability probability is approximated by a frequency given by Monte Carlo simulations, and we compute a 95% confidence interval at which the viability probability belongs. We obtain two 3D graphics (one for each type of strategies) as can be seen in Fig. 2.

Both graphics in Fig. 2 are a representation of the "value" of the strategy as a function of the sustainability thresholds (see eq. 8). For any given couple of sustainability thresholds, one can rank the alternative management strategies using their viability probability. This is useful to identify circumstances under which each strategy is likely to perform better than the other. Fig. 3 exhibits the strategy with the best viability probability for each couple $(p, y_{\min}) \in [0.15, 0.25] \times [0.7, 1.4]$ of biological and economic thresholds. We represent the domains, in terms of sustainability thresholds, where one strategy strictly performs better than the other, that is the domain at which the confidence interval for one type of strategy lies strictly above the confidence interval for the other strategy. The best policy type is identified by a specific color: the light gray 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 black area has exactly the opposite meaning, and the intermediary dark gray area identifies the threshold levels at which the performance of both policy types cannot be statistically distinguished (that is, where the confidence intervals cross). Interestingly, Fig. 3 depicts pairs of thresholds at which a given type of strategy strictly dominates (in the sense of maximizing the viability probability) over the other

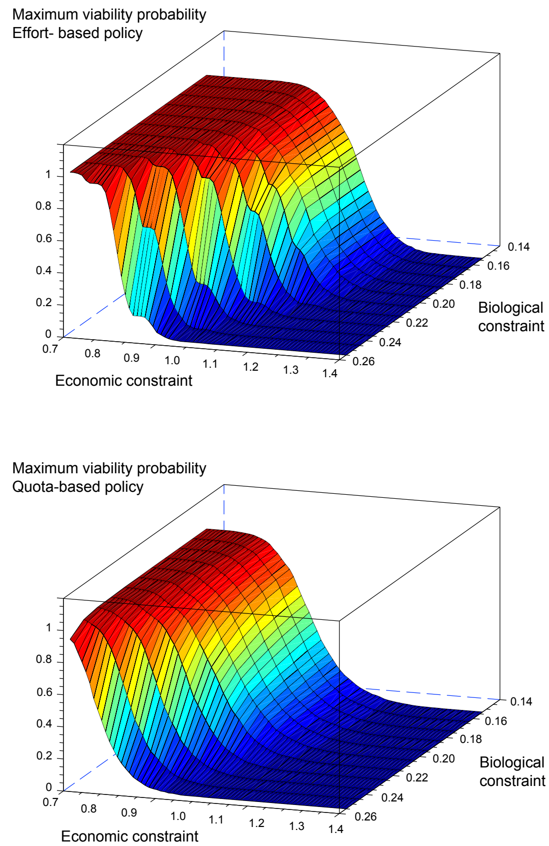

Figure 2: Maximal viability probability of effort (up) and quota (bottom) strategies (1,000 Monte-Carlo simulations).

type of strategy. It is thus helpful to select sustainability objectives, and the best strategy to achieve them. Our simulations show that CES performs better than CQS for all thresholds achievable with a viability probability larger than 0.1.

Such graphical representations may be useful in the choice of sustainability objectives, by exhibiting the necessary trade-offs between the policy objectives represented by the sustainability thresholds [34], along with the consideration of the related risk to fail. The trade-offs between thresholds

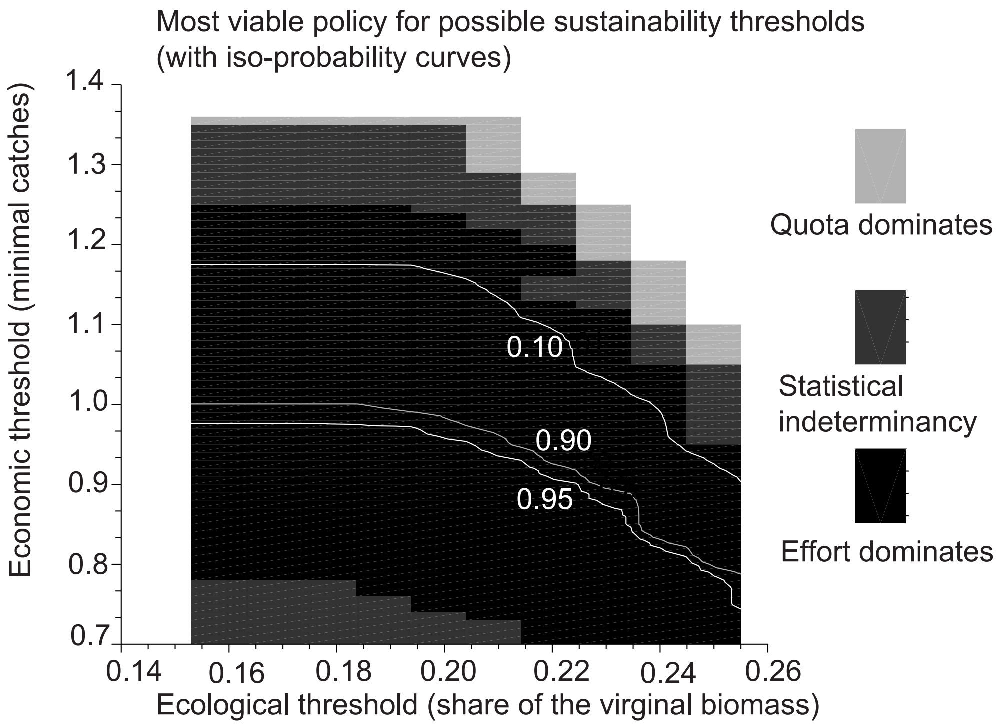

Figure 3: Comparison of the CES and CQS policy families (1,000 Monte Carlo's simulations).

for a given risk level (eq. 9) can be obtained by determining the thresholds achievable at the given risk level. We have plotted lines denoting the iso-probabilities at a level of 95%, 90% and 10% in Fig. 3. The thresholds $(p, y_{\min})$ below a given line are guaranteed with a viability probability no lower than the corresponding percentage. Note that these trade-offs are between sustainability objectives, and not between different management strategies.

4.3 Economic interpretation: a particular case of "prices versus quantities"

We can interpret the previous result on the dominance of effort over quotas strategies in the context of the economic debate on "prices versus quantities" in fisheries economics. Weitzman [50] examined analytically the regulatory issue of instrument choice when future fish stock is uncertain. He noticed that

> the conventional wisdom among fisheries economists is that, for regulating the fishing industry, "prices" are an instrument inferior to "quantities." The argument is grounded [...] on the idea that regulating fisheries with price is less efficient than regulating with quantities - in part because of the potential problems associated with highly uncertain randomly fluctuating fish stocks. [50, p.326]

First note that a management strategy using direct control of fishing effort has similar features as tax based management [15, 50]. By imposing a maximal fishing effort, one imposes a maximal marginal cost, which interrupts the fishing period before the open access equilibrium. When the stock level is uncertain and considering a given catch level (or expected one), setting a constant effort implies uncertainty on catches, and thus on revenue, while the costs are certain. On the contrary, setting a constant quota yields a certain revenue but uncertain costs. Depending on the shape of revenue and cost functions, the expected profit of the two strategies is different [27]. Under usual economic conditions, when the revenue function is linear in the catches and the cost function convex (which is the case when the catch rate depends on the size of the stock), the constant effort strategy dominates the constant quota strategy in terms of expected profit [41]. When present catches affect future availability of the resource, constant effort strategy reduces the risk of under-utilization of capital and over-exploitation of the stock. Nevertheless, when catches per unit of effort are also stochastic, constant quota strategies may be superior to constant effort strategies [15]. Management with quotas is also superior when considering market effects (when the prices depend on the landed quantities, with a low demand elasticity), when utility is defined as the sum of industrial profit and consumer's surplus [15, 27], or for some specific fisheries (schooling fisheries without search costs) [26, 28, 32].

In the spirit of these results, we analyze the relative performance of either fishing effort or quota regulation tools when the purpose of the regulator is not to maximize expected profit, but to sustain the fishery by avoiding both economic and biological crises. In our model of the Chilean Jack-Mackerel fishery, and for sustainability objectives achievable with a viability probability higher than 10%, our simulations show that effort strategies are never dominated by quota strategies.[27] Our results mean that effort strategies dominate quota strategies for elastic markets and catches depending on the stock size when one considers sustainable management, with economic and ecological objectives. The stochastic viability results and the economic results of [27, 41, 50] give the same recommendations for this type of fisheries.

As for the results of the previously described economic literature, our result is not general to any stochastic viability analysis of a fishery facing uncertainty. Moreover, the instrument yielding the highest viability probability may depend on both the properties of the bio-economic system, and on the nature and level of the viability constraints. From a general point of view, as for the economic approach, the optimal strategy in the stochastic viability framework may not correspond to a "simple rule" (constant quota

[27]Quota strategies only dominate effort strategies for very high sustainability thresholds, which can be guaranteed with only a probability close to zero (i.e., much less than 0.1). Note also that for thresholds achievable with a viability probability very close to one, both strategies cannot be formally ranked due to imprecision (confidence intervals).

or effort), and these "second-best" instruments have to be compared for each case under study.

5 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 multicriteria evaluation methods to rank the potential management strategies, taking into account uncertainty. This is the purpose of the Management Strategy Evaluation approach, which characterizes potential management strategies 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 without tools to rank the various management strategies.

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, and treating the constraint thresholds as variable parameters. 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 strategy is one that results in the highest viability probability. The "common currency" to rank the various management decisions is the viability probability.

This approach treats all the elements of the system that have a value in the same way, as constraints. Preferences are characterized by the sustainability thresholds, and the objective is to maximize the probability to achieve the sustainability constraints. This approach is an alternative to the traditional economic approach when it is not possible to define a multi-attribute utility function. It is also a good representation of decision problems involving several stake-holders that do not accept trade-offs between (sustainability) issues, and are interested in the sustained level of their indicator.

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.

Our approach is an attempt to define a consistent sustainable management analysis, in a multicriteria framework, with an application to fisheries. The results we present are based on a case-study, with estimated parameters. While these results are derived using numerical techniques, the proposed stochastic viability methodology is general and can be applied to a wide range of problems. As an example, we examine the efficiency of two kinds of fishery management policies, namely constant fishing effort and quota, to achieve sustainability objectives defined as constraints on biological and economic indicators. Monte Carlo simulations are run to obtain estimates of the viability probability of each policy, with respect to the objectives.

The contribution of the paper is twofold. On the one hand, we develop a framework which provides a common currency to compare management strategies and to describe trade-offs between sustainability objectives, in a complementary way to the MSE approach. On the other hand, we contribute to the economic literature on the dominance of either quotas or effort strategies. We reinforce the results obtained in the expected profit framework to a multi-criteria framework accounting for the conservation issue. The method can thus be used to fill the gap between the optimality literature of economic theory and practical decision-making.

A Chilean Jack-Mackerel case study: data, parameters and model

This appendix details the model in §4.1. The model is age-structured, with a Ricker stock-recruitment function. For age groups $a = 2, \ldots, A-1$, abundance dynamics is given by

$$N_{a+1}(t+1) = \exp\left(-(M_a + \lambda(t)F_a)\right)N_a(t) \ , \quad a = 2, \ldots, A-1 \ , \tag{19}$$

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*).

Total annual catches Y, measured in million tons, are given by the *Baranov catch equation* [42, p. 255-256]:

$$Y\big(N, \lambda\big) = \sum_{a=1}^{A} \varpi_a \frac{\lambda F_a}{\lambda F_a + M_a} \left(1 - \exp\left(-(M_a + \lambda F_a)\right)\right) N_a \ , \tag{20}$$

where $(\varpi_a)_{a=1,\ldots,A}$ are the *weights* at age.

The *spawning stock biomass* (SSB) is given by the expression

$$\mathit{SSB}(N) := \sum_{a=1}^{A} \gamma_a \varpi_a N_a \ , \tag{21}$$

where $(\gamma_a)_{a=1,\ldots,A}$ are the *proportions of mature individuals* (some may be zero). Annual recruitment is a function of the SSB with a two years delay, i.e., depending on the spawning stock biomass of two periods ago:

$$N_1(t+1) = \alpha \mathit{SSB}\big(N(t-1)\big) \exp\left(\beta \mathit{SSB}\big(N(t-1)\big) + w(t)\right) \ , \tag{22}$$

where $\{w(t)\}$ is a random process reflecting the impact of climatic factors in the stock recruitment relationship. Following the statistical analysis in

[51], we simulate *El Niño* uncertain cycles using a sinusoidal function with random shocks.[28] The random process $w(t)$ supposed to capture the effects of the *El Niño* phenomenon has a periodic part and an error term, $w(t) = -0.12 \times \text{niño}(t) + \epsilon(t)$, where

- the error terms $\{\epsilon(t)\}$ are defined as $\epsilon(t) = 0.71\epsilon(t-1) - 0.65\epsilon(t-2) + \mu(t)$, where $\{\mu(t)\}$ is a sequence of i.i.d. random variables with Normal distribution $\mathcal{N}(0; 0.18)$,

- $\text{niño}(t) = \mathbf{1}_{\{-1.2\sin(18.19+2\pi(t-1951)/3.17)>0.5\}}$ is a *dummy (0 or 1) variable* reflecting the presence of *El Niño* phenomenon.

We use the parameters estimation provided by [51], which rely on official data from the *Instituto de Fomento Pesquero* (IFOP).[29] Parameters of the Ricker recruitment function at expression (22) were estimated by using linear time-series analysis. The estimated parameters were $\alpha = e^{2.39}$ and $\beta = 2.2 \cdot 10^{-7}$ [see 51, p. 56]. 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 is equal to the vector of averages values of F_a during 2001-2002.[30]

[28]Based on Chilean marine biologists advice, the authors of [51] calculated the occurrence of *El Niño* phenomenon from the *National Oceanic and Atmospheric Administration (NOAA)* data on sea surface temperatures measured at the region known as *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 estimated via statistical methods (using a non-linear iterative algorithm [51, p. 64]), to represent the different cycles of *El Niño*.

[29]Subsecretaria de Pesca, Valparaíso - Chile, SUBPESCA (2000) Cuota Global de Captura para la Pesquería del Recurso Jurel, Año 2001; and Instituto de Fomento Pesquero, Valparaíso - Chile, IFOP (2003) Informe Complementario Investigación CTP Jurel, 2003: Indicadores de Reclutamiento.

[30]See Subsecretaria de Pesca, Valparaíso - Chile, SUBPESCA (2006) Pre Informe Final.

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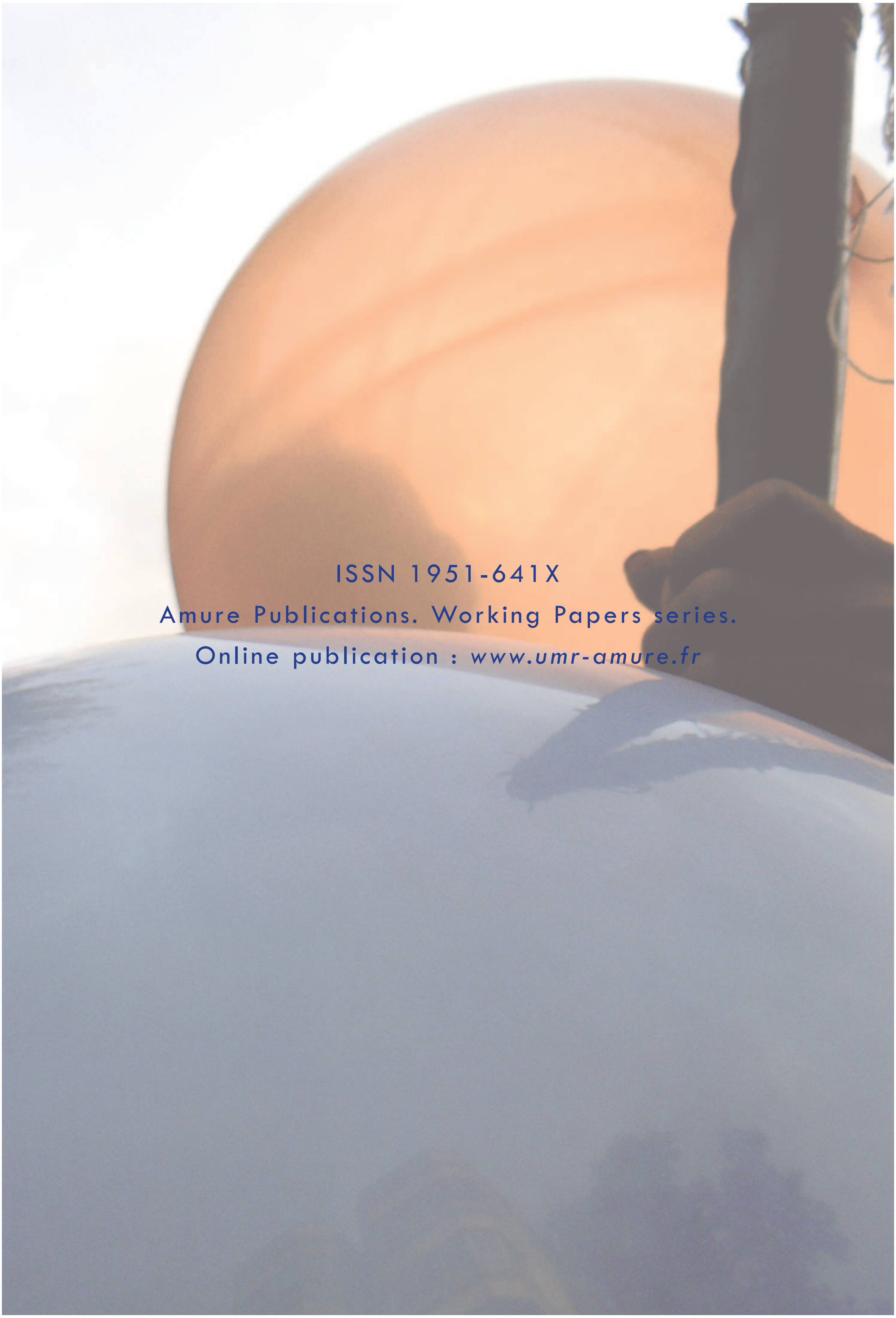

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