Risk and Sustainability: Assessing Fisheries Management Strategies

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Abstract

We develop a theoretical framework to assess the sustainability of fisheries management strategies, when the bioeconomic dynamics are marked by uncertainty and several conflicting objectives have to be accounted for. Stochastic viability ranks management strategies according to their probability to sustain economic and ecological outcomes over time. The approach is extended to build stochastic sustainable production possibility frontiers representing the trade-offs between sustainability objectives at any risk level, given the current state of the fishery. This framework is applied to a Chilean fishery faced with *El Niño* uncertainty. We study the viability of effort and quota strategies when catch and biomass levels have to be sustained. We show that i) for these sustainability objectives, whatever the level of the outcomes to be sustained, quota-based management results in a better viability probability than effort-based management, and that ii) the historical quota levels in the fishery were not sustainable.

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

1 Introduction

The analysis in this paper has its origin in some actual concerns in the management of Chilean fisheries. The Jack-Mackerel fishery is faced with *El Niño* uncertain cycles, which increase the uncertainty about the resource availability (Barber and Chavez, 1983), making management more difficult (Costello et al., 1998).[1] In addition to the usual objective of maximizing profit, current management aims at avoiding stock collapse. *Sustainable* resource management requires a framework accounting for economic and ecological objectives under risk.

The standard economic approach to assessing the performance of fisheries management strategies relies on the expected discounted utility framework (Clark and Kirkwood, 1986; Reed, 1979; Sethi et al., 2005). This approach has the great advantage of defining a unique value, the expected discounted utility of harvesting, which characterizes optimal strategies and ranks alternative management strategies. It has, however, some practical limits when applied to sustainable resource management issues encompassing several dimensions and the concern for intergenerational equity. First, accounting for ecological objectives requires defining a multi-attribute Social Welfare Function (SWF) *prior to the maximization problem*. But when uncertainties are pervasive and the sustainability issues are affecting multiple and heterogeneous stakeholders, the task of agreeing on a common SWF could become very tangling. Second, the discounted utility framework would allow for intertemporal compensation of good and bad outcomes for the system, which may raise intergenerational equity issues (in particular if the discount rate is positive).

In practice, fisheries management strategies, often defined as simple "rules of thumb," are evaluated in so-called "multicriteria" frameworks (Geromont et al., 1999; De Oliveira and Butterworth, 2004; Kell et al., 2005; Smith et al., 2007). Such methods are based on simulations and do not rely on an optimization framework. They provide no common metrics for conflicting (ecological and economic) objectives and risk. Therefore they cannot rank explicitly alternative management strategies. There is thus a gap between theory and practice in resource management. Developing

[1] In some extreme cases, recruitment uncertainty and applied management decisions have led to the collapse of important small pelagic stocks, such as the Peruvian anchovy in 1972-1973.

a practical framework based on solid theoretical grounds to assess the sustainability of fisheries management strategies under risk is a challenging task.

This paper provides a framework to rank explicitly alternative management strategies, accounting for conflicting sustainability issues and risk. This framework echoes the concept of stewardship,[2] which defines a sustainable resource management as one that *sustains economic and ecological outcomes over time*, corresponding to a “satisficing” objective *à la* Simon (1957). Technically, we build on the stochastic viability approach (De Lara and Doyen, 2008). Given a set of multidimensional indicators, referring to economic or ecological outcomes, viability is defined as the ability to sustain the levels of the indicators above some thresholds characterizing sustainability objectives (e.g., minimal biomass, minimal profit). We assess fisheries management strategies by their probability of achieving these objectives jointly and at all times over the planning horizon.

While stochastic viability has been used as a *simulation tool* to examine fisheries management issues (e.g., Doyen et al., 2012), the present paper differs from previous studies in two important respects, each constituting theoretical novelties. First, we embed stochastic viability into a *theoretical optimization framework* with economic interpretations, defining a value function for our optimization problem. This value measures the ability to sustain several outcomes over time. Second, whereas the thresholds of the viability constraints are exogenously fixed parameters in usual viability analysis, we treat these sustainability thresholds as explicit arguments of our value function. This allows us to define and build *stochastic sustainable production possibility frontiers* which describe the necessary trade-offs between sustained levels of economic and ecological outcomes and risk. Such possibility sets depend on the current (over)exploitation status of the fishery.

Our framework does not rely on an *a priori* representation of social preferences, but can be used to help revealing such preferences. Defining the actual sustainabilty thresholds amounts to determining what has to be sustained over time (Martinet, 2012). This is a social choice problem we do not address explicitly here. It corresponds to a generalized, multidimentional maximin problem (Solow, 1974; Martinet,

[2]As discussed in the Stern review for climatic change (Stern, 2006).

2011), with low substitutability between sustainability issues and a strong aversion to intertemporal inequality on all the dimensions of sustainability. Stochastic sustainable production possibility frontiers can be used to enlighten the social choice of sustainability objectives in the fishery, and reveal social preferences over sustainability issues.

These theoretical novelties allow us to build a bridge between the economic literature on optimal resource management under risk and the practical-oriented literature on sustainable fisheries management. The viability probability provides a common metrics to aggregate the outcomes of the system with respect to the several sustainability dimensions, ranking alternative management strategies. Marginal analysis makes it possible to examine the trade-offs between sustained outcomes and risk. This stochastic viability approach is thus closer to economics than the usual multi-criteria fishery management approaches. It can be implemented when no SWF is available.

We illustrate the implications of our approach in the case of the (small pelagic) Chilean Jack-Mackerel fishery subject to *El Niño* uncertainty. In particular, we compare effort-based (price-like) and quota-based (quantity-like) strategies in light of their ability to sustain both catch and biomass levels over time, given the current information on the resource stock. While the price versus quantity issue in fisheries have been extensively debated from an economic point of view, our analysis is, to our knowledge, the first attempt to examine this issue from a sustainable management perspective.

Section 2 stresses the differences between the literature in fishery economics and that on fisheries management to motivate our approach. Section 3 presents our theoretical framework to assess risk and sustainability and to compare management strategies. We apply this framework to the Chilean Jack-Mackerel fishery case-study in Section 4. We conclude with 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 expected discounted profit of harvest. Depending on the type of uncertainty and economic specifications, optimal harvesting may correspond to very specific management strategies and be hard to apply in practice.[3] Moreover, in a sustainability context, management objectives are often not limited to profit maximization. Ecosystem-Based Fishery Management aims at conserving resources and sustaining socio-economic benefits from fishing (Cochrane, 2000; Pikkitch et al., 2004). This increases the number of objectives and stakeholders (Fletcher, 2005) so that fisheries are faced with an unsustainable situation whenever one objective is not met. Giving the priority to social and economic objectives over ecological ones has been identified as an important reason for management failure in fisheries (Hilborn, 2007). *Management procedures*[4] should be ranked according to their capacity to yield acceptable results with respect to all the sustainability objectives while being robust to uncertainties (Charles, 1998).

Extending the economic optimization approach to account for ecological objectives is a delicate exercise. In theory, one could define a multi-attribute SWF characterizing completely social preferences over the various dimensions of interest prior to the optimization problem. Stakeholders, however, may not want to, or may be unable to agree on a SWF, a form of "collective" bounded rationality resulting in the impossibility to define a continuous representation of preferences over payoffs on various dimensions and risks. An alternative option would be to add ecological

[3]See Reed (1979); Clark and Kirkwood (1986); Sethi et al. (2005); Nøstbakken and Conrad (2007); Nøstbakken (2008); McCough et al. (2009). When responding to uncertain stock fluctuations, optimality may require strong yearly variations of the TAC, pulse-fishing (Da-Rocha et al., 2013), and even fishery closure when the stock size is too low (Nøstbakken, 2006), whereas fishing industries favor stability of catches (Charles, 1998).

[4]A *management procedure* (MP) is a set of rules which translates data from a fishery into a regulatory mechanism, such as total allowable catches or maximum fishing effort (Butterworth et al., 1997). 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 (De Oliveira and Butterworth, 2004).

constraints to the profit maximization problem. Note that setting the levels of these constraints is a social choice problem which should not be overlooked. In the deterministic case, the optimization problem provides the marginal cost of complying with the constraint. This information can be used in a back-and-forth process with stakeholders to adjust the constraints level and help revealing preferences over the economic and ecological outcomes. This feature is lost in the stochastic case,[5] in which a theoretical and technical issue rises: How to interpret and to handle constraints under uncertainty? One can "translate" the deterministic economic criterion into its expected value, but it is more difficult to "translate" a constraint in stochastic terms. Requiring constraint satisfaction with probability one, i.e., that the optimal strategy satisfies the constraint in all possible states of the world, usually restricts the decisions so much that the optimization problem loses its interest. Accepting a risk of constraint violation is another possibility. It amounts to considering the performance of the system with respect to the ecological constraint, by providing a measure of the risk to violate it. There are then two outcomes for each strategy: the expected economic profit and the ecological risk.

In fact, this last option is close to the *Management Strategy Evaluation* (MSE) approach.[6] MSE relies on simulations to compare the performance of given management strategies against the conflicting objectives of limiting risk to the resource, reducing TAC variation over time, and increasing average catches. The results are usually represented graphically, in a map of "mean catch – risk to the resource" (see, e.g., Smith et al., 2007). Fig. 1 displays such an output for the Chilean Jack-Mackerel fishery (MSE performed by Yepes, 2004). "Ideal" management strategies would display low risk to the resource and high mean catches, and thus lie on the South-East part of the figure. As there is no common metrics between the objectives, the two performances cannot be aggregated and undominated strategies cannot be ranked.[7]

[5] We shall see that our framework provides a somehow similar information to support the choice of sustainability constraints in the stochastic case.

[6] Various scientific tools, mainly in "multicriteria" frameworks, have been developed to support sustainable fisheries management (Smith et al., 2007). *Management Strategy Evaluation* is the most developed one (Butterworth et al., 1997; Charles, 1998; Geromont et al., 1999; Sainsbury et al., 2000; De Oliveira and Butterworth, 2004; Kell et al., 2005).

[7] Moreover, the MSE approach provides no information on the opportunity cost of the ecological

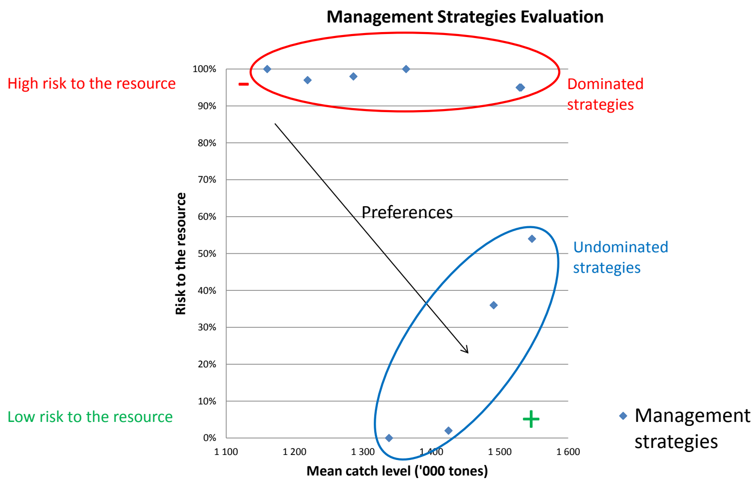

Figure 1: MSE for the Chilean Jack Mackerel fishery: performance of various management strategies in terms of risk to the resource (measured as the probability that the stock falls below 20% of the pre-exploitation spawning stock biomass) and expected mean annual catches (used as a proxy variable for the economic objective). Adapted from Yepes (2004).

The problem mainly comes from the fact that the economic and ecological objectives are not treated in the same way, one being an outcome to maximize while the other is a constraint to satisfy. The usual approach to account for risk in economics is to define preferences characterizing value (i.e., to aggregate economic and ecological outcomes in a SWF) and to account for risk by computing the expectation of value.[8] The MSE approach compares an expected economic value with an ecological risk (probability to overshoot a given ecological threshold). The ecological objective is defined apart form the economic value, which makes it difficult to aggregate the two outcomes.

Assessing the sustainability of resource management strategies under risk is thus a challenge when there is no SWF describing preferences over the different issues.

constraint and about the marginal gains from relaxing its level.

[8]For some types of utility functions, e.g., Constant Absolute Risk Aversion functions, preferences under risk may be represented by means of a linear function of expected (mean) profits and a simple proxy of risk such as the variance of profits.

To tackle this challenge, we describe a theoretical framework echoing the concept of stewardship. We assume that intertemporal equity requires sustaining economic and ecological performances of the system over time. These conditions can be represented by constraints on (ecological and economic) indicators which should be maintained above some thresholds at all times. This issue is addressed within the stochastic viability framework, which defines the (maximal) probability of satisfying jointly several viability constraints over time in dynamic uncertain models. Any management strategy satisfies the viability constraints with some probability. This *viability probability* provides a common metrics to assess and rank alternative strategies.

This approach treats all the relevant sustainability objectives as minimal outcomes to be sustained over time. Treating the viability thresholds as arguments of a the stochastic viability value function, we build stochastic sustainable production possibility frontiers, which exhibit the necessary trade-offs between the targeted sustained outcomes and risk. Such frontiers can be used in the social choice of defining sustainability objectives.

3 A metrics for risk and sustainability

Let us formalize the decision problem in a general framework. The model and method below are appropriate for setting up any stochastic viability analysis, and therefore can be applied to a variety of resource management situations or to environmental problems with stocks of pollutants. We provide examples based on the fishery case.

3.1 Modeling framework

Dynamical system Consider a resource harvesting model, which accounts for dynamics, uncertainties and exploitation decisions. The model is described by the following discrete-time control dynamical system

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

where

- the *time* index t is discrete, belonging to $\mathbb{T} = \{t_0, \dots, T\} \subset \mathbb{N}$; the time period $[t, t+1[$ is a year for instance; t_0 is the initial time ; T is the finite horizon;

- the *state* vector $x(t) \in \mathbb{X} \subset \mathbb{R}^n$ may be a vector of abundances at ages for one or for several species; the state vector could also represent abundances at different spatial patches or include capital stocks (e.g., fishing vessels);

- the *control* vector $c(t) \in \mathbb{C} \subset \mathbb{R}^p$ may represent catches or harvesting effort;

- $\omega(t) \in \mathbb{W} \subset \mathbb{R}^q$ denotes a vector of *uncertainty* which affects the dynamics at time t (e.g., recruitment or mortality uncertainties in a population dynamic model, climate fluctuations or trends, unknown technical progress, price uncertainty);

- $G : \mathbb{T} \times \mathbb{X} \times \mathbb{C} \times \mathbb{W} \to \mathbb{X}$ 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 given *initial state* for the *initial time* t_0. It is supposed to be known.

The notation $c(\cdot)$ means a *control trajectory* $c(\cdot) = \big(c(t_0), \dots, c(T)\big)$ whereas $x(\cdot) = \big(x(t_0), \dots, x(T)\big)$ stands for a *state trajectory.*

Probability distributions over scenarios A *scenario* is a sequence of uncertainty vectors denoted by $\omega(\cdot) = (\omega(t_0), \dots, \omega(T-1))$. We define the set of all possible scenarios as

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

We assume that the set of scenarios Ω is equipped with a *probability distribution* $\mathbb{P}$.[9] Formally, this probability $\mathbb{P}$ could either be an objective probability derived from a statistical model using real world data (as done in our case study in next section), or a subjective probability representing decision-makers' beliefs.

[9] Technically, the probability $\mathbb{P}$ is defined over the Borel σ-algebra of Ω. In what follows, we assume proper measurability assumptions for all the functions we consider.

Decision rules and management strategies When uncertainties affect the dynamics, *closed loop* or *feedback* controls $\widehat{c}\big(t, x(t)\big)$ taking the uncertain state evolution $x(t)$ into account display more adaptive properties than open-loop controls $c(t)$ depending only on time. A *(state) feedback* is a *decision rule* which assigns a control $c = \widehat{c}(t, x) \in \mathbb{C}$ to any state x for any time t. From now on, we shall use the term *(management) strategies* to refer to feedback decision rules. The set of all possible strategies is denoted by $\mathcal{C}$.

3.2 Stochastic Viability

Sustainability objectives described with indicators and thresholds Consider K real-valued functions $\mathcal{I}_k : \mathbb{T} \times \mathbb{X} \times \mathbb{C} \to \mathbb{R}$, for $k = 1, \ldots, K$, which represent instantaneous *indicators* having economic or ecological meaning (e.g., profit, annual catches, or spawning stock biomass). Thresholds $\tau_1 \in \mathbb{R}, \ldots, \tau_K \in \mathbb{R}$, measured in the same unit as the indicators (e.g., money, tonnes) define constraints formalizing sustainability objectives:[10]

$$\mathcal{I}_k\big(t, x(t), c(t)\big) \geq \tau_k \ , \quad \forall k = 1, \ldots, K \ , \quad \forall t = t_0, \ldots, T \ . \tag{3}$$

In the viability framework, a trajectory that does not satisfy one (or more) of the constraints at some time is not viable. At a given time period, the violation of some of the sustainability constraints is not compensated by good outcomes in other sustainability dimensions. The violation of the sustainability constraints at some time periods is not compensated by good outcomes at other time periods.[11] The requirement to satisfy all the constraints at all times reflects the idea that sustainability has to encompass ecological and economic issues in an intergenerational equity perspective.

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

[11] *For given sustainability thresholds*, there are trade-offs neither between sustainability issues nor between time periods. All trade-offs are made when the thresholds are defined (Martinet, 2011, 2012). We shall emphasize how our framework can be used to support the definition of threshold.

In a stochastic framework, it is generally impossible to satisfy the constraints for all scenarios $\omega(\cdot)$. We coin *viable scenarios* the uncertainty scenarios for which all the viability constraints are satisfied at all times under a given strategy.

Viable scenarios associated with a management strategy For any management strategy $\widehat{c}$, initial state x_0, and initial time t_0, we define the set of *viable scenarios* by:

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

For a given strategy $\widehat{c}$ and a given scenario $\omega(\cdot)$, the dynamics (1) produces a state trajectory $x(\cdot)$ and a control trajectory $c(\cdot)$ once one applies the strategy $c(t) = \widehat{c}(t, x(t))$. Therefore, any viable scenario $\omega(\cdot)$ in $\Omega_{\widehat{c},t_0,x_0}$ is such that the state and control trajectory $\big(x(\cdot), c(\cdot)\big)$ driven by the strategy $\widehat{c}$ satisfies the constraints (3).

In the ideal case where there exists a strategy $\widehat{c}$ such that $\Omega_{\widehat{c},t_0,x_0}$ coincides with Ω, viability can be achieved for all scenarios by applying this strategy. When this is not the case, as Ω is equipped with a probability $\mathbb{P}$, we can measure the likeliness of a strategy $\widehat{c}$ to meet the objectives by the probability of associated viable scenarios, $\mathbb{P}\left[\Omega_{\widehat{c},t_0,x_0}\right]$, which is called the *viability probability* associated with the management strategy $\widehat{c}$, the initial time t_0, and the initial state x_0.

Management strategy assessment by stochastic viability For any given set of sustainability thresholds $\tau_1, \ldots, \tau_K$, a management strategy can be assessed by its viability probability. To stress the dependency upon thresholds, let us introduce the notation

$$\Pi(\widehat{c}, \boldsymbol{\tau_1, \ldots, \tau_K}) = \mathbb{P} \left\{ \omega(\cdot) \in \Omega \;\middle|\; \begin{array}{l} x(t_0) = x_0 \\ x(t+1) = G\big(t, x(t), c(t), \omega(t)\big) \\ c(t) = \widehat{c}\big(t, x(t)\big) \\ \mathcal{I}_k\big(t, x(t), c(t)\big) \geq \boldsymbol{\tau_k} \;,\; k = 1, \ldots, K \\ t = t_0, \ldots, T \end{array} \right\} . \tag{5}$$

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

Note that, as for expected discounted utility, the stochastic viability analysis depends on the probability distribution $\mathbb{P}$. In particular, as we deal with intertemporal issues, one should be cautious with how $\mathbb{P}$ captures temporal dependencies between uncertainties (e.g., independent random variables, Markov chains or time series). Studying how the results are sensitive to the probability distribution is beyond the reaches of this paper.

Ranking of management strategies The stochastic viability approach ranks strategies according to their viability probability. A management strategy $\widehat{c}$ is "more viable" than another if the corresponding set of viable scenarios has a higher probability. A *most viable strategy* $\widehat{c}^{\star}(\tau_1, \ldots, \tau_K)$ is one which maximizes the viability probability $\Pi(\widehat{c}, \tau_1, \ldots, \tau_K)$ for a given set of sustainability thresholds $\tau_1, \ldots, \tau_K$ over all possible strategies $\widehat{c} \in \mathcal{C}$.

3.3 Theoretical extension of the stochastic viability framework

This paper is novel in that we treat the viability thresholds as arguments of the viability probability. This defines a value function for our sustainability problem.

A "value function" for sustained outcomes The *maximal viability probability*

$$\Pi^{\star}(\tau_1, \ldots, \tau_K) = \max_{\widehat{c} \in \mathcal{C}} \Pi(\widehat{c}, \tau_1, \ldots, \tau_K) \tag{6}$$

is the highest probability with which objectives $(\tau_1, \ldots, \tau_K)$ can be sustained. It is the value function of the stochastic viability optimization problem. This value function depends on the thresholds levels. We use this value function to describe the trade-offs among sustainability objectives.

Stochastic sustainable production possibility frontiers When the maximal viability probability function $\Pi^\star(\tau_1, \ldots, \tau_K)$ 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 $\frac{\partial}{\partial \tau_k}\Pi^\star(\tau_1, \ldots, \tau_K)$. This represents the marginal cost, in terms of viability probability, of increasing this constraint's level. It provides an information on the difficulty to sustain the corresponding outcome over time, given the other sustainability objectives.

The value function (6) can be used to build stochastic sustainable production possibility frontiers exhibiting the trade-offs between sustained levels of outcomes and viability probability. In particular, for any confidence level $\pi \in [0, 1]$, it is possible to define the threshold levels $\tau_1, \ldots, \tau_K$ which make it possible to achieve $\Pi^\star(\tau_1, \ldots, \tau_K) = \pi$. The *marginal rate of substitution* between thresholds τ_i and τ_j is then defined by

$$\frac{\partial \Pi^\star(\tau_1, \ldots, \tau_K)/\partial \tau_i}{\partial \Pi^\star(\tau_1, \ldots, \tau_K)/\partial \tau_j} = \frac{\partial \tau_j}{\partial \tau_i}_{|\Pi^\star(\tau_1,\ldots,\tau_K)=\pi} \tag{7}$$

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.

Suboptimal cases Our framework can be used even when it is not possible to identify an optimal strategy (for example, because it cannot be computed). In a second-best setting, it is possible to consider subsets of strategies $\tilde{\mathcal{C}} \subset \mathcal{C}$ and define the associated (sub-optimal) viability probability:

$$\tilde{\Pi}(\tau_1, \ldots, \tau_K) = \max_{\widehat{c} \in \tilde{\mathcal{C}}} \Pi(\widehat{c}, \tau_1, \ldots, \tau_K) \tag{8}$$

While we recognize the pitfalls of making such comparisons with an *ad hoc* reduced number of management strategies, this provides an analytical tool for comparing and ranking realistic management strategies according to a well-defined yardstick, that is, based on the corresponding viability probability. This ranking exercise could be useful to support decision-making when given strategies having management relevance (e.g., effort-based or quota-based strategies) are discussed by stakeholders.

The viability probability of the strategies then provides a metrics to rank them. In particular, letting sustainability thresholds vary, it is possible to define on which range of sustainability thresholds levels one type of strategies performs better than another.

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

We model the Chilean Jack-Mackerel fishery and use it as a case-study to apply the stochastic viability approach, and in particular the theoretical extensions described in the previous section.

4.1 Description of the fishery and management issues

The Jack-Mackerel fishery has been the largest in Chile for many years, both in terms of annual catch and economic value.[12] Like other small pelagic stocks, this fishery is faced with the recurrent appearance of *El Niño* uncertain cycles. Since the late 1990s, the fishery has been managed under a yearly-defined Total Allowable Catch (TAC) and closed entry, with a particular concern about the stability of catch levels over time. Additionally, since the mid-2000s the Jack-Mackerel fishery has been one of the pioneering in Chile to include biology-related risk indicators in its management practice.[13] These indicators provide additional information within the policy-decision process, with the underlying objective of capping biological (collapse) risk, but are not encompassed in a formal framework to trade off this risk against measures of economic return. Despite the management procedure, the Chilean Jack-Mackerel fishery is currently facing a crisis.

Historical data for the fishery are provided in the Appendix, Table 1. Year 2002

[12] Annual catch peaked at 4.4 million tons in 1995. Until recent years, value generation has been around US$ 400 millions of yearly sales.

[13] SUBPESCA, the regulatory body for Chilean fisheries, started assessing the probabilities of reducing the spawning stock biomass (SSB), relative to a historical base level, for various exogenously defined quota levels (see SUBPESCA (2004, p. 26-27) and IFOP (2006, p. 33-39)).

appears to be a turning point for two reasons: i) the biomass levels were half its peak in the late 1980s and recruitment was half its levels in the previous 5 years,[14] ii) the fish stock's spatial distribution changed (Peña Torres et al., 2014), partly moving the stock outside the Chile's EEZ, which triggered a re-opening of an international-waters jack mackerel fishery (see column (2) in Table 1).

In spite of the changes in the biology of the stock and its exploitation pattern after 2002, the Chilean fisheries regulator decided to keep basically constant TAC levels for the Chilean fleet targeting jack mackerel within and beyond the Chilean EEZ, all along the first decade of the 2000s (see column (3) in Table 1). The biomass level started a monotonic decline, from 48% of the *virginal Spawning Stock Biomass* (SSB_{virg})[15] in 2002 down to 16% in 2012. The management strategy changed only in 2011, when the TAC fell by 76% between 2010 and 2011, from 1,300 to 315 ktons, and was about 250 k-tons in 2013.

The period 2002–2011 is thus of particular interest for this fishery. It covers 10 years of management, which is the management horizon used by IFOP. It starts with a change in the biology of the stock, and ends with a collapse of the fishery and a change of the management strategy. We model this period, taking 2002 as the initial year for our simulations, with a 10 years horizon.

Our modeling exercise has two objectives. First, we assess the sustainability of some management strategies and compare these strategies to the historical evolution of the fishery. Second, we build the stochastic sustainable production possibility frontiers for the fishery given the 2002 stock. This allows us to determine what were the levels of sustainable outcomes given the stock at the beginning of the modeling period.

[14] This was probably related to lagged effects from the very strong 1997/98 El Niño event (Peña Torres et al., 2007, 2014).

[15] The Chilean fishery research institute (IFOP) estimated this parameter at $SSB_{\text{virg}} = 14.3$ million tons. They use the maximum recorded SSB in this fishery (during year 1988) as a proxy.

4.2 Bioeconomic model[16]

Biology: We describe the dynamics of the Chilean Jack-Mackerel stock by an age-class model (Quinn and Deriso, 1999; Tahvonen, 2009) with a Ricker recruitment function.[17] Time is measured in years. Initial year is $t_0 = 2002$ and the final horizon is $T = 2011$. The time index $t = t_0, t_0 + 1, \ldots, T$ 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 $A - 1$.

A dynamics of the form of eq. (1) is detailed in the Appendix (eqs. 11, 13 and 14). The state vector ($A + 1$-dimensional) is $x(t) = \big(N_1(t), \ldots, N_A(t), \mathit{SSB}\big(N(t-1)\big)\big)$, where the spawning stock biomass (SSB) is defined by eq. (13). The fishing activity is represented by a *fishing effort multiplier* $\lambda(t)$, supposed to be applied continuously during the period t. The control is thus $c(t) = \lambda(t)$. Total annual catches Y, measured in million tons, are given by the Baranov catch equation (eq. 12).

***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, which 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 (Reed, 1979; Clark and Kirkwood, 1986; Clark, 1990).

(a1) Demand is infinitely elastic. Indeed, harvest from this fishery is mainly processed as fish meal, a commodity faced with high demand substitution. This

[16] Data, parameters and computational details are described in the Appendix.

[17] The Ricker model is frequently used for species with highly fluctuating recruitment, involving high fecundity as well as high natural mortality rates (Begon and Mortimer, 1986). These two features characterize small pelagic species, such as Jack-Mackerel.

fishery is thus essentially a price-taking industry, and we assume that any unit harvested is sold for a fixed price, invariant in time.

(a2) Per unit harvest costs 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 assuming that fishing effort has a constant unit cost, and that Catches Per Unit of Effort (CPUE) decrease when the stock decreases.

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. We assume that no extra fishing effort is done once the marginal profit is nil. This implies that there is an upper bound for fishing effort.

For fisheries satisfying these assumptions, price and cost levels do not have a qualitative effect on our results. Usually, a regulator observes prices, but fishing costs are private information, depending on vessels' specific factors. Profit functions are thus very difficult to estimate, unless strong assumptions are made on fleet homogeneity. Therefore, in practice, the usual approach is to use catches as a proxy for revenue and fishing effort related variables as proxy for costs. As quotas are defined in quantity terms in practice, it is reasonable to focus on harvest quantity and fishing effort as proxy of revenue and fishing costs. This assumption is the same as, for example, in Reed (1979), Clark and Kirkwood (1986) and Sethi et al. (2005), in which the expected discounted sum of harvest is maximized instead of the expected discounted sum of profit.

4.3 Economic and biological sustainability objectives

We consider the *ecological objective* of sustaining the *SSB* above some limit defined as a percentage of SSB_{virg}. This objective is formalized by the constraint

$$\frac{SSB\big(N(t)\big)}{SSB_{\text{virg}}} \geq p \ , \quad \forall t = t_0, t_0+1, ..., T \ , \tag{9}$$

where the threshold p denotes the desired minimum percentage of SSB_{virg} to be preserved over time. In our analysis, $p \in [0.15; 0.25]$, which means that the constraint on the $SSB(N(t))$ varies from 15% to 25% of the virginal SSB.[18] The constraint (9) corresponds to the following indicator and threshold: $\mathcal{I}_1(t, x(t), c(t)) = \frac{SSB\big(N(t)\big)}{SSB_{\text{virg}}}$ and $\tau_1 = p$.

We also consider the *socio-economic objective* of sustaining the annual yield above a level $y_{\min}$:

$$Y(N(t), \lambda(t)) \geq y_{\min} \ , \quad \forall t = t_0, t_0 + 1, ..., T \ . \tag{10}$$

The minimum level of landings to be sustained over time ($y_{\min}$) can take values from $[0; 2]$ million tons, corresponding to relevant catch levels observed in this fishery all along the 2000s. The constraint (10) corresponds to the following indicator and threshold: $\mathcal{I}_2(t, x, c) = Y\big(N, \lambda\big)$ and $\tau_2 = y_{\min}$. This constraint presumes that the fishery regulator aims at keeping a minimum level of fishing activity, possibly due to socioeconomic considerations.

4.4 Viability assessment of management strategies

Using the stochastic viability approach, we compare management strategies for the Chilean Jack-Mackerel fishery.

Even when optimization approaches provide a description of "optimal" management strategies, fisheries are often managed with much simpler tools.[19] Constant fishing 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. The optimal strategy may be neither of these two (Hannesson and Steinshamn, 1991), but these rules of thumb are still frequently discussed as potential management strategies (and sometimes indeed

[18] In the case of South African small pelagic fisheries (sardines and anchovies) in the late 1980s and early 1990s, the fishery regulator considered $p = 0.2$ when applying such biological criteria (Butterworth and Bergh, 1997).

[19] For example, Singh et al. (2006) 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 optimal policy would do it.

used) in some fisheries. Chilean fisheries were *de facto* managed under a constant effort rule in the 1980s and 1990s (frozen maximum effort). Since then, a quota system has been in use, with *a posteriori* very small changes in the TAC levels from year to year. For example, the pursued management strategy for the Jack-Mackerel fishery over the studied period does resemble a constant quota-type of policy (see Table 1).

We thus focus on two different types of strategies: constant fishing effort and constant quota, both stationary over a fixed period of 10 years.

A *constant effort strategy* (CES) is a strategy defined by a constant effort[20] $\lambda(t, N) = \overline{\lambda}$. The set of all possible constant effort strategies is denoted by $\tilde{\mathcal{C}}^E \subset \mathcal{C}$.

A *constant quota strategy* (CQS) is a strategy implicitly defined by a constant quota $\overline{Y}$. The associated fishing effort multiplier $\widehat{\lambda}(t, N)$ is such that $Y\big(N, \widehat{\lambda}(t, N)\big) = \overline{Y}$ when this is possible, i.e., when the corresponding effort level is below the upper bound for fishing effort. If this is not the case, the actual catch level may be lower than the quota. The set of all possible constant quota strategies is denoted by $\tilde{\mathcal{C}}^Q \subset \mathcal{C}$.

For each subset of strategies $\tilde{\mathcal{C}}^E$ and $\tilde{\mathcal{C}}^Q$, we compute the associated maximal viability probability as a function of the two sustainability thresholds: For each couple $(p, y_{\min}) \in [0; 2] \times [0.15; 0.25]$ of economic and ecological thresholds,[21] we define, within each subset of management strategies, the level of the policy instrument which results in the highest viability probability (best constant quota, or best constant effort, to sustain the given objectives). The viability probability is approximated by a frequency given by Monte Carlo simulations (over $1,000$ simulations), and we compute a 95% confidence interval at which the viability probability belongs. These viability probabilities are displayed in Fig. 2. For each strategy (left-hand side panel for constant-effort strategies and right hand-side panel for constant quota strategies), we draw iso-probability curves over the two thresholds, for the levels of maximal viability probability $\{0; 0.1; 0.5; 0.9; 0.99; 1\}$. Both graphics in Fig. 2 are a represen-

[20] In our model, fishing mortality is proportional to fishing effort when the fishing technology is constant. The constant effort strategy is thus identical to the constant fishing mortality strategy depicted here.

[21] Technically, we discretize the intervals.

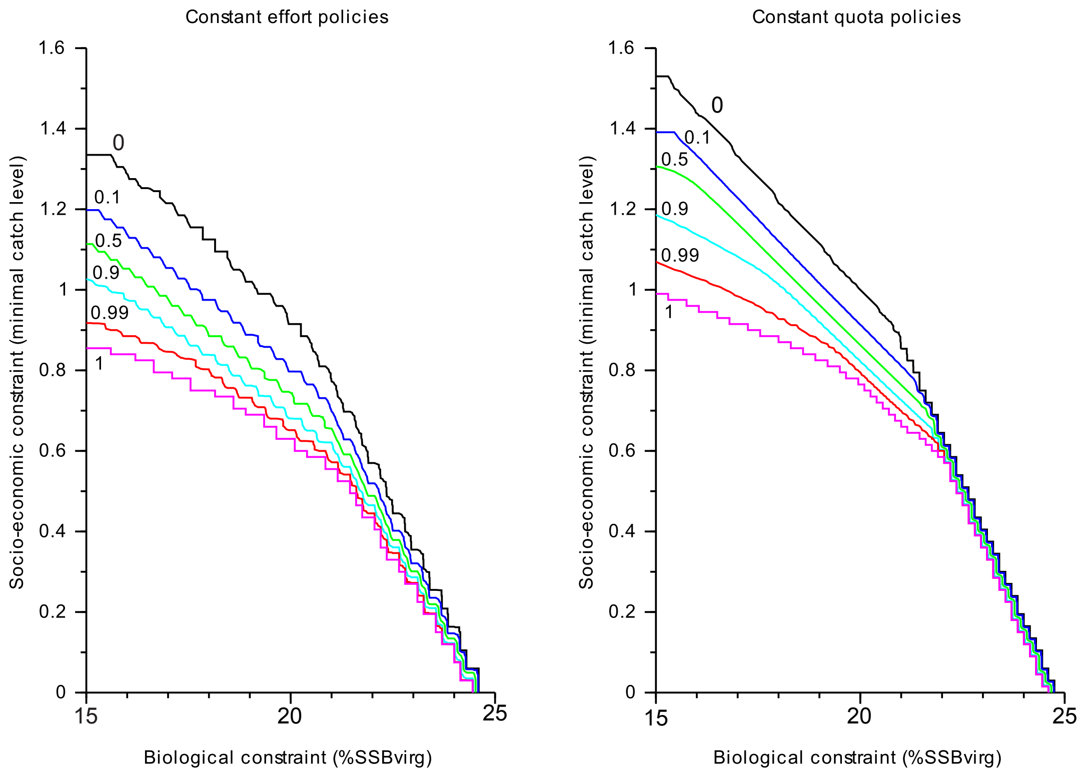

Figure 2: Maximal viability probability of effort and quota strategies (1,000 Monte-Carlo simulations). Isoprobability cirves are drawn for values $\{0; 0.1; 0.5; 0.9; 0.99; 1\}$.

tation of the "stochastic viability value" of each type of strategy as a function of the sustainability thresholds (see eq. 5).

Ranking management strategies For any given couple of sustainability thresholds, one can rank the alternative management strategies using their viability probability. It allows us to identify sustainability objectives for which a strategy is likely to perform better from a viability point of view than the other. To do so, we determine if the confidence interval for the viability probability of one type of strategies lies strictly above the confidence interval for the other strategies. Fig. 3 exhibits the strategies with the highest viability probability for each couple $(p, y_{\min})$ of biological and economic thresholds. The domain, in terms of sustainability thresholds, where constant-quota strategies strictly perform better than constant effort strategies is in black. The gray area corresponds to threshold levels at which the performance of both policy types cannot be statistically distinguished (that is, where the confidence intervals cross). This happens only for viability probabilities close to 1, i.e., for objectives which are easily sustained. The white area corresponds to unsustainable objectives, i.e., thresholds with a viability probability close to zero.

We conclude from this analysis that, for any sustainability objective in the studied range, constant-quota strategies perform better than constant-effort strategies to sustain catches and biomass levels.[22]

This dominance of quota-based strategies over effort-based strategies is not surprising given the nature of the sustainability constraints considered. To explain this, let us refer to the theoretical result of De Lara and Martinet (2009). In a general framework illustrated with an application to fishery, they show that, when the dynamics and the viability constraints satisfy some monotonicity properties, the maximal viability probability is achieved with the feedback rule which maximizes the escapement level given the satisfaction of the viability constraints at the current time. This management strategy can be interpreted as a "precautionary rule." It ensures the satisfaction of the economic objective at present time while maximizing the probability to achieve the economic and ecological objectives in the future.[23] When the economic constraint is a minimal catch level, the rule corresponds to a constant quota at the constraint's level.

As the Ricker recruitment function is non-monotonic, with a declining part for

[22]This results is robust to the initial state of the fishery. We performed a sensitivity analysis for different initial stocks defined as multiples of the 2002 stock (from 60% to 150%). The output of this sensitivity analysis is available on request.

[23]Note that, for many fisheries, the International Council for the Exploration of the Sea (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) (De Lara et al., 2007; Kell et al., 2005). By construction, this strategy leads the stock close to the ecological constraint, with a risk of fishery closure in the short-medium term if the stock falls below the biological conservation threshold. The strategy maximizing the viability probability is conservative and results in keeping the resource stock as "far" as possible from the biological threshold, given the economic objective.

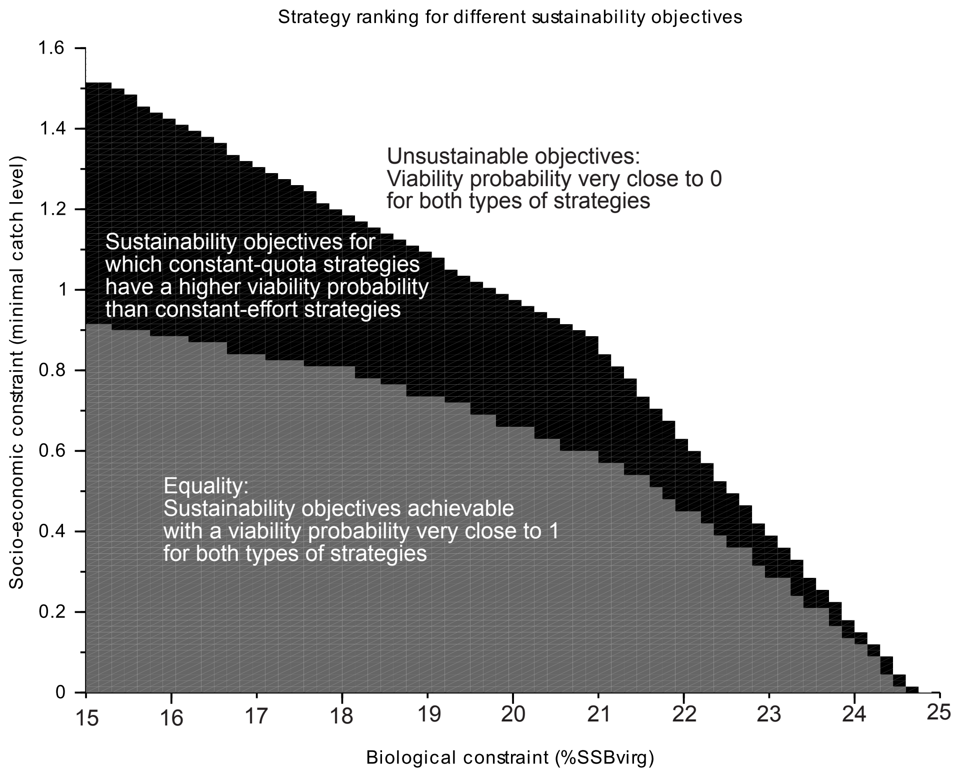

Figure 3: Comparison of the CES and CQS policy types (1,000 Monte Carlo's simulations).

large stocks, the model studied here is not monotonic in the sense of De Lara and Martinet (2009). We have noticed, however, that the range of SSB modeled belongs to the monotonic part of the Ricker function, which means that the model behaves as if it were monotonic. As one of the viability constraint is a minimal catch level, a constant quota at this level results in the highest viability probability.

The issue of determining which of effort-based and quota-based strategies dominates in fisheries economics is a particular case of the "prices versus quantities" debate. A management strategy using direct control of fishing effort has similar features as tax based management (Danielsson, 2002; Weitzman, 2002). By imposing a maximal fishing effort, one imposes a maximal marginal cost, which interrupts the fishing period before the open access equilibrium. Controlling the effort is like having a particular landing fee (such as a very large fee starting at some point). Such fees are (relatively) better able to control the (marginal) fishing effort (or cost), but suffer the drawback of being unable to control catch levels. On the contrary, harvest quotas have the advantage of fixing the total quantity of fish being caught, but suffer from the drawback of being unable to control the possible excessive effort being exerted to fish down a stock that is experiencing a low recruitment for the fishing period. The related literature has shown that, depending on the characteristics of the fishery (i.e., its biological dynamics and economic structure) and the type of uncertainty affecting the model (i.e., whether fish stock and/or economic returns are uncertain), either quota or effort tools may perform better in terms of discounted payoffs (Hannesson and Steinshamn, 1991; Quiggin, 1992; Danielsson, 2002; Jensen and Vestergaard, 2003; Hannesson and Kennedy, 2005; Hansen, 2008). In the stochastic viability framework, the result not only depends on the characteristics of the fishery under study, but also on the nature of the sustainability objectives.

Stochastic sustainable production possibility frontiers Fig. 2 presents what we have defined as stochastic sustainable production possibility frontiers in the theoretical analysis of section 3.3. The lines denoting the iso-probabilities represent the trade-offs between sustainability thresholds $(p, y_{\min})$ at various viability probability levels, as characterized by eq. 7. For any given viability probability level, one has to reduce a sustainability threshold to increase the other. There is also a trade-off between the sustainability threshold and the confidence in sustainability achievement. Increasing the thresholds results in a decrease of viability probability.[24]

Such graphical representations may be useful to support the social choice of sustainability objectives. They exhibit the necessary trade-offs between the policy objectives represented by the sustainability thresholds, along with the risk of failing to (simultaneously) achieve them.[25] When no SWF can be determined prior to the evaluation of management strategies, and there is a strong concern for sustaining eco-

[24]The figure could be made 3-dimensional, with the viability probability as a function of the thresholds, to emphasize these two different trade-offs.

[25]Note that these trade-offs are between sustainability objectives, and not between different management strategies (as it was the case for the MSE of Fig. 1).

logical and economic outcomes over time, presenting the trade-offs over all possible sustainability objectives to stakeholders may help them revealing their preferences.

Discussion We can draw some policy-oriented conclusions from our analysis. The important result is not the dominance of quota over effort strategies, but the representation of the trade-offs between sustainability issues by means of stochastic sustainable production possibility frontiers.

At the early 2000s biomass levels were already experiencing (and almost for a consecutive decade) a worsening status. As a consequence of this, our simulation results report non-viable solutions for any threshold pair with $p \geq 25\%$, either under CQS or CES, whatever the minimum catch threshold.

Over the examined period, the TAC in the fishery has been maintained above 1.3 millions tons. Actual catches did not sustained this level. Notwithstanding the ecological constraint, one can see in Fig. 2 that this catch level is not sustainable with a high probability. Even the best policy among those studied has a low viability probability. This is illustrated with Fig. 4, which compares simulated trajectories for the best constant-quota and constant-effort strategies for sustainability thresholds $(p, y_{\min}) = (0, 1.3)$ to the historical data. The catch level of 1.3 million tons is sustained only in few scenarios (one for CES, and three for CQS).

The main message to the Chilean regulation bodies would be that, notwithstanding the choice of the instrument, the historical quota targets were poorly sustainable. The information encompassed in our stochastic sustainable production possibility frontiers could have been of some help in setting lower sustainability targets. For example, Fig. 5 represents simulated trajectories for the best constant-quota and constant-effort strategies for sustainability thresholds $(p, y_{\min}) = (0.2, 0.8)$, which are achievable with a higher probability than historical levels of quotas. All the depicted trajectories are viable.

However, these results should be interpreted with cautious. One should not underestimate political economy considerations. A basic reason for pursuing the high quota management strategy, despite worsening biomass numbers, was that the Chilean authorities wanted to maintain, as long as possible, high numbers of 'his-

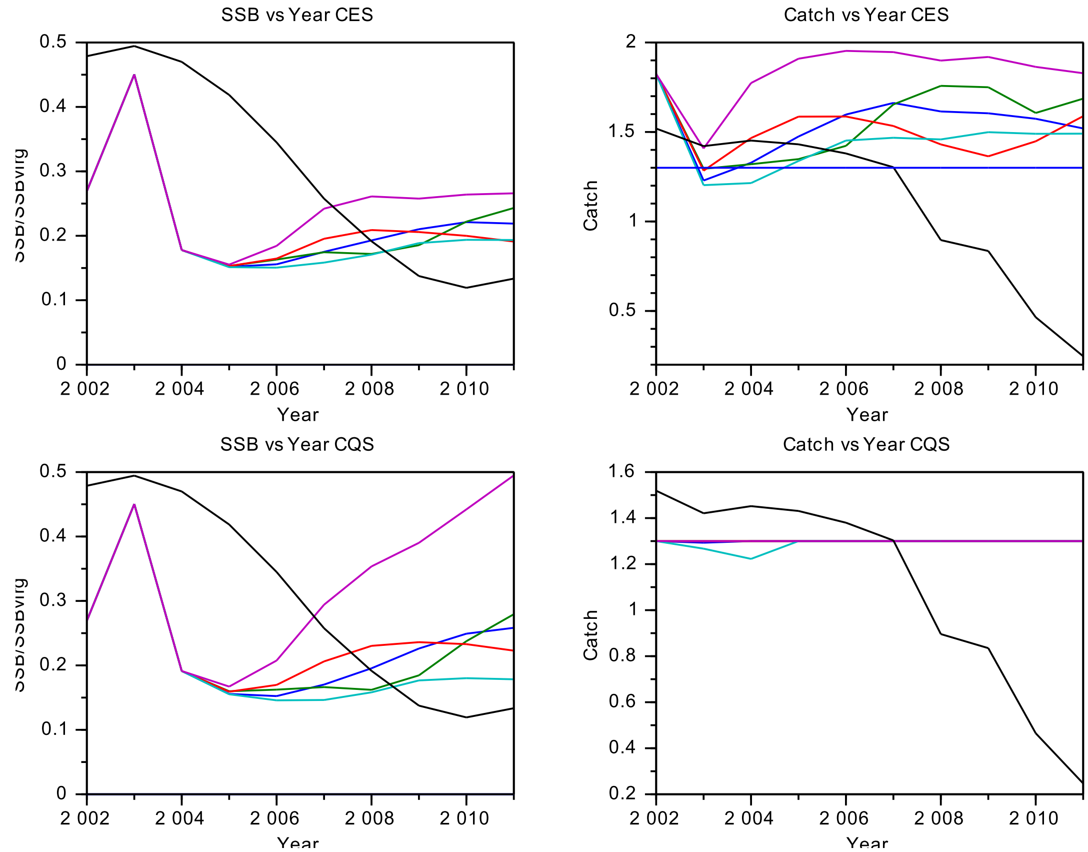

Figure 4: Examples of trajectories under CQS and CES for sustainability thresholds $(p, y_{\min}) = (0, 1.3)$, compared with historical data (5 simulations).

torical fishing presence' of the Chilean fleet operating in this fishery[26]; and this with a view on strengthening Chile's bargaining position in case of facing in the near future multi-country negotiations about the allocation of country-specific TACs for this common-pool stock.[27] Time lags were indeed needed to find a more reason-

[26]The drastic 2011 fall in the TAC for the Chilean fleet was related to a change of Government authorities in Chile, together with the (expected) plain realization that biomass levels (and real catch levels) had become inconsistent with maintaining the previous TAC levels.

[27]Since the early 2000s, expectations started to emerge about the possibility of creating a new (multi-country) Regional Fisheries Management Organization (RFMO) for fishing this straddling stock. Initial formal talks for establishing a new RFMO for fishing jack mackerel in the Eastern South Pacific were started in 2006 (by Chile, Australia and New Zealand). By March 2014, 11 nations (Chile included) had ratified their full membership in this new multi-country (RFMO). The

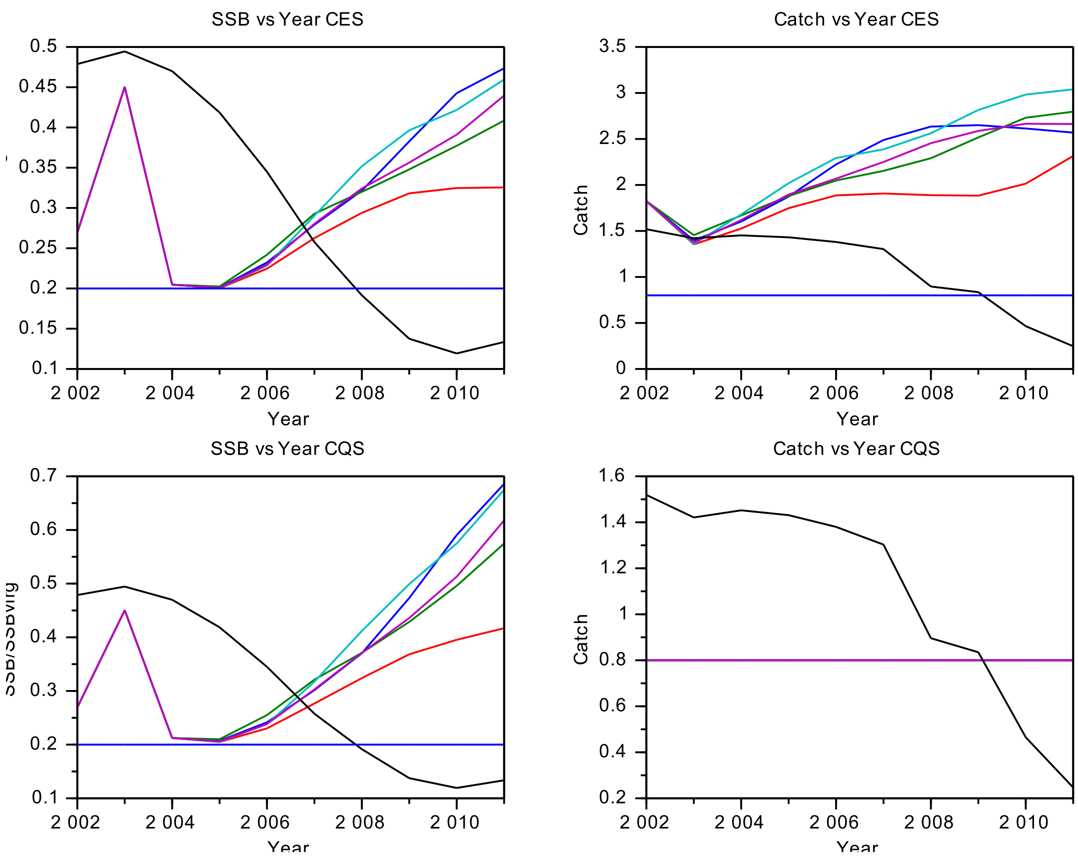

Figure 5: Examples of trajectories under CQS and CES for sustainability thresholds $(p, y_{\min}) = (0.2, 0.8)$, compared with historical data (5 simulations).

able (multi-country) management solution, and those lags conditioned the Chilean authorities' decision to keep 'as-if constant' TACs (and the resulting 'high' Chilean catches), as a response to the common-pool stock issue created by the partial redistribution of the jack mackerel stock into open seas waters beyond Chile's EEZ.

enforcement of formally binding fishing management measures (including the allocation of multi-country TACs) indeed started from 2013. (By mid-2012, another 21 nations were still debating whether or not to become members of this new RFMO).

5 Conclusions

Many natural resources management problems, such as fisheries management, are marked by dynamics and uncertainty. When there are conflicting economic, ecological and social objectives, multicriteria evaluation methods are required 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 metrics for comparing and trading-off conflicting issues, decision-makers are left without tools to rank the various management strategies.

To contribute to policy-oriented decision making in natural resource management problems, we have developed a framework based on stochastic viability. A set of constraints represents the various sustainability objectives. Within this framework, management strategies are ranked according to the probability that the resulting intertemporal trajectory satisfies all of the objectives all along the planning horizon. The viability probability ranks the various management options, defining the strategy which results in the highest viability probability.

This approach is complementary to the traditional economic approach when it is not possible to define a multi-attribute social welfare function. The objective is to maximize the probability to achieve the sustainability constraints. The stochastic viability is a good representation of decision problems involving several stakeholders interested in the sustained level of different indicators. All the dimensions of sustainability are treated in the same way, as constraints representing minimal rights to be guaranteed to all generations. Preferences of the decision-maker are expressed when sustainability thresholds are defined.

The theoretical extension of stochastic viability presented in this paper can help the stakeholders in defining what should be sustained. Our stochastic viability value function exhibits the trade-offs between sustainability objectives (thresholds) and viability probability. By building stochastic sustainable production possibility frontiers, it is possible to describe the set of objectives that can be sustained with some probability.

The proposed stochastic viability methodology is general and can be applied to a wide range of problems. As an example, we examined the management of a real fishery, with estimated parameters. Using numerical techniques, we examined the efficiency of effort and quota based management strategies in achieving sustainability objectives defined as constraints on biological and economic indicators. Monte Carlo simulations were run to estimate the viability probability of each policy, with respect to the objectives.

The main contribution of the paper is to develop a framework which provides a common metrics to compare management strategies and to describe trade-offs between sustainability objectives, in a complementary way to the MSE approach. The proposed approach can thus be used to fill the gap between the optimality literature of economic theory and practical decision-making.

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

Historical data for the Chilean Jack-Mackerel fishery Table 1 details the historical values of interest for the fishery.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Total Catch	Total Catch DWFNs	TAC	F. Effort Multiplier	Recruits	SSB	Total
	Chilean Fleet	(beyond Chilean EEZ)	Chilean Fleet	Chilean Fleet			Biomass
	(10^3 tons)	(10^3 tons)	(10^3 tons)	(implicit λ value)	(10^6 individuals)	(10^3 tons)	(10^3 tons)
1980	562	340	-		21738	10564	15973
1981	1061	438	-		27215	10825	17114
1982	1495	733	-		27652	10335	17861
1983	865	849	-		25645	10432	17471
1984	1426	1060	-		47886	10265	19017
1985	1457	799	-		60875	10653	20827
1986	1184	838	-		28735	12190	21942
1987	1770	863	-		15962	13822	22698
1988	2138	863	-		17644	14304	22534
1999	2391	876	-		23051	13652	21673
1990	2472	872	-		26461	12616	20751
1991	3020	544	-		20834	11428	19708
1992	3212	38	-		16344	10377	18002
1993	3236	0	-		14933	9392	16140
1994	4041	0	-		16942	7824	14545
1995	4404	0	-		18434	5775	12596
1996	3883	0	-		21071	4557	10378
1997	2917	0	-		24326	3844	9345
1998	1613	0	-		21460	4070	8862
1999	1220	0	1902		24704	4815	9622
2000	1235	2	-		24298	5643	10771
2001	1650	20	1425		20597	6312	11720
2002	1519	76	1625	0,32	12873	6848	11852
2003	1421	158	1350	0,46	8365	7073	11559
2004	1452	295	1475	0,45	6339	6722	10793
2005	1431	244	1484	0,42	3112	5988	9482
2006	1380	363	1400	0,39	5725	4934	8167
2007	1303	439	1600	0,36	7040	3685	6812
2008	896	405	1600	0,22	5808	2740	5348
2009	835	372	1400	0,17	7011	1967	4364
2010	465	240	1300	0,08	7826	1706	3586
2011	247	61	315	0,03	7158	1910	3418
2012	227	40	252	0,02	10892	2286	4034
2013	242	47	250				

Table 1: (a) DWFNs: Total annual catch of Distant Water Fishing Nations' Fleets (fishing jack mackerel outside the Chilean EEZ). (b) The Chilean fleet's TAC at column (3) is binding for catches obtained both within and beyond the Chilean EEZ. The first year with TAC in this fishery was 1999; this policy was resumed in 2001 (more details at Gomez-Lobo et al. 2011). (c) For deducing the Chilean fleet's (implicit) fishing effort multiplier (λ) at column (4), we replaced at the Baranov equation (13) the annual catch $Y(N, \lambda)$ by its real historical values (column 1) and we simulated the stock dynamics: starting from the initial vector of abundances at age (for year 2002), we applied the stock dynamics (equation 12) while considering the deterministic version of the Ricker recruitment function (equation 15), including the deterministic effect of El Niño events (in those years when it occurred, based on the definition stated at footnote 31). Sources: (1)-(2), (5)-(7): IFOP (2013); (3): Subsecretaría de Pesca (Chilean Fisheries Regulator); (4): authors' own calculations

Biological model This appendix details the model in §4.2.

The model is age-structured, with a Ricker stock-recruitment function. Abundance dynamics are given by

$$\begin{cases} N_{a+1}(t+1) = \exp\left(-(M_a + \lambda(t)F_a)\right)N_a(t) \ , \quad a = 1, \ldots, A-2 \\ N_A(t+1) = \exp\left(-(M_{A-1} + \lambda(t)F_{A-1})\right)N_{A-1}(t) + \exp\left(-(M_A + \lambda(t)F_A)\right)N_A(t) \end{cases} \tag{11}$$

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 year 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* (Quinn and Deriso, 1999, p. 255-256):

$$Y\big(N, \lambda\big) = \sum_{a=1}^{A} \varpi_a \, \frac{\lambda F_a}{\lambda F_a + M_a} \left(1 - \exp\left(-(M_a + \lambda F_a)\right)\right) N_a \, , \tag{12}$$

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

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

$$\mathit{SSB}(N) := \sum_{a=1}^{A} \gamma_a \varpi_a N_a \ , \tag{13}$$

where $(\gamma_a)_{a=1,\ldots,A}$ are the *proportions of mature individuals* at age a (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:[28]

$$N_1(t+1) = \alpha \mathit{SSB}\big(N(t-1)\big) \exp\left(\beta \mathit{SSB}\big(N(t-1)\big) + w(t)\right) \ , \tag{14}$$

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

We use the parameters estimation provided by Yepes (2004), which rely on official data from the *Instituto de Fomento Pesquero* (IFOP).[29] Parameters of the Ricker recruitment function at expression (14) were estimated by using linear time-series

[28] This 2-years delayed effect is due to the biological growth dynamics of the species.

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

analysis. The estimated parameters were $\alpha = e^{2.39}$ and $\beta = -2.2 \cdot 10^{-7}$ (see Yepes, 2004, 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]

Stochastic model Following the statistical analysis in Yepes (2004), we simulate *El Niño* uncertain cycles using a sinusoidal function with random shocks.[31] 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 estimated error terms $\{\epsilon(t)\}$ corresponds to $\epsilon(t) = 0.71\epsilon(t-1) - 0.65\epsilon(t-2) + \mu(t)$, 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.

Simulation process 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 (De Lara et al., 2006). One can even obtain a closed-form solution for some problems (De Lara and Martinet, 2009). Determining optimal strategies in dynamical optimization problems under uncertainty is, however, not easy. Optimization in the stochastic viability frame-

[30] See Subsecretaria de Pesca, Valparaíso - Chile, SUBPESCA (2006) Pre Informe Final. Investigación Evaluation y CTP Jurel 2006.

[31] Based on Chilean marine biologists advice, Yepes (2004) 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 the difference of the current sea surface temperature (SST) with respect to the historical average of SST obtained from the period 1971-2000. Then a series of 3-months moving average is computed, and it is said that *El Niño* occurs when this average is greater than 0.5 °C during five consecutive months (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 (Yepes, 2004, p. 64)), to represent the different cycles of *El Niño*.

work is not an exception. In particular, the curse of dimensionality can be a serious obstacle to compute optimal viability strategies.

From a practical point of view, it is possible to estimate the viability probability of any given strategy by means of Monte Carlo simulations. A random generator is used to produce scenarios following the distribution $\mathbb{P}$. For each scenario, a given management strategy is applied. If, for the corresponding trajectory, all the viability constraints in (4) are respected in each time period over the whole planning horizon, the scenario is viable for the applied management strategy. When the number of scenario tested is large, the frequency of viable scenarios can be used as an approximation of viability probability.

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