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Risk and Sustainability: Assessing Fishery Management Strategies

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Abstract We develop a theoretical framework to assess the sustainability of fishery 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 (1) 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 (2) the fishery's historical quota levels were not sustainable given the stock levels in the early 2000s.

Keywords Sustainability · Risk · Fishery economics and management · Stochastic viability

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1 Introduction

The analysis in this paper originates in real concerns related to the management of Chilean fisheries. The jack-mackerel fishery is being challenged by uncertain *El Niño* cycles, which increase uncertainty about the availability of the resource (Barber and Chavez 1983), making management of the fishery more difficult (Costello et al. 1998).[1] In addition to the usual objective of maximizing profits, current management is aimed at avoiding stock collapse. *Sustainable* resource management requires a framework that takes account of both economic and ecological objectives under risk and over time.

The standard economic approach to assessing the performance of fishery 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. However, it has 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 the definition of a multi-attribute social welfare function (SWF) *prior to the maximization problem*. However, if uncertainties are pervasive and if the sustainability issues affect multiple and heterogeneous stakeholders, the task of agreeing on a common SWF can be extremely intricate. Second, the discounted utility framework allows for intertemporal compensation of good and bad outcomes for the system, which may raise intergenerational equity issues (particularly if the discount rate is positive).

In practice, fishery management strategies, often defined as simple "rules of thumb," are evaluated in so-called "multicriteria" frameworks (Geromont et al. 1999; Oliveira and Butterworth 2004; Kell et al. 2005; Smith et al. 2007). These 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 alternative management strategies explicitly. Thus, there is a gap in resource management between theory and practice. Developing a practical framework based on solid theoretical grounds to assess the sustainability of fishery management strategies under risk is a challenging task.

This paper proposes a framework which accounts for conflicting sustainability issues and risk, and provides an explicitly ranking of alternative management strategies. This framework echoes the concept of stewardship,[2] which defines sustainable resource management as a strategy that *sustains economic and ecological outcomes over time*, corresponding to a "satisficing" objective *à la* Simon (1955). 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 these indicators above some thresholds characterizing sustainability objectives (e.g., minimal biomass, minimal profit). We assess fishery management strategies according to their probability of achieving these objectives jointly, and at all times, over the planning horizon.

While stochastic viability has been used in previous studies as a *simulation tool* to examine fishery management issues (e.g., Doyen et al. 2012), the present paper differs in two important respects, each of which constitutes theoretical novelty. First, we embed stochastic viability in a *theoretical optimization framework* with economic interpretations, defining a value function for our optimization problem. This value measures the ability to sustain several outcomes

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

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

over time. Second, while in viability analysis the thresholds of the viability constraints are usually exogenously fixed parameters, 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 reveal some of these preferences. Defining actual sustainability thresholds amounts to determining what should be sustained over time (Martinet 2012). This is a social choice problem which is not addressed explicitly here. It corresponds to a generalized, multidimensional maximin problem (Solow 1974; Martinet 2011), with low substitutability among sustainability issues, and strong aversion to intertemporal inequality on all sustainability dimensions. Stochastic sustainable production possibility frontiers can be used to inform the social choice of sustainability objectives in the fishery, and to reveal social preferences related to sustainability issues.

These theoretical novelties allow us to bridge the gap 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. It can be used to rank alternative management strategies. Marginal analysis makes it possible to examine the trade-offs between sustained outcomes and risk. Thus, our approach is closer to economics than the usual multi-criteria fishery management approaches. It can be implemented if no SWF is available.

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

Section 2 highlights the differences between the fishery economics literature and the fishery management literature which were the motivation for our approach. Section 3 presents our theoretical framework to assess risk and sustainability and compare management strategies. In Sect. 4, we apply this framework to the Chilean jack-mackerel fishery case-study. Section 5 concludes by discussing the relevance of our results for practical fisheries management.

2 Background and Settings

Optimality in fishery economics is usually defined as maximization of the expected discounted profit of the 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 is aimed

[3] See Reed (1979), Clark and Kirkwood (1986), Sethi et al. (2005), Nøstbakken and Conrad (2007), Nøstbakken (2008), McGough et al. (2009). When responding to uncertain stock fluctuations, optimality may require strong yearly variations of the total allowable catch (TAC), pulse-fishing (Da-Rocha et al. 2014), and even fishery closure if the stock size is too small (Nøstbakken 2006), whereas fishing industries favor stability of catches (Charles 1998).

at conserving resources and sustaining the socio-economic benefits from fishing (Cochrane 2000; Pikkitch et al. 2004). This increases the number of objectives and stakeholders (Fletcher 2005) with the result that fisheries are faced with unsustainable situations whenever one of these objectives is not met. Prioritizing social and economic objectives over ecological targets has been identified as an important reason for management failure in fisheries (Hilborn 2007). *Management procedures* (MP)[4] should be ranked according to their capacity to yield acceptable results with respect to all 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 that would fully characterize social preferences over the various dimensions of interest, prior to the optimization problem. However, stakeholders may be unable to agree on a SWF. This form of "collective" bounded rationality results in the impossibility to define a continuous representation of preferences over payoffs across various dimensions and risks. An alternative option would be to add ecological 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 reveal preferences over economic and ecological outcomes. This feature is lost in the stochastic case,[5] where a theoretical and technical issue emerges, i.e., how to interpret and handle constraints under uncertainty. It is possible to "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 decisions to the extent that the optimization problem loses its interest. Another possibility would be accepting a risk of constraint violation. This amounts to considering the performance of the system with respect to the ecological constraint, by providing a measure of the risk of violating it. There are then two outcomes for each strategy: the expected economic profit, and the ecological risk.

This last option, in fact, 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). Figure 1 displays the results for the Chilean jack-mackerel fishery. "Ideal" management strategies present low risk to the resource and high mean catches, and are depicted in the South-East of the figure. Since there is no common metrics between objectives, the two performances cannot be aggregated, and non-dominated strategies cannot be ranked.[7]

[4] A MP is a set of rules which translates fishery data into a regulatory mechanism, such as TAC 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 (Oliveira and Butterworth 2004).

[5] It will be seen that our framework provides somewhat 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). MSE is the most developed (Butterworth et al. 1997; Charles 1998; Geromont et al. 1999; Sainsbury et al. 2000; Oliveira and Butterworth 2004; Kell et al. 2005).

[7] Moreover, the MSE approach provides no information on the opportunity cost of the ecological constraint or the marginal gains from relaxing its level.

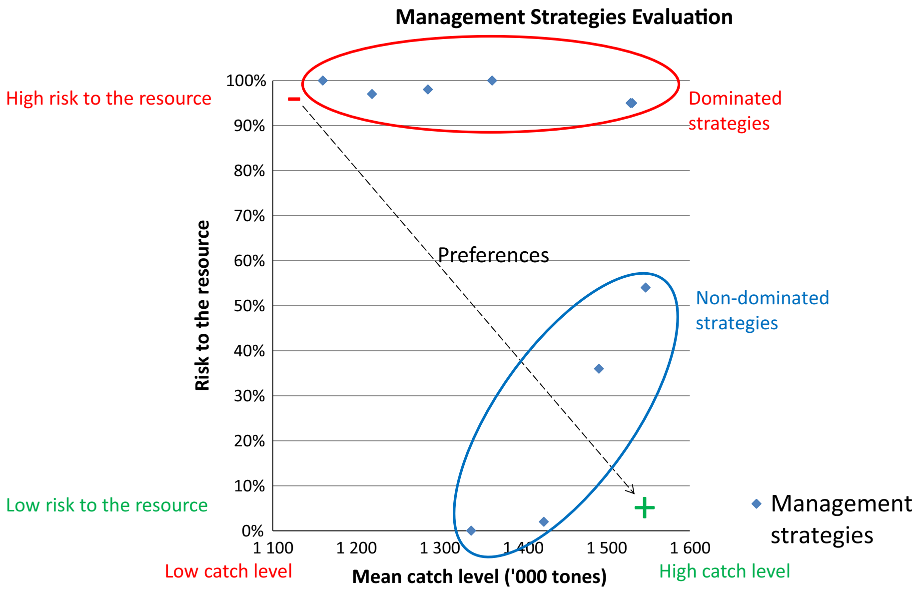

Fig. 1 MSE for the Chilean Jack Mackerel fishery: performance of various management strategies in terms of risk to the resource (measured as the probability that the stock falls below 20 % of the pre-exploitation spawning stock biomass) and expected mean annual catches (used as a proxy variable for the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

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

Thus, assessing the sustainability of resource management strategies under risk is difficult when there is no SWF describing the preferences related to different issues. To address this challenge, we propose a theoretical framework that reflects the concept of stewardship. We assume that intertemporal equity requires the economic and ecological performance of the system to be sustained 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 in a stochastic viability framework which defines the (maximal) probability of satisfying jointly several viability constraints over time in dynamic, uncertain models. Any management strategy satisfies these 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. Defining the viability thresholds as arguments of the stochastic viability value function, we build stochastic sustainable production possibility frontiers, which exhibit

[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 for risk such as variance of profits.

the necessary trade-offs between the targeted sustained outcomes and risk. These frontiers can be used in the social choice of sustainability objectives.

3 A Metrics for Risk and Sustainability

Let us formalize the decision problem in a general framework. The model and method described 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 fisheries case.

3.1 Modeling Framework

3.1.1 Dynamic system

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

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

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 example; t_0 is the initial time ; T is the finite horizon;
- the *state* vector $x(t) \in \mathbb{X} \subset \mathbb{R}^n$ could be a vector of abundance-at-age for one or for several species; it could also represent abundances at different spatial patches or include capital stocks (e.g., fishing vessels);
- the *control* vector $c(t) \in \mathbb{C} \subset \mathbb{R}^p$ could denote 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 dynamic population model, climate fluctuations or trends, unknown technical progress, price uncertainty);
- $G : \mathbb{T} \times \mathbb{X} \times \mathbb{C} \times \mathbb{W} \to \mathbb{X}$ represents the *dynamics* of the system; it could be one of the numerous dynamic population models, such as logistic or age-class models; it could 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 $x(\cdot) = \big(x(t_0), \dots, x(T)\big)$ denotes a *state trajectory*.

3.1.2 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 be either an objective probability derived from a statistical model

[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.

using real world data (as in our case study in Sect. 4), or a subjective probability representing the decision-maker's beliefs.

3.1.3 Decision Rules and Management Strategies

When uncertainties affect the dynamics, *closed loop* or *feedback* controls $\widehat{c}\big(t, x(t)\big)$ accounting for the uncertain state evolution $x(t)$ 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. Hereafter, we 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

3.2.1 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* with economic or ecological meaning (e.g., profit, annual catches, Spawning Stock Biomass—SSB). Thresholds $\tau_1 \in \mathbb{R}, \ldots, \tau_K \in \mathbb{R}$, measured in the same unit as the indicators (e.g., money, tons) 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. 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 constraints at all times reflects the idea that sustainability has to encompass ecological and economic issues in an intergenerational equity perspective.

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

3.2.2 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* as:

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

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

[11] *For given sustainability thresholds*, there are no trade-offs, either among sustainability issues or among time periods. All trade-offs occur when the thresholds are defined (Martinet 2011, 2012). We emphasize how our framework can be used to support the definition of the thresholds.

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 the strategy $c(t) = \widehat{c}(t, x(t))$ is applied. Therefore, a viable scenario $\omega(\cdot) \in \Omega_{\widehat{c},t_0,x_0}$ is one where the state and control trajectories $\big(x(\cdot), c(\cdot)\big)$ driven by the strategy $\widehat{c}$ satisfy the constraints (3).

In the ideal case where a strategy $\widehat{c}$ exists such that $\Omega_{\widehat{c},t_0,x_0}$ coincides with Ω, viability can be achieved for all scenarios by applying this strategy. If this is not the case, since Ω is equipped with a probability $\mathbb{P}$, we can measure the likelihood that a strategy $\widehat{c}$ will 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.

3.2.3 Management Strategy Assessment by Stochastic Viability

For any given set of sustainability thresholds $\tau_1, \dots, \tau_K$, a management strategy can be assessed by its viability probability. To stress the dependency on thresholds, we introduce the notation

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

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 in the case of expected discounted utility, stochastic viability analysis depends on the probability distribution $\mathbb{P}$. In particular, since we are dealing with intertemporal issues, we need to be cautious about how $\mathbb{P}$ captures temporal dependencies among uncertainties (e.g., independent random variables, Markov chains, or time series). Investigating the sensitivity of the results to the probability distribution is beyond the scope of this paper.

3.2.4 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 strategy if the corresponding set of viable scenarios has a higher probability. A *most viable strategy* $\widehat{c}^\star(\tau_1, \dots, \tau_K)$ is one that maximizes the viability probability $\Pi(\widehat{c}, \tau_1, \dots, \tau_K)$ for a given set of sustainability thresholds $\tau_1, \dots, \tau_K$ over all possible strategies $\widehat{c} \in \mathcal{C}$.

3.3 Theoretical Extension to the Stochastic Viability Framework

This paper is original in treating the viability thresholds as arguments of the viability probability. This defines a value function for our sustainability problem.

3.3.1 A "Value Function" for Sustained Outcomes

The *maximal viability probability*

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

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

3.3.2 Stochastic Sustainable Production Possibility Frontiers

When the maximal viability probability function $\Pi^\star(\tau_1, \ldots, \tau_K)$ varies smoothly with respect to the threshold levels (as generally 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 the level of this constraint. It provides information on the difficulty of sustaining the corresponding outcome over time, given other sustainability objectives.

The value function (6) can be used to build stochastic sustainable production possibility frontiers exhibiting the trade-offs among 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 $\tau_1, \ldots, \tau_K$ at which $\Pi^\star(\tau_1, \ldots, \tau_K) = \pi$. The *marginal rate of substitution* between thresholds τ_i and τ_j along the corresponding iso-value viability probability curve is then defined by

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

This rate measures the necessary trade-offs between the two 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.

3.3.3 Suboptimal Cases

Our framework can be used also if it is not possible to identify an optimal strategy (e.g., 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 involved in 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 used to inform stakeholders in the discussion of given strategies with management relevance (e.g., effort-based or quota-based strategies). The viability probability of the strategies then provides a metrics for ranking them. In particular, by letting sustainability thresholds vary, it is possible to define within which range of sustainability threshold levels one type of strategy 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 fishery in Chile for many years, in terms of both annual catch and economic value.[12] Like other small pelagic stocks, jack-mackerel stocks are affected by the recurrences of *El Niño* in uncertain cycles. Since the late 1990s, the fishery has been managed under a yearly-defined TAC and closed entry, taking particular account of the stability of catch levels over time. Additionally, since the mid-2000s, the jack-mackerel fishery has pioneered (in Chile) the inclusion of biology-related risk indicators in its management practices.[13] These indicators provide additional information for the policy decision making process, with the underlying objective of capping biological (collapse) risk; however, they are not applied within a formal framework allowing trade off of this risk against measures of economic return. Despite its management strategies, the Chilean jack-mackerel fishery is currently in crisis.

Historical data on the jack-mackerel fishery are provided in the Appendix, Table 1. Year 2002 appears to be a turning point for two reasons: (1) biomass levels were half the peak in the late 1980s, and recruitment was half the levels in the previous five years,[14] (2) the spatial distribution of the stock changed (Peña Torres et al. 2014), moving part of the stock outside Chile's Exclusive Economic Zone (EEZ), which triggered the re-opening of an international-waters jack mackerel fishery (see Table 1 column (2)).

Despite the changes in the biology of the stock and its exploitation pattern after 2002, the Chilean fisheries regulator decided to keep TAC levels almost constant for the Chilean fleet targeting jack mackerel within and beyond the Chilean EEZ over the period 2000–2010 (see Table 1 column (3)). Biomass levels began a monotonic decline, from 48 % of *virgin SSB* (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 1300 to 315 k-tons; in 2013 it was around 250 k-tons.

Thus, the period 2002–2011 is 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 in management strategy. We model this period over a 10 year horizon, taking 2002 as the initial year of our simulation.

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

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12 Annual catch peaked at 4.4 million tons in 1995, and value generation was around US$ 400 millions of yearly sales until the 2010s.

13 SUBPESCA, the regulatory body for Chilean fisheries, started assessing the probabilities of reducing the SSB, relative to a historical base level, for various exogenously defined quota level. Sec SUBPESCA (2004, pp. 26–27) and IFOP (2006, pp. 33–39).

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. It uses the maximum recorded SSB for this fishery (in 1988) as a proxy.

4.2 Bioeconomic Model [16]

4.2.1 Biology

We describe the dynamics of the Chilean jack-mackerel stock using an age-class model (Quinn and Deriso 1999; Tahvonen 2009) with a Ricker recruitment function.[17] Time is measured in years. The initial year is $t_0 = 2002$ and the final year 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 $a \in \{1, \ldots, A\}$ be an age class index, all expressed in years. The vector $N = (N_a)_{a=1,\ldots,A} \in \mathbb{R}_+^A$ is a vector of abundance-at-age: for $a = 1, \ldots, A-1$, $N_a(t)$ is the number of individuals aged between $a - 1$ and a at the beginning of year t; $N_A(t)$ is the number of individuals older than $A - 1$.

The dynamics of the form of Eq. (1) is provided in the Appendix (Eqs. 11, 13 and 14). The state vector ($A + 1$-dimensional) is $x(t) = \big(N_1(t), \ldots, N_A(t), SSB\big(N(t-1)\big)\big)$, where the SSB is defined by Eq. (13). Fishing activity is represented by a *fishing effort multiplier* $\lambda(t)$, assumed to be applied continuously during the period t. The control then is $c(t) = \lambda(t)$. Total annual catches Y, measured in million tons, are given by the Baranov catch equation (Eq. 12).

4.2.2 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, whose frequency and intensity are uncertain. We simulate the uncertain *El Niño* cycles using a model with a periodic part and an error term, to produce a cycle with random shocks. Details are provided in the Appendix.

4.2.3 Economics

We make the following standard economic assumptions (Reed 1979; Clark and Kirkwood 1986; Clark 1990).

(a1) Demand is infinitely elastic. The harvest from this fishery goes mainly to fish meal, a commodity with high demand substitution. Therefore, this fishery is essentially a price-taking industry, and we assume that any unit harvested is sold for a given, exogenous price.

(a2) Per unit harvest costs are not dependent on harvest volume and vary with population abundance. These costs increase as the size of the population decreases. This is equivalent to assuming that fishing effort has a constant unit cost, and that Catches Per Unit of Effort (CPUE) decrease if the stock decreases.

Under these assumptions, since the CPUE decreases when stock size falls, there is a minimal stock size below which the marginal cost of fishing effort (which is constant) is higher than the marginal revenue from fishing effort. We assume that no extra fishing effort occurs once the marginal profit is nil. This implies that fishing effort has an upper bound.

For fisheries satisfying these assumptions, price and cost levels do not have a qualitative effect on our results. The regulator usually observes prices but fishing costs are private

[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.

information and depend on factors specific to fishing vessels. Thus, profit functions are difficult to estimate without strong assumptions related to fleet homogeneity. In practice, the most frequent approach is to use catches to proxy for revenue, and fishing effort related variables to proxy for costs. Since in practice quotas are defined in quantity terms, it is reasonable to focus on harvest quantities and fishing effort to proxy for revenue and fishing costs. This assumption is in line with, for example, Reed (1979), Clark and Kirkwood (1986) and Sethi et al. (2005), where the expected discounted sum of harvest rather than the expected discounted sum of profit is maximized.

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

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

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 between 15 and 25 % of SSB_{virg}.[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 $y_{\min}$:

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

The minimum level of landings to be sustained over time ($y_{\min}$) can take values from 0 to 2 million tons, corresponding to catch levels observed in this fishery in the first decade of 2000. 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 maintaining a minimum level of fishing activity, due possibly 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.

Although optimization approaches provide a description of "optimal" management strategies, many fisheries are managed using much simpler tools.[19] Constant fishing effort and constant quotas are two basic management strategies. The former approach, known also as fixed fishing mortality, is based on advice from biologists and results in fluctuating harvests as stocks fluctuate. The optimal strategy may be neither of these approaches (Hannesson and Steinshamn 1991) but these rules of thumb are still frequently proposed (and indeed used sometimes) as potential management strategies in some fisheries. In the 1980s and 1990s,

[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] E.g., Singh et al. (2006) describe 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 catches over time more than the optimal policy.

Chilean fisheries were *de facto* managed under a constant effort rule (frozen maximum effort). In 2000, a quota system was applied with *a posteriori* very small changes to TAC levels from year to year. For example, the management strategy applied to the jack-mackerel fishery over the studied period resembles a constant quota-type policy (see Table 1).

We 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 CES 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 $Y\big(N, \widehat{\lambda}(t, N)\big) = \overline{Y}$ whenever this is possible, i.e., if the corresponding effort level is below the upper bound for fishing effort. If it is not, the actual catch level may be lower than the quota. The set of all possible CQS 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 pair $(p, y_{\min}) \in [0; 2] \times [0.15; 0.25]$ 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). We compute a 95 % confidence interval for its value. These viability probabilities are displayed in Fig. 2. For each strategy (left-hand panel for CES and right hand-side panel for CQS), 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 represent the "stochastic viability value" of each type of strategy as a function of the sustainability thresholds (see Eq. 5).

4.4.1 Ranking Management Strategies

For any given pair of sustainability thresholds, we can rank the alternative management strategies using their viability probability. This allows us to identify the levels of sustainability objectives for which a strategy is likely to perform better than the other from a viability point of view. We determine whether the confidence interval for the viability probability of one type of strategy lies strictly above the confidence interval for the other strategy. Figure 3 depicts the strategy type with the highest viability probability for each pair $(p, y_{\min})$ of biological and economic thresholds. The domain, in terms of sustainability thresholds, where CQS performs strictly better than CES is shaded black. The gray area corresponds to the threshold levels at which the performance of both policy types cannot be statistically distinguished (i.e., confidence intervals intersect). 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, CQS perform better than CES 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

[20] In our model, fishing mortality is proportional to fishing effort if the fishing technology is constant. Thus, a CES is identical to the constant fishing mortality strategy depicted here.

[21] Technically, we discretize the intervals.

[22] This result 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 %).

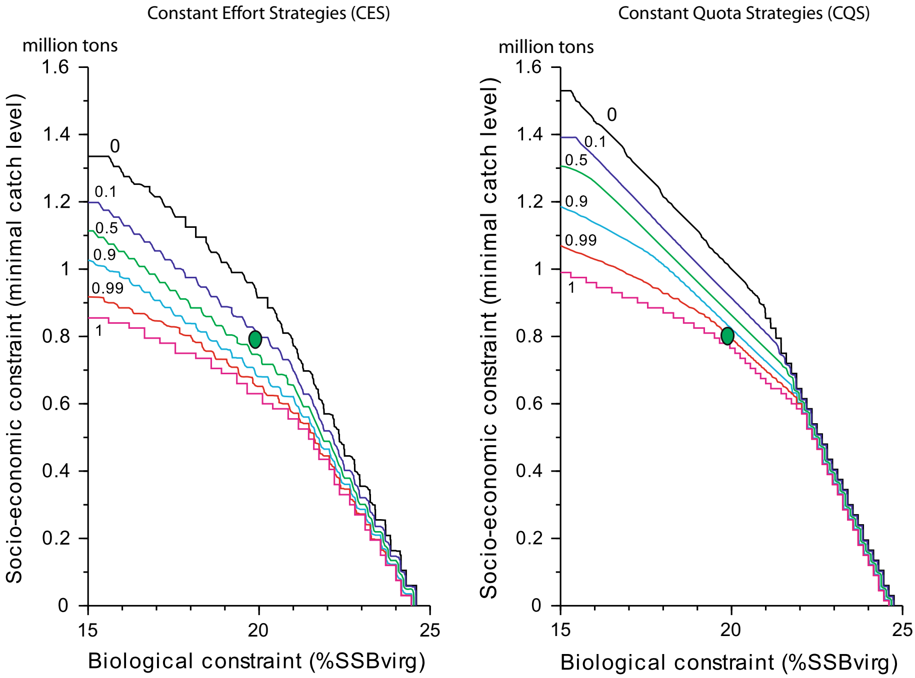

Fig. 2 Maximal viability probability of effort and quota strategies (1000 Monte-Carlo simulations). Isoprobability curves are drawn for values {0, 0.1, 0.5, 0.9, 0.99, 1}. (*Green circle* at (20,0.8) corresponding to the sustainability thresholds used for the simulations of Fig. 5). (Color figure online)

to the theoretical result in De Lara and Martinet (2009). In a general framework with an application to fishery, they show that if the dynamics and viability constraints satisfy some monotonicity properties, the maximal viability probability is achieved with the feedback rule which maximizes the escapement level given that the viability constraints are satisfied at the current time. This management strategy can be interpreted as a "precautionary rule." It ensures the achievement of economic objective at the present time while maximizing the probability of economic and ecological objectives being achieved in the future.[23] When the economic constraint is a minimal catch level, the rule corresponds to a constant quota at the level of the constraint.

Since the Ricker recruitment function is non-monotonic, with a declining part for large stocks, the model studied here is not monotonic in the sense of De Lara and Martinet (2009). However, 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 problem of determining which of the effort-based and quota-based strategies dominates in fishery economics is a particular case of the "prices versus quantities" debate. A

[23] Note that, for many fisheries, the International Council for the Exploration of the Sea (ICES) management strategy is based on a rather different strategy: the catch level is set at the highest level compatible with the biological conservation target *in 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 the 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 the resource stock kept as "far" as possible from the biological threshold, given the economic objective.

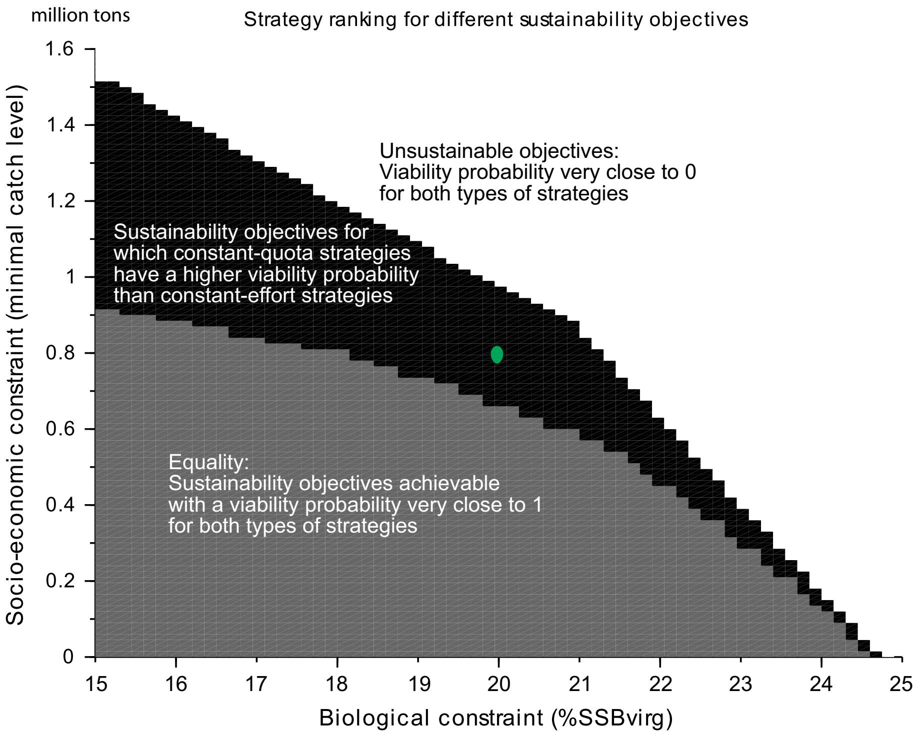

Fig. 3 Comparison of CES and CQS policy types (1000 Monte Carlo's simulations). (*Green circle* at (20,0.8) corresponding to the sustainability thresholds used for the simulations of Fig. 5). (Color figure online)

management strategy based on direct control of fishing effort has similar features to 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 similar to imposing a particular landing fee (such as a very high fee starting at some point). Landing fees are a (relatively) better solution to control the (marginal) fishing effort (or cost) but suffer from the drawback of inability to control catch levels. Harvest quotas, on the other hand, have the advantage that they fix the total quantity of fish caught but suffer from the drawback of inability to control the possible excess effort exerted to fish down a stock that is experiencing low recruitment in the fishing period. The related literature shows 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 depends not only on the characteristics of the fishery under study but also on the nature of the sustainability objectives.

4.4.2 Stochastic Sustainable Production Possibility Frontiers

Figure 2 presents what was defined in the theoretical analysis of Sect. 3.3 as stochastic sustainable production possibility frontiers. 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, it is necessary to reduce one sustainability threshold to increase another. There is also a trade-off between the sustainability thresholds and confidence in achieving sustainability. Increasing the thresholds results in a decreased viability probability.[24]

These graphical representations are useful to support the social choice of sustainability objectives. They depict the trade-offs between the policy objectives represented by the sustainability thresholds, and the risk of failing to (simultaneously) achieve them.[25] When no SWF can be determined prior to the evaluation of management strategies, and the interest is in sustaining ecological and economic outcomes over time, presenting the trade-offs over all possible sustainability objectives to stakeholders may help to reveal their preferences.

4.4.3 Discussion

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

In the early 2000s, biomass levels had been experiencing (for almost a decade) worsening status. As a consequence, 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 period analyzed, the TAC was maintained at above 1.3 million tons; however, actual catches did not match this level. Notwithstanding the ecological constraint, Fig. 2 shows that the probability of sustaining the TAC level was not high. Even the best policy among those studied has a low viability probability (around 50 %). This is illustrated in Fig. 4, which compares simulated trajectories for the best CQS and CES for sustainability thresholds $(p, y_{\min}) = (0, 1.3)$, to the historical data (dashed line). The catch level of 1.3 million tons is sustained only in few scenarios (1 for CES, and 3 for CQS).

The main message to the Chilean regulator is that, notwithstanding the choice of instrument, historical quota targets were not sustainable. The information provided by our stochastic sustainable production possibility frontiers could have helped to set lower sustainability targets. For example, Fig. 5 represents simulated trajectories for the best CQS and CES for sustainability thresholds $(p, y_{\min}) = (0.2, 0.8)$, which are achievable with a higher probability than historical levels of quotas (see the green circle at these threshold levels on Figs. 2, 3). The viability probability for CES is quite low, close to 10 %. None of the depicted trajectories are viable. The viability probability for Constant Quota Strategies is very close to one. All the depicted trajectories are viable.

However, these results should be interpreted with caution and political economy considerations should not be underestimated. One of the basic reasons for pursuing the high quota management strategy despite worsening biomass numbers, was that the Chilean authorities wanted to maintain, for as long as possible, high 'historical fishing presence' of Chilean fleet operating in this fishery,[26] with a view to strengthening Chile's bargaining position in case

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, not different management strategies (as was the case for the MSE in Fig. 1).

26 The drastic 2011 fall in the TAC for the Chilean fleet was related to the change of government in Chile and the (expected) realization that biomass levels (and real catch levels) were inconsistent with previous TAC levels.

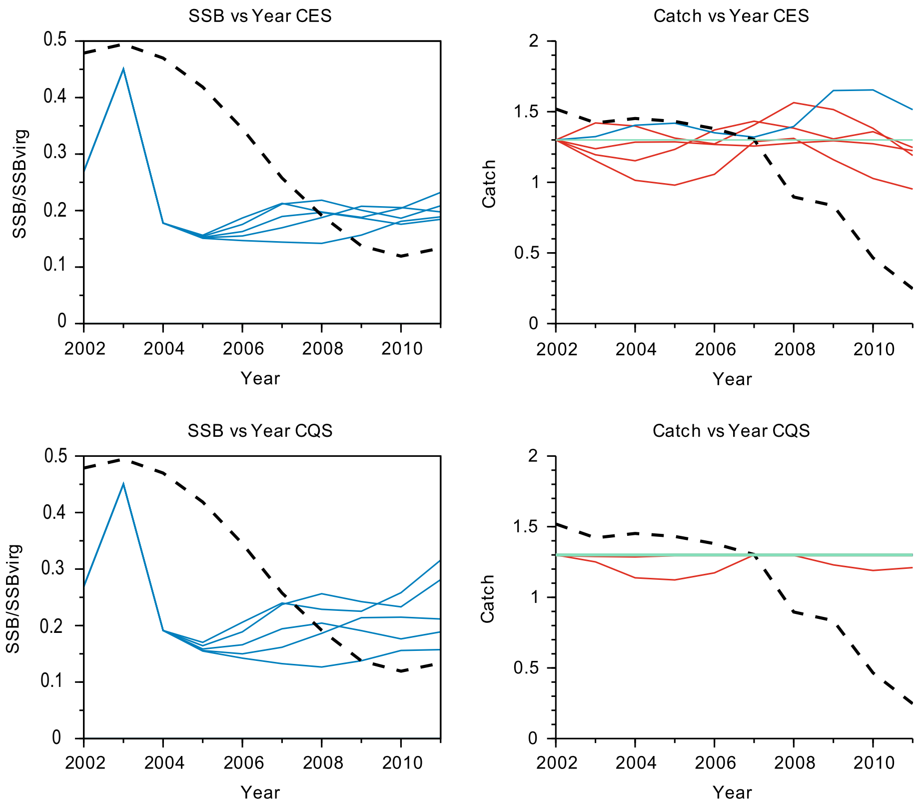

Fig. 4 Examples of trajectories under CQS and CES (five simulations corresponding to five different uncertainty scenarios) for sustainability thresholds $(p, y_{\min}) = (0, 1.3)$, compared to historical data (*dashed line*). The yield threshold is represented by a *horizontal* (*green*) *line*. Catch levels equal the threshold level if constant quota trajectories are feasible. Viable trajectories are in *blue*. Non-viable trajectories are in *red*. (Color figure online)

of future multi-country negotiations about the allocation of country-specific TACs for this common-pool stock.[27] Time lags were necessary to find a more reasonable (multi-country) management solution, and those lags prompted the Chilean authorities' decision to maintain TAC 'as-if constant' (and maintain the resulting 'high' Chilean catches), in 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.

[27] Since the early 2000s, the possibility of creating a new (multi-country) Regional Fisheries Management Organization (RFMO) for fishing this straddling stock has been on the table. Initial formal discussions over the establishment of a RFMO related to jack mackerel fishing in the Eastern South Pacific started in 2006 (involving Chile, Australia and New Zealand). In March 2014, 11 nations (including Chile) had ratified their full membership of this RFMO. Enforcement of formally binding fishing management measures (including allocation of multi-country TACs) started in 2013. (In mid-2012, another 21 nations were debating whether or not to become members of this RFMO).

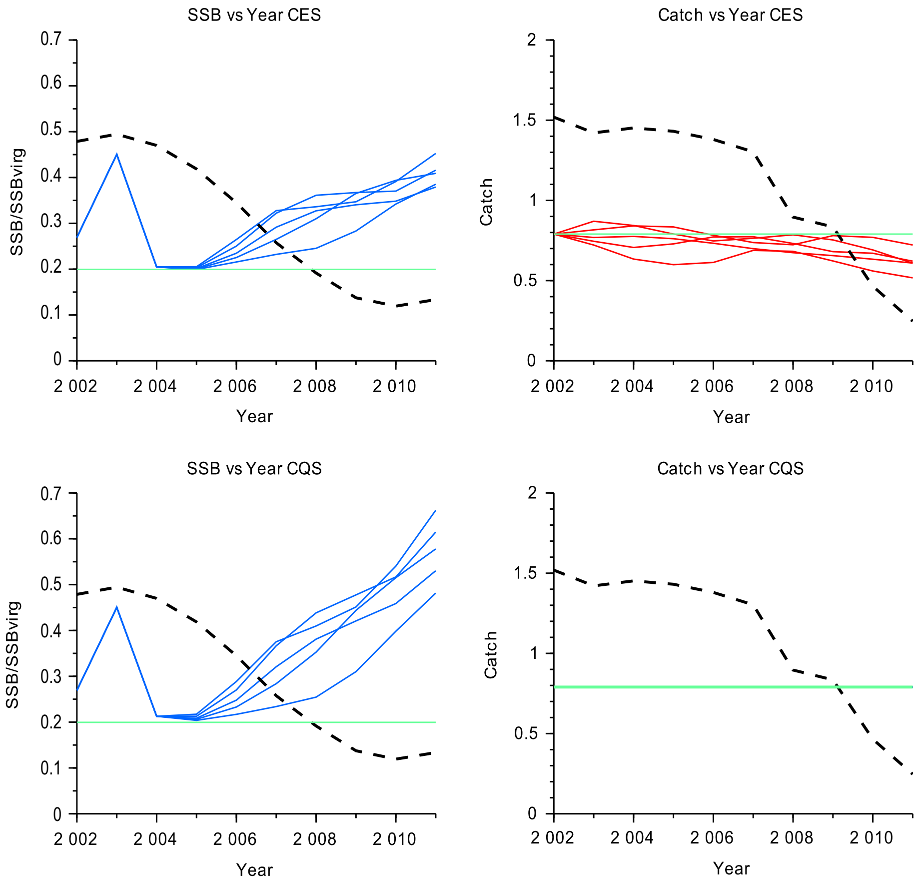

Fig. 5 Examples of trajectories under CQS and CES (five simulations corresponding to five different uncertainty scenarios) for sustainability thresholds $(p, y_{\min}) = (0.2, 0.8)$, compared to historical data (*dashed line*). The biomass and yield thresholds are represented by a horizontal (*green*) line. Catch levels equal the threshold level for all constant quota trajectories. Viable trajectories are in *blue*. Non-viable trajectories are in *red*. (Color figure online)

5 Conclusions

Many problems related to the management of natural resources, such as fisheries, are marked by dynamics and uncertainty. When there are conflicting economic, ecological and social objectives at stake, multicriteria evaluation methods that take account of uncertainty are required to rank potential management strategies. One such method is the Management Strategy Evaluation approach, which characterizes potential management strategies using a set of performance statistics. However, due to the absence of a common metrics for comparing and trading-off conflicting issues, decision-makers are devoid of tools to rank the various management strategies.

To contribute to policy-oriented decision making related to natural resources management problems, we have developed a framework based on stochastic viability. A set of constraints is used to represent the various sustainability objectives of the dynamic ecological economic system. In this framework, management strategies are ranked according to the probability that the resulting intertemporal trajectory satisfies all the objectives over the planning horizon. The viability probability ranks the various management options, defining the strategy that results in the highest viability probability.

This approach acts to complement the traditional economic approach when it is not possible to define a multi-attribute social welfare function. The objective is to maximize the probability of achieving the sustainability constraints. Stochastic viability provides a good way to model decision problems involving several stakeholders interested in sustaining the levels of various indicators. All sustainability dimensions are treated in the same way as constraints representing the minimal rights to be guaranteed to all generations. The decision-maker's preferences are expressed when sustainability thresholds are defined.

The theoretical extension to stochastic viability presented in this paper should help stakeholders to define what should be sustained. Our stochastic viability value function exhibits trade-offs between sustainability objectives (thresholds) and viability probability. Building stochastic sustainable production possibility frontiers allows the set of objectives that can be sustained with some probability to be described.

The proposed stochastic viability methodology is general, and can be applied to a wide range of problems. For example, in this paper we examined the management of a real fishery, using estimated parameters. We applied numerical techniques to examine the efficiency of effort- and quota-based management strategies for 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 these objectives.

The main contribution of the paper is the development of a framework which provides a common metrics to compare management strategies and to describe the trade-offs among sustainability objectives, in a way that complements the MSE approach. We suggest that the proposed approach fills the gap between the theoretical economics literature on optimality, and practical decision-making.

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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.

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 in column (3) is binding for catches within and beyond the Chilean EEZ. The first year to which TAC was applied in this fishery was 1999; the policy was resumed in 2001 (for more details see Gomez-Lobo and J. Pe na Torres, and P. Barria, (2011)). (c) To deduce the Chilean fleet's (implicit) fishing effort multiplier (λ) in column (4), we replaced the annual catch $Y(N, \lambda)$ by its real historical values (column 1) in the Baranov equation (12) and simulated the stock dynamics: starting from the initial vector of abundances at age (for year 2002); we then applied the stock dynamics (equation 11) while considering the deterministic version of the Ricker recruitment function (equation 14), including the deterministic effect of El Niño events (in those years when it occurred, based on the definition in footnote 31). Sources: (1), (2), (5–7): IFOP (2013); (3): Subsecretaría de Pesca (Chilean Fisheries Regulator); (4): authors' own calculations

	(1) Total catch Chilean fleet (10^3 tons)	(2) Total catch DWFNs (Beyond Chilean EEZ) (10^3 tons)	(3) TAC Chilean fleet (10^3 tons)	(4) F. effort multiplier Chilean fleet (Implicit λ value)	(5) Recruits (10^6 individuals)	(6) SSB (10^3 tons)	(7) Total Biomass (10^3 tons)
1980	562	340	–		21,738	10,564	15,973
1981	1061	438	–		27,215	10,825	17,114
1982	1495	733	–		27,652	10,335	17,861
1983	865	849	–		25,645	10,432	17,471
1984	1426	1060	–		47,886	10,265	19,017
1985	1457	799	–		60,875	10,653	20,827
1986	1184	838	–		28,735	12,190	21,942
1987	1770	863	–		15,962	13,822	22,698
1988	2138	863	–		17,644	14,304	22,534
1999	2391	876	–		23,051	13,652	21,673
1990	2472	872	–		26,461	12,616	20,751
1991	3020	544	–		20,834	11,428	19,708
1992	3212	38	–		16,344	10,377	18,002
1993	3236	0	–		14,933	9392	16,140
1994	4041	0	–		16,942	7824	14,545
1995	4404	0	–		18,434	5775	12,596
1996	3883	0	–		21,071	4557	10,378
1997	2917	0	–		24,326	3844	9345

Table 1 continued

	(1) Total catch Chilean fleet (10^3 tons)	(2) Total catch DWFNs (Beyond Chilean EEZ) (10^3 tons)	(3) TAC Chilean fleet (10^3 tons)	(4) F. effort multiplier Chilean fleet (Implicit λ value)	(5) Recruits (10^6 individuals)	(6) SSB (10^3 tons)	(7) Total Biomass (10^3 tons)
1998	1613	0	–		21,460	4070	8862
1999	1220	0	1902		24,704	4815	9622
2000	1235	2	–		24,298	5643	10,771
2001	1650	20	1425		20,597	6312	11,720
2002	1519	76	1625	0.32	12,873	6848	11,852
2003	1421	158	1350	0.46	8365	7073	11,559
2004	1452	295	1475	0.45	6339	6722	10,793
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	10,892	2286	4034
2013	242	47	250				

Biological Model

We provide details of the model in Sect. 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, pp. 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

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

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-year delay, i.e., depending on the spawning stock biomass of two periods earlier:[28]

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

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

We use the parameter estimation proposed in Yepes (2004), which relies on official data from the *Instituto de Fomento Pesquero* (IFOP).[29] Parameters of the Ricker recruitment function at expression (14) were estimated using linear time-series analysis. The estimated parameters are $\alpha = e^{2.39}$ 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

[28] This 2-year 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; and Instituto de Fomento Pesquero, Valparaíso - Chile: Informe Complementario Investigación CTP Jurel, 2003: Indicadores de Reclutamiento.

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

[31] Based on Chilean marine biologists advice, Yepes (2004) calculates the occurrence of the *El Niño* phenomenon based on *National Oceanic and Atmospheric Administration (NOAA)* data on sea surface temperatures

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 $\{\epsilon(t)\}$ correspond 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). It is possible to obtain a closed-form solution for some problems (De Lara and Martinet 2009). Determining optimal strategies in dynamic optimization problems under uncertainty is not easy. Optimization in the stochastic viability framework is not exceptional. In particular, the curse of dimensionality can be a serious obstacle to the computation of 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 scenarios tested is large, the frequency of viable scenarios can be used as an approximation of the viability probability.

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Footnote 31 continued
measured at the region known as *Niño 3.4* (120W-170W, 5N-5S). NOAA computes the *Oceanic El Niño Index (ONI)* as the difference in current sea surface temperature (SST) with respect to the historical average SST for the period 1971–2000. We then computed a three-month moving average series, on the basis that *El Niño* occurs if this average is greater than 0.5°C for five consecutive months (see the expression of niño*(t)*). The ONI is modeled via a sinusoidal function whose parameters are estimated using a non-linear iterative algorithm (Yepes, 2004, p.64), to represent the different cycles of *El Niño*.

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