Risk averse policies foster bio-economic sustainability in mixed fisheries

Abstract

This paper examines the role of risk aversion on the sustainable management of mixed fisheries. We consider a bio-economic model of multiple species harvested by a single fleet with uncertain costs of effort. We assume that the regulatory agency aims at reaching MMEY (Multispecies Maximum Economic Yield) by maximizing the expected utility of total profits, where the utility function captures risk aversion. We show analytically that such a risk-averse MMEY mitigates the risk of biological and economic overexploitation of the different species. It further enhances biodiversity in the sense of evenness within the portfolio of the fishery. However risk aversion also lessens the expected profit and food production. Thus, risk aversion implies a trade-off between different bio-economic goals. These findings are illustrated with the case study of the Australian South East Fishery, where small risk aversion levels allow for high global bio-economic performances and balanced management objectives, therefore fostering sustainability.

Keywords

Multispecies fishery, ecosystem-based fisheries management, maximum economic yield, uncertainty, risk aversion, overexploitation

1 Introduction

Marine ecosystems and fisheries are under pressure worldwide (McWhinnie, 2009). In response, ecosystem-based fishery management (EBFM) has been put forward as an effective and holistic approach for managing world fisheries (Pikitch et al., 2004). This approach generally aims at integrating the ecological and economic complexities of fisheries, and at implementing a multi-criteria framework that allows to sustainably balance ecological and socio-economic objectives (Thébaud et al., 2014; Doyen et al., 2017). The EBFM approach also seeks to embrace the multiple ecological and economic uncertainties that fishermen and managers usually face (Sethi et al., 2005). The general objective of this paper is to examine the extent to which an ecosystem approach can be tailored to deal with uncertainty and multi-criteria challenges.

Operationalizing the EBFM approach requires new models, to integrate the multiple bio-economic complexities at play (Plagányi, 2007) as well as the uncertainties that are inherent to fisheries (Dowling et al., 2015; Fulton et al., 2016; Sanchirico et al., 2008). These new models enable to evaluate the capacity for public policies to ensure economic profitability together with biological sustainability (Doyen et al., 2012; Péreau et al., 2012; Schuhbauer and Sumaila, 2016).

In that respect, the use of monospecific reference points in multispecies fisheries is increasingly criticized (Legović and Geček, 2010). For instance, monospecific maximum sustainable yield (MSY) targets have been shown to affect the structure of harvested ecosystems (Walters et al., 2005). Moreover, although maximum economic yield (MEY) favor higher biomasses than MSY policies in single-species fisheries (Clark, 2010; Dichmont et al., 2010), it does not account for potential ecological interactions in mixed fisheries (Hoshino et al., 2017). Instead of single-species reference points, there have been attempts at defining multispecies MSY (MMSY) and MEY (MMEY) policies, at which total catches or total profits are maximized (Mueter and Megrey, 2006; Guillen et al., 2013). Such global harvesting policies may however enhance biodiversity losses: while MMSY policies are likely to threaten low-productivity species, MMEY policies induce the overexploitation of stocks with low economic value (Clark, 2006; Tromeur and Doyen, 2016).

Optimal harvesting policies are generally based on deterministic models that do not account for the multiple bio-economic uncertainties facing fishermen and managers (Grafton et al., 2010). Beddington and May (1977) have shown for instance that the uncertain growth of fish stocks could affect the definition of biological reference points. Likewise, Charles and Munro (1985) suggested that biological uncertainty favors more conservationist policies. Uncertainty in fish prices associated with growth stochasticity has also been found to induce potential trade-offs between mean profits and their variance (Gourguet et al., 2014). In that perspective, designing portfolios of harvested species has been proposed as a strategy to balance profits with volatility (Edwards et al., 2004). Fisheries are also characterized by uncertain variable costs. In particular, fuel costs mainly depend on the price of fossil fuels, that are highly volatile assets (Cheilari et al., 2013; Tyedmers, 2004).

Dealing with bio-economic uncertainty in fisheries management implies accounting for attitudes towards risk. Individual fishermen as well as managers may be characterized by risk-averse attitudes (Brick et al., 2012). These behaviors have been shown to affect the definition of optimal sustainable yields (Ewald and Wand, 2010). Accounting for risk aversion in uncertain fisheries may thus help to define ecosystem-based management tools that allow to balance ecological and economic risks and to promote biological sustainability (Doyen et al., 2017).

The aim of this paper is to evaluate the bio-economic merits of risk-averse attitudes under cost uncertainty, as well as to question their relevance in operationalizing ecosystem-based management and multispecies reference points. To do so, we use a bio-economic model with multiple species and a single fleet, and we model preferences by a quadratic utility function. This allows us to derive analytical conditions for a sustainable stochastic MMEY. Thereby, we build a general analytical framework to evaluate how risk-averse attitudes impact sustainability in multispecies fisheries. In particular, we show how risk aversion affects food production, profit variability and biodiversity. These analytical results are illustrated using the case study of the South East Fishery in Australia.

The paper is organized as follows. In section 2, we present the bio-economic model describing the management of mixed fisheries relying on risk-averse MMEY policies. In section 3, we examine the impact of risk aversion on ecological and economic performances of these MMEY. Finally, we illustrate in section 4 the theoretical results with the case of the South East Fishery in Australia.

2 Bio-economic model

2.1 Multispecies dynamics and equilibrium yield

We consider N species jointly harvested by a single fleet. It is assumed that no ecological interaction occurs between the species. The dynamics of every species $i = 1, \ldots, N$ is described by a Gompertz growth (Fox, 1970) in discrete time as follows:

$$x_i(t+1) = x_i(t)\left(1 + r_i \ln\left(\frac{K_i}{x_i(t)}\right) - q_i e(t)\right) \tag{1}$$

where $x_i(t)$ denotes the stock of species i at time t, r_i its intrinsic rate of growth, K_i its carrying capacity, q_i its catchability and $e(t)$ the fishing effort at time t. Parameters r_i, K_i and q_i are assumed to be strictly positive.

We compute the following equilibrium stocks and efforts for every species i:

$$x_i(e) = K_i \exp\left(-\frac{q_i e}{r_i}\right) \tag{2}$$

or equivalently

$$e(x_i) = -\frac{r_i}{q_i} \ln\left(\frac{x_i}{K_i}\right). \tag{3}$$

The harvest at equilibrium for every species i is then defined as follows :

$$h_i(e) = q_i e x_i(e) = q_i K_i e \exp\left(-\frac{q_i e}{r_i}\right) \tag{4}$$

Such a relation points to the non linear nature of the equilibrium yields for the different species.

2.2 Uncertain profits and MMEY objective

Extending the concept of MEY to the multispecies framework, we consider the multispecies maximum economic yield (MMEY) which aims at maximizing total profits, defined as the difference between total revenues derived from harvesting the different species and the costs of fishing effort. The total profit $\pi(t)$ of the fishery at time t is thus defined by :

$$\begin{aligned}\pi(t) &= \sum_{i=1}^{N} p_i h_i(t) - c(t)e(t) \\ &= e(t)\left(\sum_{i=1}^{N} p_i q_i x_i(t) - c(t)\right)\end{aligned} \tag{5}$$

where p_i is the price of species i at time t and $c(t)$ is the per-unit-effort cost of fishing at time t. Costs of effort $c(t)$ are assumed to vary stochastically through time. The probability distribution of variable cost c is assumed to be independently and identically distributed with expectation $\overline{c}$ and standard deviation σ_c namely:

$$\mathbb{E}[c(t)] = \overline{c} \quad \text{and} \quad \mathbb{V}\text{ar}[c(t)] = \sigma_c^2 \tag{6}$$

Many fisheries are regulated by regional agencies, that apply general directives at regional levels. An example is the Australian Fisheries Management Agency, which objective is to implement an ecosystem-based management of Australia's exclusive economic zone (Scandol et al., 2005). Such fisheries can therefore be modeled as monopolistic firms, which behavior is dependent on economic incentives. We assume that the management objective, inspired by MMEY, is defined so as to maximize the expected utility of aggregated profits (5) at equilibrium:

$$\max_{e \text{ satisfying } (3)} \mathbb{E}(U(\pi)) \tag{7}$$

where U is a utility function capturing risk aversion. Risk averse attitudes being common in society (Binswanger, 1980) and in fishermen communities (Brick et al., 2012), we assume the policy maker to be risk-averse (Eeckhoudt et al., 2005). For the sake of simplicity, we rely on a quadratic utility function consistent with portfolio theory or with mean-variance analysis (Edwards et al., 2004; Baldursson and Magnússon, 1997):

$$U(\pi(t)) = U_\lambda(\pi(t)) = \pi(t) - \frac{\lambda}{2}(\pi(t) - \mathbb{E}[\pi(t)])^2, \tag{8}$$

where $\lambda \geq 0$ is a a coefficient capturing risk aversion of the policy maker. Hereafter, we will simply call it *risk aversion level*. For $\lambda = 0$, the economy is said to be risk-neutral while for $\lambda > 0$, it is said to be risk-averse.

Combining (6), (8) and (7), for each value of λ, the optimal risk-averse MMEY effort denoted by e_λ^{MMEY} solves the following maximization problem (9) :

$$\max_{e \text{ satisfying (3)}} \sum_i p_i q_i x_i e - \overline{c}e - \frac{\lambda}{2}\sigma_c^2 e^2. \tag{9}$$

Using equilibrium equation (2), the optimality problem reads as follows

$$\begin{gathered} \max_{e\geq 0} V_\lambda(e), \\ \text{with the objective function} \\ V_\lambda(e) = \sum_i p_i q_i K_i e \exp\left(-\frac{q_i e}{r_i}\right) - \overline{c}e - \frac{\lambda}{2}\sigma_c^2 e^2. \end{gathered} \tag{10}$$

In what follows, we study how risk aversion impacts the optimal fishing effort. Note that high fishing efforts favor the social objective of maintaining jobs in the fishing industry, while it may induce biological and economic overexploitation of fish stocks, potentially affecting food security.

2.3 Overexploitation

In line with FAO (2016), we consider that a species is biologically overharvested if its biomass is smaller than its MSY biomass (where catch at equilibrium is maximal).

In the case of the Gompertz dynamics given by (1), using first order conditions of optimality, MSY is explicitly characterized by

$$x_i^{\text{MSY}} = \frac{K_i}{\exp(1)} \quad \text{and} \quad e_i^{\text{MSY}} = \frac{r_i}{q_i} \tag{11}$$

The equilibrium condition (3) can be written

$$x_i = x_i^{\text{MSY}} \exp\left(1 - \frac{e}{e_i^{\text{MSY}}}\right). \tag{12}$$

Consequently, the equilibrium biomass of a particular species i is smaller than its MSY biomass when the global harvesting effort in the fishery is larger than the monospecific MSY effort of this species. A species is thus considered overharvested when

$$e > e_i^{\text{MSY}}, \tag{13}$$

that is when the harvesting effort is larger than its monospecific MSY effort. If it is equal to the MSY effort, the species is said to be fully exploited.

Likewise, we consider that a species is economically underexploited if its biomass is smaller than its risk-neutral MEY biomass (where the monospecific risk-neutral utility function at equilibrium is maximal). In a risk-neutral fishery, the optimal MEY strategy is implicitly defined as maximizing the individual expected profit from fish :

$$\mathbb{E}(\pi_i) = p_i h_i - \overline{c} e \tag{14}$$

Using first order conditions of optimality, MEY for species i is explicitly characterized by

$$x_i^{\text{MEY}} = \frac{K_i}{\exp\left(1 - W\left(\frac{\overline{c}\exp(1)}{p_i q_i K_i}\right)\right)} \quad \text{and} \quad e_i^{\text{MEY}} = \frac{r_i}{q_i}\left(1 - W\left(\frac{\overline{c}\exp(1)}{p_i q_i K_i}\right)\right), \tag{15}$$

where W is defined by the Lambert function $W\left(\frac{\overline{c}\exp(1)}{p_i q_i K_i}\right)$, that gives the solution for

e in $\frac{\bar{c}\exp(1)}{p_i q_i K_i} = e\exp(e)$. As parameters given to W are positive, the MEY effort is always smaller than the MSY effort. In the monospecific case, MEY is thus always more conservative than MSY. Moreover, when costs reach zero, effort at MEY equals effort at MSY.

The next section aims at using this model to assess the bio-economic sustainability of a risk-averse MMEY. We focus on the impact on risk aversion on biological and economic overexploitation. We also evaluate aggregated metrics of bio-economic sustainability, such as profitability, productivity and biodiversity.

3 Results

In this section, we analyze the impact of risk aversion on various aspects of bio-economic sustainability: employment (measured by the fishing effort), profitability (linked with economic overexploitation), biological sustainability and diversity (linked with biological overexploitation), and food security (linked with catches).

Note first that the optimal solution of (10) exists since for any λ, the objective function $V_\lambda(e)$ is continuous on $\mathbb{R}^+$ and satisfies $V_\lambda(0) = 0$ and $\lim\limits_{e\to\infty} V_\lambda(e) = -\infty$ Hence, function V_λ has an upper bound on $\mathbb{R}^+$ which implies the existence of a maximum effort. Hereafter for the sake of simplicity we consider the following asssumptions on the objective function $V_\lambda(e)$:

Assumption A: The optimum of $V_\lambda(e)$ is unique for any λ. It is denoted by $e_\lambda^{\mathrm{MMEY}}$.

Assumption B: The objective function $V_\lambda(e)$ is concave on the interval $[0; \max_i(r_i/q_i)]$[1].

These assumptions hold true in the single species case as well as for the numerical example of the South East Fishery investigated in section 4. Assumptions A and B are also illustrated by Figure 1.

At MMEY, risk aversion reduces the fishing effort:

Under assumption A, we first show that the MMEY effort as defined in (7) or (10) is decreasing with respect to the risk aversion level.

Proposition 1. *The optimal effort $e_\lambda^{\mathrm{MMEY}}$ is a decreasing function of the risk aversion level λ. Furthermore, the optimal MMEY effort with risk aversion is always lower than without risk aversion: $e_\lambda^{\mathrm{MMEY}} \leq e_0^{\mathrm{MMEY}}$*

Proof. See Appendix A.1.

This result is illustrated in a two-species fishery (Figure 1), where the purpose of risk-neutral MMEY leads to overharvest the species with the lowest growth rate. As expected from Proposition 1, increasing risk aversion reduces the optimal harvesting effort. Reduced efforts imply lower costs and thus lower profit variability. However, a large reduction of fishing activity and effort induced by a high risk aversion may also raise social concerns and question the social acceptability of such a policy, as discussed in Péreau et al. (2012).

[1]Implying that its first derivative

$$V'_\lambda(e) = \sum_i p_i q_i K_i \exp\left(-\frac{q_i e}{r_i}\right)\left(1 - \frac{q_i}{r_i} e\right) - \lambda\, \sigma_c^2 e - \overline{c}$$

increases with e and that its second derivative

$$V''_\lambda(e) = -\sum_i p_i K_i \frac{q_i^2}{r_i} \exp\left(-\frac{q_i e}{r_i}\right)\left(2 - \frac{q_i}{r_i} e\right) - \lambda\, \sigma_c^2,$$

is negative on the interval $[0; \max_i(r_i/q_i))]$

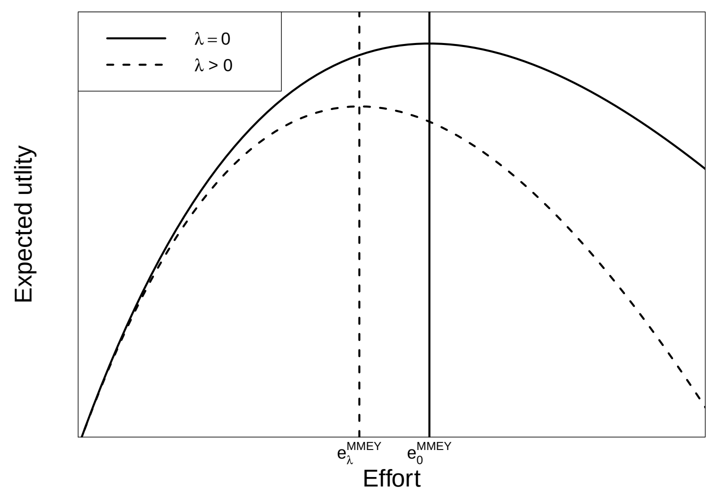


Figure 1: Expected utility versus effort in a risk-neutral (solid line) and in a risk-averse (dashed line) fishery. In the risk-neutral case ($\lambda = 0$), expected utility is equal to expected profits.

At MMEY, risk aversion limits expected profit:

As fishing efforts are reduced, it also turns out that a risk-averse attitude leads to a decline in expected profit. This negative effect on expected profit increases with risk aversion.

Proposition 2. *The expected profit at the optimal risk-averse effort* $\mathbb{E}[\pi(t, e_\lambda^{\mathrm{MMEY}})]$ *is a decreasing function of the risk aversion level* λ*. In particular,* $\mathbb{E}[\pi(t, e_\lambda^{\mathrm{MMEY}})] \leq \mathbb{E}[\pi(t, e_0^{\mathrm{MMEY}})]$.

Proof. See Appendix A.1.

This proposition is illustrated in Figure 1, where expected profits are represented by the solid line. Shifting from a risk-neutral to a risk-averse MMEY effort leads to a decrease in expected (mean) profits. Risk averse policies thus imply losses in the average possible (random) profits. This illustrates the well-known trade-off between mean-related expectations and risk-related variance or standard deviation (Sanchirico et al., 2008; Gourguet et al., 2014). But note that for risk-averse agents (dashed line in Figure 1), this shift brings higher utility levels, including lower risk and variance.

At MMEY, risk aversion mitigates biological overexploitation:

As risk aversion reduces the optimal fishing effort, it is expected to alleviate overexploitation and therefore promote biological sustainability. The following proposition claims that for each species there exists a level of risk aversion which avoids the overexploitation of this species at a risk-averse MMEY. A corollary is that there exists a level of risk aversion that precludes biological overexploitation of all species, and therefore guarantees the conservation of the entire ecosystem at MMEY. Let us define the associated risk aversion level

$$\lambda_{sus}(i) = \max\left(0, \frac{\sum_j p_j h'_j(e_i^{\text{MSY}}) - \bar{c}}{\sigma_c^2 e_i^{\text{MSY}}}\right), \quad \text{with} \quad h'_j(e) = \frac{\partial h_j(e)}{\partial e}$$

and

$$\lambda_{sus} = \max_{i=1,\ldots,N} \lambda_{sus}(i) \tag{16}$$

We obtain the following proposition:

Proposition 3. *For every species i, there exists a level of risk aversion $\lambda_{sus}(i)$ such that for all $\lambda \geq \lambda_{sus}(i)$,*

$$e_\lambda^{\text{MMEY}} \leq e_i^{\text{MSY}}, \tag{17}$$

which implies that species i is underharvested or fully harvested. Furthermore, the level of risk aversion λ_{sus} promotes the biological sustainability of all species.

Proof. See Appendix A.1.

Note that if species i is already underharvested or fully harvested at MMEY, $\lambda_{sus}(i) = 0$. Figure 2 exemplifies the levels of viable risk aversion $\lambda_{sus}(i)$ with respect to the coefficient of variation $\sigma_c^2/\bar{c}$ capturing cost uncertainty in a three species fishery. For every value of $\sigma_c^2/\bar{c}$, we compute a value of $\lambda_{sus}(1)$ (respectively $\lambda_{sus}(2)$) that is sufficient to ensure that $e^{\text{MMEY}} \leq e_1^{\text{MSY}}$ (respectively $e^{\text{MMEY}} \leq e_2^{\text{MSY}}$). We do not define a sustainable risk aversion level for species 3, as this species is underharvested even in the risk-neutral situation. According to Proposition 3, the risk aversion level that avoids overexploitation of all species is $\lambda_{sus} = \lambda_{sus}(1)$.

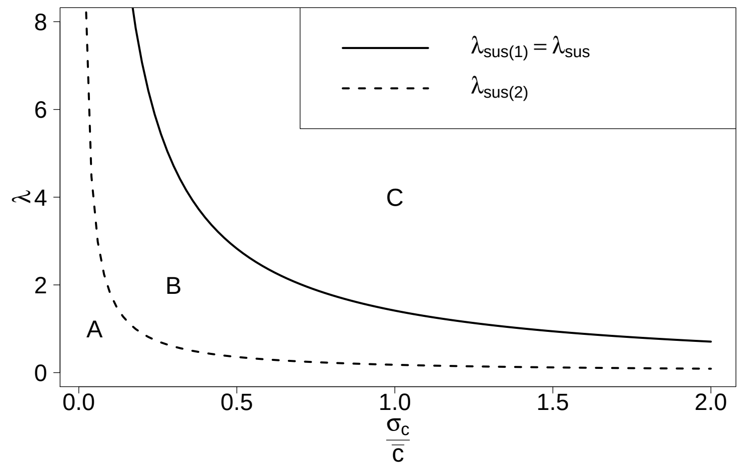


Figure 2: Sustainable risk aversion level λ_{sus} for two species in a three species fishery. Parameters are set to $r_1 = 1$, $r_2 = 2$, $r_3 = 20$, $q_1 = q_2 = q_3 = 1$, $K_1 = K_2 = K_3 = 1$, $p_1 = p_2 = p_3 = 2$, $\bar{c} = 1$. In zone A only species 3 is underharvested; in zone B species 2 and 3 are underharvested; in zone C all species are underharvested.

At MMEY, risk aversion mitigates economic overexploitation:

At MMEY, species are economically overexploited if the MMEY effort is larger than their monospecific MEY effort, as defined in (15). As shown here, risk aversion can reduce economic overexploitation. Let us define the associated risk aversion level

$$\lambda_{eff}(i) = \max\left(0, \frac{\sum_j p_j h_j'(e_i^{\text{MEY}}) - \bar{c}}{\sigma_c^2 e_i^{\text{MEY}}}\right), \quad \text{with} \quad h_j'(e) = \frac{\partial h_j(e)}{\partial e}$$

and

$$\lambda_{eff} = \max_{i=1,\dots,N} \lambda_{eff}(i) \tag{18}$$

We obtain the following proposition:

Proposition 4. *For every species i, there exists a level of risk aversion $\lambda_{eff}(i)$ such that for all $\lambda \geq \lambda_{eff}(i)$,*

$$e_\lambda^{\text{MMEY}} \leq e_i^{\text{MEY}}, \tag{19}$$

which implies that species i is economically under- or fully harvested. Furthermore, at the risk aversion level λ_{eff} none of the species is economically overexploited.

Proof. See Appendix A.1.

According to Proposition 4, risk aversion may reduce the risk of economic overexploitation in the fishery. As Proposition 3, this reveals that risk aversion reduces the pressure on stocks, hence improving economic performance.

At MMEY, risk aversion may restrict food supply:

As the MMEY fishing effort is reduced by risk aversion, it gets closer to the MSY effort of biologically overharvested species, thus increasing their catches. On the contrary, it moves away from the MSY effort of biologically underharvested species, thus reducing their catches. Thus for risk aversion levels above the sustainable threshold λ_{sus} defined in (16), the catches of every species decline with risk aversion.

Proposition 5. *For high enough risk aversion levels $\lambda \geq \lambda_{sus}$, at risk-averse MMEY, the optimal catches $h_i(e_\lambda^{\mathrm{MMEY}})$ of every species decrease with risk aversion.*

Proof. See Appendix A.1.

This result highlights the potential negative consequences of high risk aversion levels in terms of food production and security. Such an outcome may alter the acceptability of this risk-averse strategy for small scale fisheries where seafood production is critical for local subsistence and food security.

At MMEY, risk aversion enhances biodiversity:

As shown in Proposition 3, risk aversion reduces overharvesting and therefore increases the total biomass of the fishery. To investigate the impact of these changes on biodiversity, we use the Simpson index, which is defined as the inverse of the sum of squared biomass shares:

$$S = \frac{1}{\sum_i \gamma_i^2} \quad \text{with} \quad \gamma_i = \frac{x_i}{\sum_j x_j}. \tag{20}$$

This index is often used to quantify biodiversity and takes into account the number of species, as well as the share of every species in terms of abundance. High Simpson indices imply large numbers of species or an even distribution of biomass among species. We obtain the following result:

Proposition 6. *Risk aversion improves the biodiversity of the fishery in the sense of the Simpson index.*

Proof. See Appendix A.1.

According to Proposition 6, risk aversion increases the homogeneity of the distribution of species in the ecosystem by balancing the relative abundances of the different species. As catches are dependent on species biomass, the distribution of catches is also more even in a risk-averse fishery. Risk-aversion thus allows for a diversification of multispecies yields. Diversification of catches is notably an objective of balanced harvesting policies, where all species are harvested relative to their productivity (Marcia, 2011).

4 Case study : the South East Fishery in Australia

We illustrate the analytical findings of previous section 3 with the Australian South East Fishery (hereafter called SEF). The SEF is a multispecies fishery that plays a major socio-economic role in the coastal communities of south-east Australia. The fishing fleet is mainly composed of trawlers (51 vessels at sea in 2014) that catch about 18000 tons of multiple fish species per year, corresponding to an approximate value of 40 million AUD. In what follows, we first describe the method to calibrate the bio-economic model for the SEF. We then analyse the performance of risk-averse MMEY in terms of profitability, biodiversity conservation, production and diversification. This allows us to exemplify the potential beneficial impacts of risk aversion on bio-economic sustainability.

4.1 Calibration of the bio-economic model

To identify the parameters (r_i, K_i, q_i) of dynamics (1) for the different species, we use the method described in Sporcic and Haddon (2016), that defines standardized fishing zones and sums up catch data for each year. We use data on total catch $h(t)$ per year for each species and on the value of catch rates $h(t)/e$. Following Haddon (2010), for each species we choose parameters that minimize the sum of squared residuals between catch data and surplus production models. We select the 8 species that display the best fits. Supplementary details on the calibration method can be found in Appendix A.2.

Price data arise from the *Sydney fish market* for period 1994 to 2008. Daily prices are converted to average monthly prices. Cost data are derived from the *Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES)*. We rely on cost data from 2002 to 2012, and on the total numbers of days at sea for trawlers in year 2009. We deduce an average cost per day and a variance of costs per day for the whole SEF. The variance of costs is about four times higher than the mean value. This could be related to the 30% share of fuel costs in the total costs of the fishery, which also take crew costs, maintenance costs and operational costs into account (Cheilari et al., 2013). The economic environment of the fishery has been coping with important changes due to the substantial oil market fluctuations during 2008 and the recent economic crisis. Our study is relevant in this context of highly varying costs for the fishery. Estimated bio-economic parameters are summarized in Table 1.

Table 1: Calibrated parameters of the selected species for the case study. The estimated average cost of effort is $\bar{c} = 96$ AUD/day while the estimated variance is $\sigma_c^2 = 390$ (AUD/kg)^2. The coefficient of variation in the SEF market is thus $\frac{\sigma_c}{\bar{c}} = 21\%$.

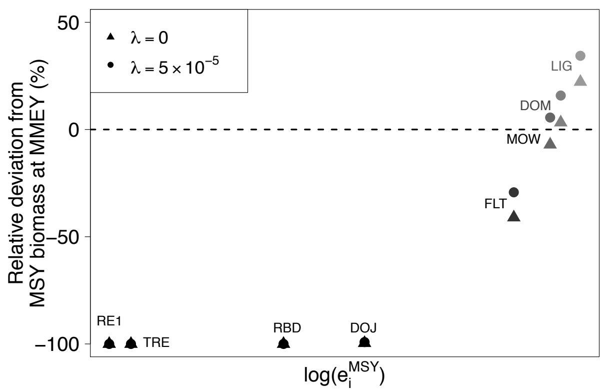
Species i	Abbreviations	growth rate r_i (%/year)	Carrying capacity K_i (t)	Catchability q_i (/year)	Price p_i (AUD/kg)
Ocean Perch	RE1	4.92	12297	1.18×10^{-4}	4.47
Silver Trevally	TRE	0.31	1	6.01×10^{-6}	2.91
Ribaldo	RBD	0.35	1	1.54×10^{-6}	3.79
John Dory	DOJ	2.45	27060	4.90×10^{-6}	8.91
Flathead	FLT	13.34	164315	6.24×10^{-6}	3.86
Morwong	MOW	2.07	66243	6.82×10^{-7}	3.07
Mirror Dory	DOM	14.54	193463	4.31×10^{-6}	3.31
Ling	LIG	14.54	269285	3.56×10^{-6}	6.12

4.2 Biological and economic overexploitation

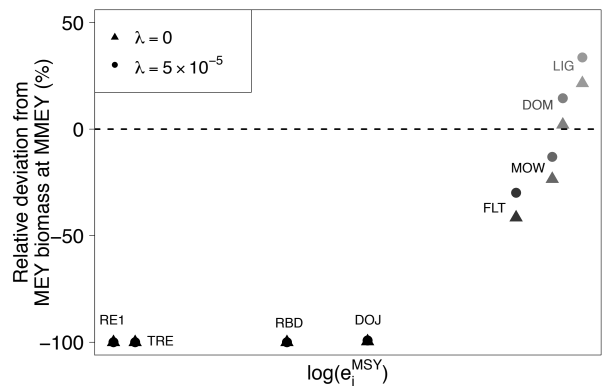
To illustrate the joint impact of risk aversion and cost uncertainty on the South East Fishery, we first compare the effect of risk-neutral and risk-averse situations on biological and economic overexploitation. We then illustrate the trade-offs and synergies between ecological, social and economic objectives in a concluding graph.

The impact of risk aversion on the biological overexploitation of individual species is shown in Figure 3a. We compare the MSY biomass of all harvested species to their biomass at MMEY. To achieve this, we define the deviation from MSY biomass of species i as the difference between MSY biomass of species i and MMEY biomass, normalized by the MSY biomass of species i. Hence, if the deviation is negative, species i is biologically overharvested at MMEY. As expected from Proposition 3, risk aversion reduces the harvesting pressure on all stocks. In particular, it leads to a interesting improvement in the exploitation status of Flathead, Ling, Morwong and Mirror Dory. For instance, Mirror Dory is overharvested in a risk-neutral situation but becomes underharvested with risk aversion. John Dory, Ribaldo, Silver Trevally and Ocean Perch display very low biomass in the risk-neutral situation, so that the relative improvement with risk aversion is not significant.

The impact of risk aversion on economic overexploitation is shown in Figure 3b. To compare the MEY biomass of all species to their biomass at MMEY, we define the deviation of species i from MEY biomass at MMEY. As expected from Proposition 4, risk aversion reduces the economic overexploitation of all stocks. Again, risk aversion leads to an important improvement in the exploitation status of Flathead, Ling, Morwong and Mirror Dory. The improvement in the exploitation status of John Dory, Ribaldo, Silver Trevally and Ocean Perch is also barely noticeable, due to the low individual optimal efforts of these species.



(a)



(b)

Figure 3: Illustration of the impact of risk aversion on biological and economic overexploitation at MMEY. (a) Relative deviations from MSY biomass at MMEY in a risk-neutral and in a risk-averse scenario. (b) Relative deviations from MEY biomass at MMEY in a risk-neutral and in a risk-averse scenario. The darker the symbol of the species, the more endangered it is.

4.3 Policy implications

As shown in Section 4.2, a risk-averse management of the South East Fishery could induce changes in bio-economic performances. This section is dedicated to a better understanding of how these results can help to design management policies.

The consequences of risk aversion on multiple management indicators is synthesized in Figure 4, which compares the bio-economic performances of MMEY in a risk-neutral case ($\lambda = 0$), in a low risk aversion case ($\lambda = 5.10^{-5}$), and in a high risk aversion case ($\lambda_{sus}(DOJ) = 4.10^{-3}$). In the latter case the level of risk aversion was set to avoid the overexploitation of John Dory, according to Proposition 3. This also allows for a sustainable exploitation of Lings, Mirror Dory, Morwong and Flathead, as the monospecific MSY effort of these species is higher than the MSY effort of John Dory. As the sustainable exploitation of Ocean Perch, Ribaldo and Silver Trevally entails even higher levels of risk aversion, we chose to focus our analysis on the sustainable exploitation of John Dory.

Risk aversion reduces the MMEY effort, which implies a reduction in the number of active fishermen. As the effort decreases, expected revenues and total catches are also reduced. This observation is consistent with Propositions 1, 2, and 5. Indeed, lower yields in the risk-averse case are coherent with the current observation that, for many species in the SEF, actual catches are lower than the prescribed Total Allowable Catch (TAC). The impact of risk aversion on economic indicators strongly depends on the level of risk aversion: high levels of risk aversion entail a more than 60% reduction in profits and catches, while low levels of risk aversion induce moderate decreases.

On the contrary, the Simpson index accounting for biodiversity in the fishery improves with risk aversion, and so does the number of biologically underexploited species. This is consistent with analytical results described in Proposition 6. Note however that low levels of risk aversion lead to low increases in the diversity index, which can be related to high biomass differences between under- and overexploited species. Therefore, a low level of risk aversion reduces overexploitation, but it does not achieve a more even distribution of biomass among species.

Economic security is defined here as the inverse of the standard deviation of profits. Thus, high values capture low profit variability. As expected, this metric increases with risk aversion. In particular, the value of the economic security index in the low risk aversion case is only 20 % that of the high risk aversion case.

Altogether, these results highlight a first trade-off between the economic performance of the fishery and its ecological sustainability, a second trade-off between expected profits and economic security, and a synergy between ecological indicators and economic security. The strength of these trade-offs and synergies is balanced by risk aversion levels, as illustrated in Figure 4.

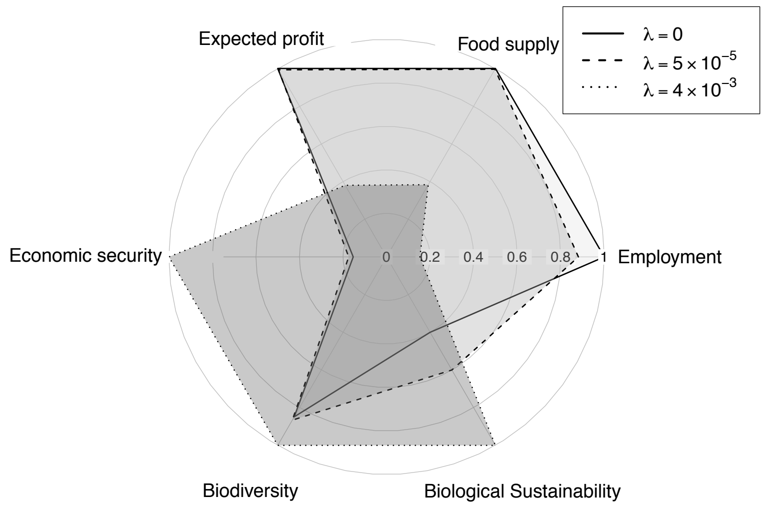


Figure 4: Illustration of the different trade-offs at stake in the South East Fishery for three different levels of risk aversion ($\lambda = 0$, $\lambda = 5 \times 10^{-5}$ and $\lambda = \lambda_{sus(DOJ)} = 4 \times 10^{-3}$). Each indicator is normalized relatively to its maximum value.

To precisely quantify the impact of risk aversion on the level of performance of the fishery, the relationship between the area of the radar chart and the risk aversion level is computed in Figure 5. The area of the radar is a global indicator of performance that equally weights all indicators. As expected from Figure 4, there exists a maximum area value for a small level of risk aversion (about 3×10^{-5}), indicating a maximal global performance of the fishery. The function displays abrupt increases, that can be attributed to overharvested species becoming underharvested. The maximum area is reached when the less overharvested species (which is Morwong, following Fig. 3) becomes underharvested. More generally, for small levels of risk aversion ranging from approximately 3×10^{-5} to 1×10^{-4}, the overall bio-economic performance of the fishery is better than in the risk-neutral case.

The relationship between the centroid distance from the origin of the radar chart and the level of risk aversion is also computed in Figure 5. The centroid is the arithmetic mean position of all indicators, and it thus describes the balance between management objectives. Reduced distance of the centroid from the origin informs on an improved balance between management objectives. In Figure 5, we plot the inverse of the centroid distance from the origin. It turns out that the balance between indicators is maximized at an intermediate level of risk aversion ($\lambda = 7.9 \times 10^{-4}$). Therefore, the optimal balance between management objectives does not coincide with maximum bio-economic performance, as given by the area of the radar chart. Nevertheless, reaching the maximum performance level allows to improve the balance between objectives, as compared to the risk-neutral situation. As a result, small levels of risk aversion foster bio-economic sustainability as compared to the risk-neutral situation. Higher risk aversion levels may also improve the balance between objectives, but at the expense of global performance.

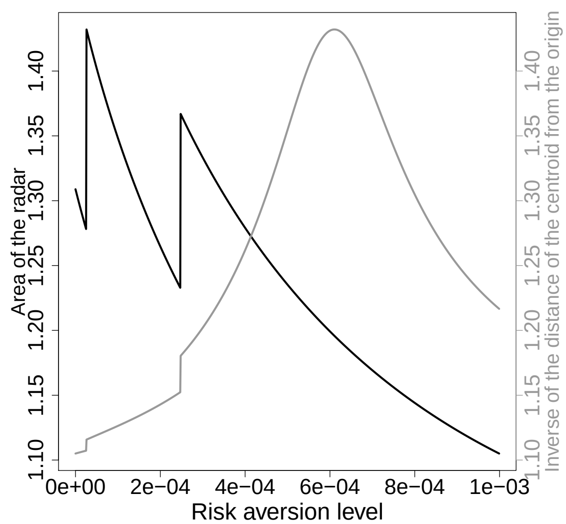


Figure 5: Relationship between the global performance of the fishery and the risk aversion level of the policy maker. In black, the relationship between area of the radar chart and risk aversion levels. Stepwise increases are due to the fact that previously overharvested species become underharvested. The maximum value of the area is obtained for a level of risk aversion (about 3×10^{-5}) leading to the underharvest of Morwong (the most productive of the overharvested species under a risk-neutral scenario). The gray curve represents the relationship between the inverse centroid distance from the origin and risk aversion levels. The maximum of the curve (corresponding to the minimum centroid distance from the origin) is obtained for an intermediate risk aversion level (7.9×10^{-4}).

This case study on the South East Fishery highlights the potential benefits of risk-averse policies when dealing with economic uncertainty. In particular, low levels of risk aversion allow to reconcile ecological and economic performances, and could thus facilitate the implementation of an ecosystem-based management of this fishery.

5 Conclusion

In this paper, we examine the consequences of uncertainty and risk aversion on optimal harvesting strategies in mixed fisheries involving technical interactions. Using a bio-economic model of multiple species harvested by a single fleet and a quadratic utility function, we analyze the impacts of risk-averse attitudes on the outcomes of a multi-species maximum economic yield (MMEY) policy and extend some results from the deterministic case (Clark, 2006; Tromeur and Doyen, 2016). We show how risk aversion can affect overharvest and extinction of species, as well as optimal profits. These results bring novel insights into the potentially beneficial impacts of precautionary attitudes in mixed fisheries run under MEY policies.

Many fisheries are currently managed by specific regulating agencies, at regional or national levels. An example of such an organization is the Australian Fisheries Management Authority, which is based on the involvement of stakeholders, such as fishery industry members or conservation agencies members (Smith et al., 1999). This co-management may allow to account for fishermen's aversion towards economic risk (Brick et al., 2012). This is especially relevant as fuel costs have experienced large fluctuations in the last decade (Cheilari et al., 2013). Accounting for uncertainty and risk aversion is thus an emerging challenge in fisheries management, and a central objective of the ecosystem-based approach (Doyen et al., 2017).

To adress such issues, we first show that uncertainty in operating costs reduces the optimal MMEY effort as risk aversion increases. Risk aversion in MMEY-driven fisheries thus mitigates the overexploitation of species with low productivity and low value, and helps to maintain biodiversity in fisheries. Thus, accounting for uncertainty and risk aversion in setting effort limits can actually improve the ecological performance of fisheries. A similar synergy between reduced variability of profits and ecological performance has been pointed out in agroecosystems by Mouysset et al. (2013). This synergy is due to a diversification of regional land uses, often associated with a focus on less intensive and less profitable agricultural practices. Thus, as in our study, risk aversion reduces exploitation intensity and profitability, which in turn increases biodiversity. This result also suggests that potential stabilizing subsidies on costs could reduce the effect of risk aversion and thus increase harvesting pressures. In that sense, such stabilizing subsidies could be accounted for as *capacity-enhancing*, following the classification by Sumaila et al. (2010).

Second, we show that risk aversion brings lower levels of mean or expected economic performance. Accounting for uncertainty and risk aversion in fisheries management may therefore hamper the economic efficiency of fisheries. We thus highlight a trade-off between economic performance and economic security, which is associated with a trade-off between economic performance and ecological performance (Cheung and Sumaila, 2008). In addition to lower economic performance, risk aversion induces lower expected (mean) yields. This result may partly explain the current problem of undercaught TAC (Total Allowable Catch) the South East Fishery is experiencing. Indeed, according to the Australian Fisheries Management Authority, at the end of 2015, 23 of the 34 species groups under TAC were less than 50% caught. Of the major quota species, only four had catches above 80% of the TACs. This situation is obviously caused by numerous different reasons, but the adoption of risk-averse approaches by local fishery managers may be one of them.

Third, we find that accounting for risk aversion and cost uncertainty can help to manage the trade-offs and synergies between multiple management objectives. In particular, we show that in the Australian South East Fishery small levels of risk aversion improve the global bio-economic performance of the fishery, as well as the balance between management objectives. The increase in global performance is notably mediated by the increase in biodiversity and therefore the diversification in harvested species. As risk aversion fosters bio-economic sustainability in such multi-objective contexts, it should be considered a key parameter in ecosystem-based fisheries management approaches (Pikitch et al., 2004).

In this study we focused on cost uncertainty, while fisheries are affected by multiple layers of uncertainty. Price volatility is a common feature of fisheries (Dahl and Oglend, 2014), and has been shown to impact the fishing decisions of risk-averse fishermen (Brick et al., 2012). As a consequence, we suggest that price-stabilizing mechanisms such as price ceilings or price floors may affect the bio-economic performance of fisheries. Fish stock dynamics are also uncertain (Edwards et al., 2004), and are subject to stochastic environmental disturbances. Moreover, harvesting has been shown to alter fish population dynamics (Hsieh et al., 2006). As biological uncertainty hinders the estimation of fish stocks, it has been found to affect the definition of reference points such as MSY (May et al., 1978). This data-related uncertainty hinders the ecosystem-based management of multispecies fisheries, which requires similar levels of knowledge for all harvested stocks.

We also assumed that all species are ecologically independent, while harvesting some species is known to have cascading effects in trophic networks (Finnoff and Tschirhart, 2003). Maximizing total yield in a predator-prey community can for instance induce severe predator depletion and reduce the resilience of the harvested system (Tromeur and Loeuille, 2017). Furthermore, uncertainty in the dynamics of harvested predator-prey communities may lead to unstable dynamics and extinction (Tu and Wilman, 1992).

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A Appendix

A.1 Proofs of propositions

Proof of Proposition 1

Let e_λ^{MMEY} be the effort (unique from assumption A) that maximizes the function $V_\lambda(e)$, and let $\Delta\lambda > 0$ be a variation of λ. We have

$$V_{\lambda+\Delta\lambda}(e_\lambda^{\text{MMEY}}) = V_\lambda(e_\lambda^{\text{MMEY}}) - \frac{\Delta\lambda}{2}\sigma_c^2 e_\lambda^{\text{MMEY}2}$$

As $V_{\lambda+\Delta\lambda}$ reaches its maximum at $e_{\lambda+\Delta\lambda}^{\text{MMEY}}$, we have

$$V_{\lambda+\Delta\lambda}(e_{\lambda+\Delta\lambda}^{\text{MMEY}}) \geq V_{\lambda+\Delta\lambda}(e_\lambda^{\text{MMEY}})$$

or equivalently

$$V_\lambda(e_{\lambda+\Delta\lambda}^{\text{MMEY}}) - \frac{\Delta\lambda}{2}\sigma_c^2 {e_{\lambda+\Delta\lambda}^{\text{MMEY}}}^2 \geq V_{\lambda+\Delta\lambda}(e_\lambda^{\text{MMEY}}).$$

Finally, as

$$V_\lambda(e_{\lambda+\Delta\lambda}^{\text{MMEY}}) - V_{\lambda+\Delta\lambda}(e_\lambda^{\text{MMEY}}) = \frac{\Delta\lambda}{2}\sigma_c^2 e_\lambda^{\text{MMEY}2},$$

we obtain the following relationship:

$$\frac{\Delta\lambda}{2}\sigma_c^2 e_\lambda^{\text{MMEY}2} \geq \frac{\Delta\lambda}{2}\sigma_c^2 {e_{\lambda+\Delta\lambda}^{\text{MMEY}}}^2$$

As we consider that $\Delta\lambda > 0$ and that fishing efforts are positive, we deduce that

$$e_\lambda^{\text{MMEY}} \geq e_{\lambda+\Delta\lambda}^{\text{MMEY}},$$

and $\lambda \to e_\lambda^{\text{MMEY}}$ is thus a decreasing function. As a consequence, the risk-neutral MMEY effort is necessarily larger than a risk-averse MMEY effort : $e_0^{\text{MMEY}} \geq e_\lambda^{\text{MMEY}}, \forall\, \lambda \geq 0$.

Proof of Proposition 2

As e_0^{MMEY} is a maximum for $\mathbb{E}(U_0)$, it follows that the expected profit at $e_\lambda^{\mathrm{MMEY}}$ is lower than at e_0^{MMEY}, namely

$$\mathbb{E}[\pi(t, e_\lambda^{\mathrm{MMEY}})] \leq \mathbb{E}[\pi(t, e_0^{\mathrm{MMEY}})]$$

More generally, we have

$$\frac{\partial \mathbb{E}[\pi(t, e_\lambda^{\mathrm{MMEY}})]}{\partial \lambda} = \frac{\partial \mathbb{E}[\pi(t,e)]}{\partial e}(e_\lambda^{\mathrm{MMEY}})\frac{\partial e_\lambda^{\mathrm{MMEY}}}{\partial \lambda}$$

From Proposition 1, we know that

$$\frac{\partial e_\lambda^{\mathrm{MMEY}}}{\partial \lambda} < 0. \tag{a}$$

Let us now prove that $\dfrac{\partial \mathbb{E}[\pi(t,e)]}{\partial e}(e_\lambda^{\mathrm{MMEY}}) > 0$. First, since $e_\lambda^{\mathrm{MMEY}}$ is the optimal solution of program (10), we can use the first order condition

$$\frac{\partial \mathbb{E}[V_\lambda(\pi(t,e))]}{\partial e}(e_\lambda^{\mathrm{MMEY}}) = 0$$

Using the very definition of the utility function V_λ, the criteria to optimize can be written

$$\mathbb{E}[V_\lambda(\pi(t,e))] = \mathbb{E}[\pi(t,e)] - \frac{\lambda}{2}\sigma_c^2 e^2$$

Thus we deduce

$$\begin{aligned}
\frac{\partial \mathbb{E}[\pi(t,e))]}{\partial e}(e_\lambda^{\mathrm{MMEY}}) &= \frac{\partial \mathbb{E}[V_\lambda(\pi(t,e))]}{\partial e}(e_\lambda^{\mathrm{MMEY}}) + \lambda\,\sigma_c^2 e_\lambda^{\mathrm{MMEY}} \\
&= \lambda\,\sigma_c^2 e_\lambda^{\mathrm{MMEY}}
\end{aligned}$$

Therefore,

$$\frac{\partial \mathbb{E}[\pi(t,e))]}{\partial e}(e_\lambda^{\mathrm{MMEY}}) \geq 0. \tag{b}$$

By virtue of inequalities (a) and (b), we conclude that

$$\frac{\partial \mathbb{E}[\pi(t, e_\lambda^{\text{MMEY}})]}{\partial \lambda} \leq 0.$$

Proof of Proposition 3

We denote by V_λ' the first derivative of the objective function $V_\lambda(e)$:

$$V_\lambda'(e) = \sum_i p_i q_i K_i \exp\left(-\frac{q_i e}{r_i}\right)\left(1 - \frac{q_i}{r_i} e\right) - \lambda\,\sigma_c^2 e - \bar{c}. \tag{21}$$

From Assumption B, we know that the derivative of $V_\lambda'(e)$, which can be written

$$V_\lambda''(e) = -\sum_i p_i K_i \frac{q_i^2}{r_i} \exp\left(-\frac{q_i e}{r_i}\right)\left(2 - \frac{q_i}{r_i} e\right) - \lambda\,\sigma_c^2, \tag{22}$$

is negative on the effort range $[0, \max_i(e_i^{\text{MSY}})]$.

Let us now derive the expression of the sustainable risk aversion. Species i is not overexploited if $e_\lambda^{\text{MMEY}} \leq e_i^{\text{MSY}}$, that is if $V_\lambda'(e_i^{\text{MSY}}) \leq V_\lambda'(e_\lambda^{\text{MMEY}}) = 0$, as V_λ' is decreasing with respect to effort e. It follows :

$$\sum_j p_j h_j'(e_i^{\text{MSY}}) - \bar{c} \leq \lambda\,\sigma_c^2 e_i^{\text{MSY}}$$

where catch at equilibrium $h_j(e)$ is defined in equation (4). We deduce that

$$\lambda_{sus}(i) = \max\left(0, \frac{\sum_j p_j h_j'(e_i^{\text{MSY}}) - \bar{c}}{\sigma_c^2 e_i^{\text{MSY}}}\right).$$

Proof of Proposition 4

Species i is not economically overharvested whenever $e_\lambda^{\text{MMEY}} \leq e_i^{\text{MEY}}$. This condition is equivalent to $\sum_j p_j h_j'(e_i^{\text{MEY}}) - \bar{c} - \lambda\,\sigma_c^2 e_i^{\text{MEY}} \leq 0$ which holds true for sufficiently high values of risk aversion. As for Proposition 3, we thus have

$$\lambda_{eff}(i) = \max\left(0, \frac{\sum_j p_j h_j'(e_i^{\text{MEY}}) - \bar{c}}{\sigma_c^2 e_i^{\text{MEY}}}\right).$$

Proof of Proposition 5

We have

$$\frac{\partial h_i(e^*)}{\partial e} = q_i x_i (1 - \frac{q_i}{r_i} e) \geq 0 \iff e < e_i^{\text{MSY}}$$

Hence :

$$\frac{\partial h_i(e^*)}{\partial \lambda} = \frac{\partial h_i}{\partial e}(e^*) \frac{\partial e^*}{\partial \lambda} \leq 0 \text{ when } e^* \leq e_i^{\text{MSY}}$$

Moreover, whenever $\lambda \geq \lambda_{sus}$, from previous Proposition 3, for every species we have $e^* \leq e_i^{\text{MSY}}$. We conclude that the catches of all species decrease in that case of high risk aversion.

Proof of Proposition 6

Proof. The inverse Simpson index is defined by the following formula:

$$S = \frac{1}{\sum_i \gamma_i^2}.$$

As risk aversion reduces the optimal fishing effort, increasing risk aversion increases biodiversity if

$$\frac{\partial S}{\partial e} \leq 0$$

which is equivalent to

$$-2S^2 \sum_i \gamma_i \frac{\partial \gamma_i}{\partial e} \leq 0,$$

or

$$\sum_i \gamma_i \frac{\partial \gamma_i}{\partial e} \geq 0.$$

It turns out that

$$\sum_i \gamma_i \frac{\partial \gamma_i}{\partial e} = \sum_i \frac{x_i}{\sum_j x_j} \frac{x_i}{(\sum_j x_j)^2} \sum_j x_j \left(\frac{q_j}{r_j} - \frac{q_i}{r_i} \right).$$

Thus, defining the following function:

$$f_k : x \to \frac{x}{\sum_{i \neq k} \frac{q_i}{r_i} x_i + \frac{q_k}{r_k} x},$$

it follows :

$$\frac{\partial S}{\partial e} \leq 0 \iff \frac{\sum_i x_i^2}{\sum_j \frac{q_j}{r_j} x_j^2} \geq \frac{\sum_i x_i}{\sum_j \frac{q_j}{r_j} x_j} \iff \sum_i f_i(x_i^2) \geq \sum_i f_i(x_i).$$

Note that $\forall k$, $x \to f_k(x)$ is an increasing function:

$$f_k'(x) = \frac{\sum_{i \neq k} \frac{q_i}{r_i} x_i + \frac{q_k}{r_k} x - \frac{q_k}{r_k} x}{(\sum_i \frac{q_i}{r_i} x)^2} = \frac{\sum_{i \neq k} \frac{q_i}{r_i} x_i}{(\sum_i \frac{q_i}{r_i} x)^2} \geq 0.$$

Assuming that the biomass of every species is greater than 1 (otherwise, the stock of species is sufficiently low to consider the species as extinct), we have

$$\forall i, x_i \leq x_i^2 \Rightarrow \forall i, f_i(x_i) \leq f_i(x_i^2).$$

Summing among species leads to $\sum_i f_i(x_i^2) \geq \sum_i f_i(x_i)$ and thus $\partial S/\partial e \leq 0$, which implies that $\partial S/\partial \lambda \geq 0$. The Simpson index is therefore decreasing with effort and increasing with risk aversion. As the number of species is not affected by increasing efforts, the increased inverse Simpson index indicates an increased evenness in the repartition of species biomass.

A.2 Case study

Calibration of models

The theoretical values of catches are compared with the observed values $h^{obs}(t)$ for years 2004 to 2014. We used data on catch per year $h^{obs}(t)$ and catch rates $h^{obs}(t)/e^{obs}(t)$, which gave us yearly values of effort. We were then able to compute our theoretical monospecific harvest from fish $h_i = q_i e x_i = q_i e K_i \exp(-q_i e/r_i)$. The parameters (q_i, K_i, r_i) were estimated by minimizing the sum of squared differences between theoretical and observed values :

$$\min_{r_i,q_i,K_i\geq 0} ||h_i - h_i^{obs}||^2 = \min_{r_i,q_i,K_i\geq 0} \sum_{t=2004}^{2014} (h_i(t) - h_i^{obs}(t))^2.$$

We only selected species for which the residual sum of squares was smaller than 10 (see Table 2).

Table 2: Residual sum of squares of the selected species for the Gompertz model. Only species with residuals smaller than 10 were selected.

Species i	Abbreviations	Gompertz
Flathead	FLT	1.05
John Dory	DOJ	0.77
Ling	LIG	1.52
Mirror Dory	DOM	1.91
Morwong	MOW	0.78
Ocean Perch	RE1	0.5
Ribaldo	RBD	1.42
Silver Trevally	TRE	3.18