Fisheries management: what uncertainties matter?

Jules Selles

To cite this version:

| Jules Selles. Fisheries management: what uncertainties matter? . 2018. hal-01824238
**Fisherries management: what uncertainties matter?**

Selles Jules$^{1,2}$*

$^1$IFREMER (Institut Français de Recherche pour l’Exploitation de la MER), UMR MARBEC, Avenue Jean 9 Monnet, BP171, 34203 Sète Cedex France.

$^2$LEMNA, Université de Nantes, IEMN-IAE, Chemin de la Censive-du-Tertre, BP 52231, 44322 Nantes Cedex France.

*corresponding author, email: jules.selles@gmail.com, tel: +33 (0)779490657

**Abstract**

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Uncertainty is pervasive in fisheries management. Bioeconimists have undertaken long-standing effort to derive economically optimal management rules under uncertainty and provide explicitly optimal feedback solutions. Based on this body of work, we determine the importance of different kinds of uncertainty in the definition of harvest control rules. The performances of harvest policies which dictate how harvest is determined as a function of the state of the resource are sensitive to uncertainty. We discuss six sources of uncertainties and illustrate how these have affected the management process. We then describe how those classes of uncertainty affect optimal harvest control rules. We summarize the conclusions of economists based on structural assumptions affecting objective functions under different classes of uncertainties. We identify common classes of harvest control rules and the resulting precaution of the harvest strategy. Finally, we discuss the opportunities to develop fully adaptive management to decide upon structural assumptions through the extension of Markov decision process and feedback solutions to complex models.

**Keywords**— Bioeconomic modeling; Uncertainty; Fisheries management; Optimal resource management; Harvest policy; Harvest strategies; Control rules.
1 Introduction

Despite many fisheries are highly regulated, overexploitation of fish stocks is still a problem worldwide and rebuilding fisheries is central in scientists debates (Ricard et al. 2009, Worm et al. 2009, Costello et al. 2016, Froese et al. 2018). The failures of fishery management have been linked to the inherent characteristics of fish stocks and the influence of the global market-driven by growing demand for fishery products (Seijo et al. 1998, Cochrane 2000, Caddy & Seijo 2005, Sethi et al., 2010, Collette et al. 2011, Longo & Clark 2012, Pons et al. 2017). Management difficulties have been also attributed to ignoring uncertainties that characterize fishery systems and to respond with a lack of caution in management. Risks\(^1\) associated with uncertainties and multiple objectives permeate fisheries management (Francis & Shotton 1997, Cochrane 2000, Hilborn 2007, Sethi 2010). Many fisheries have experienced overfishing\(^2\) as a result of risky and short sighted management policies (Clark 1973b, Garcia 1996, Hilborn et al. 2001, Grafton 2007, Clark 2010).

In face of uncertainty, the concept of the precautionary approach has been employed widely among nations and fishery agencies (e.g. in Regional Fishery Management Organisations, RFMOs, de Bruyn et al. 2013) to account explicitly for uncertainties in decision making (FAO 1996, Garcia 1996). Precautionary principles are the basis to ensure that the lack of full scientific knowledge (i.e. certainty) should not be an incentive to postpone effective measure to prevent unsustainable exploitation (UNCED, 1993). Besides, they have been translated into the adoption of management reference points to avoid risks. Limit and target reference points have been adopted and management decision should ensure that the risk of exceeding limit reference points is very low and that target reference points should be respected on average (FAO 1996). The biomass \(B_{\text{MSY}}\) that can produce the maximum sustainable yield (MSY) constitutes the central reference point for fisheries referred to in international agreements and instruments (UNCLOS 1982, UNFSA 1995, FAO 1995). Alongside the implementation of precautionary principles, the Ecosystem-Based Fisheries Management (EBFM, FAO 2003, Garcia et al. 2003, Pikitch et al. 2004) has promoted the development of complex

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\(^1\) Risk entails the ideas of uncertainty and loss, the Food and Agriculture Organisation (FAO) refers to average forecasted loss (FAO, 1996).

\(^2\) Biological and economic overfishing (Murawski 2000 defines overfishing in the context of Ecosystem-Based Fisheries Management).
models integrating all features of the social-ecological system encompassing the fishery. Such Integrated Ecological–Economic Fisheries Models (IEEFMs or simply bioeconomic models) have been increasingly used in the support of fisheries management with the aim to account for complex feedbacks effect between fishing activities, and ecosystem dynamics (for a review see Lehuta et al. 2016 and Nielsen et al. 2018). However, the increasing complexities of IEEFMs reduce confidence in forecasting and the ability to disentangle the way in which uncertainty is propagated (Garcia & Charles 2007, Schrank & Pontecorvo 2007, Rochet and Rice 2009, Kraak et al. 2010, Planque 2015). In face of such difficulties, Harvest Control Rules (HCRs) have been promoted to enhance transparency and to consider explicitly the ecological, economic and social goals of the triple bottom line (Cochrane 2000, Hilborn 2007). HCRs provide a simple scientific based management strategy which depends on available data, knowledge and management objectives (Punt 2010). The main contribution of the implementation of HCRs is the integration of the scientific advice into the political realm through the direct proposition of management strategy to deciders (Kvamsdal, 2016). However, the construction of HCRs is mainly based on empirical work and may fail to take into account key uncertainties of the fishery system (Deroba & Bence 2008, Liu et al. 2016). The bioeconomics literature on renewable resource and fishery management models several classes of uncertainty and provide explicitly optimal feedback solutions. The framework considers a social planner seeking to maximize the net present value of the fishery. Optimal Instead of relying only on simulation methods to evaluate the performance of control rules, HCRs derived from such bioeconomic models can provide guidelines on how setting harvest policies when uncertainty is considered. The objective of this review is to bring insights into the importance of different kinds of uncertainty in the definition of harvest control rules. The pursuit of this goal raises an important question: what uncertainties matter when determining control rules? We base our review on the long-standing effort to derive economically optimal management rules under uncertainty. First, we describe the place of bioeconomic modeling approach and feedback solutions in fishery management under different sources of uncertainties arising throughout the management process. Then, we identify the shape and the cautious of optimal management strategies under the source of uncertainties previously identified. Finally, we offer conclusions about the relative importance of different kind of uncertainties on the definition of HCRs.
2 Fishery management and uncertainties

2.1 Adaptive management, HCRs and MSE

Modern fishery management promotes adaptive management (Walters, 1986) as the new standard framework to address decision problems under uncertainty. Adaptive management is an approach for simultaneously managing and learning about the resource which consists imply to learn by doing and upgrade management policies with new observations (Williams & Brown 2016). Searching for optimal harvest policy corresponds to an attempt to apply adaptive management to fishery management. Clark and Munro (1975) seminal work was the first attempt to develop feedback solution to fishery management. They defined the optimal harvest rate as a function of the resource level. Bioeconomic feedback solutions have inspired the development HCRs (Kvamsdal et al. 2016). HCRs have been developed in response to the need for less complex decision framework integrating the precautionary approach (Kvamsdal et al. 2016). HCRs consist in a predefined series of actions (i.e. total allowable catch limits, TACs) determined as a response of the observation of the state of the fishery (i.e. biological information such as biomass level, Figure 1). However, HCRs are usually not derived from formal IEEFM optimization models, but are commonly simple rules based on expert opinion. The latter point implies that although HCRs may include several precautionary elements it does not constitute a standalone method to fully account for uncertainties.

Management Strategy Evaluation (MSE) has been proposed as leading method for coupling both IEEFM and HCRs. It consists of associating single species management model (i.e. Virtual Population Analysis VPA): a decision model (HCR) and an “operating model” (IEEFM) accounting for alternative modeling hypothesis. MSEs are used to evaluate the extent to which HCR achieve their goals (i.e. reaching \( B_{\text{target}} \)). Given the uncertainty integrated into the operating model, MSEs are used to quantify the risk represented by uncertainties throughout the decision process from observations and assessment models to implementation (Butterworth 2007, Punt et al. 2010). Therefore MSE based on simulation modeling has increasingly been used to evaluate the impact of the main recognized sources of uncertainty in fishery systems (e.g. in the Commission for the Conservation of Southern Bluefin Tuna, Kurota et al. 2010, for a review see Punt...
et al. 2016). The objective is to find HCRs that are robust to uncertainties and to provide managers with a set of management options that encompass the precautionary approach.

Figure 1: Conceptual framework of Management strategy evaluation (MSE) (adapted from Kell et al. 2007) and an example of a precautionary constant catch harvest control rule incorporating biomass target ($B_{\text{target}} > B_{\text{MSY}}$), buffer area and limit (adapted from Froese et al. 2010) with a hypothetical equilibrium yield ($Y$) from a surplus production model.

HCRs and MSEs found their essence in ‘top-down’ management scheme where a central regulatory body is in charge of the management and the evaluation of the resource. A typical decision-making structure (Figure 2) is composed of a scientific assessment group giving management advice to managers and to an advisory committee (including resource users) which in turn inform a political authority where responsibility for the final decisions lies. Each country or RFMO has its own institutional chain from scientific fisheries research to political and enforcement decisions (e.g. the Common Fisheries Policy in the European Union, Daw & Gray 2005 or in RFMOs, Lodge et al. 2007). In any case, the central institution typically sets the total allowable catch (TAC) and further inputs restrictions (e.g. seasonal, size catch limit) and specifying the enforcement procedures.

Large uncertainties related to resource, economic and social states are common in fishery management and lead to high transaction costs. Williamson (1985) argued that institutions are established to minimise transaction costs. Thus, in such complex

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3 Management transaction costs within fisheries can be classified into three categories included in the fishery management cycle (Abdullah et al. 1998, Figure 3): information costs related to the resource assessment, decision-making costs related to the policy making and operational costs included monitoring, control and enforcement costs (or implementation costs).
systems, the hierarchical and centralized structures of fishery institution have emerged from the high uncertainties in the information on fishery systems (Abdullah 1998, Nielsen 2003). However, the conjunction of centralised institution, high uncertainties levels and complexities in model used for management have narrowed confidence and legitimacy of fishery management institutions (Daw and Gray, 2005, Hauge et al. 2007, Kraak et al. 2010, Dankel et al. 2012). The loss of legitimacy is, in turn, increasing substantially transaction costs related to monitoring and enforcement of regulated fishing activities (Abdullah 1998, Nielsen 2003). Thus, reducing uncertainty surrounding scientific advice should concomitantly decrease management costs. HCRs can facilitate a fisheries governance system where regulators and fishers work together to decide on overall harvest strategy based on predefined HCRs (Kvamsdal et al. 2016). HCRs by integrating management rules (i.e. TAC) in the realm of scientific advice reduce uncertainty with regard to handling and communication of uncertainty (Rosenberg 2007, Kraak et al. 2010, Dankel et al. 2012).

Nevertheless, HCRs leave aside key political issues such as the allocation of fishing rights imposing high transaction costs. They are mainly distributed on the basis of historical catches negotiation (in RFMOs, Cox 2009, Bailey et al. 2013) rather than economic rationality (Marszalec 2017). Rights-based management such as Individual Transferable Quotas (ITQs), or cooperatives (i.e. Producers Organisations) and community quotas (with or without ITQs) is a complementary solution to provide fishers with good incentives for compliance and efficient allocation regulated through market (Hilborn 2004, Grafton et al. 2006, Beddington et al. 2007, Grafton 2008). ITQs, co-management and collective actions have been brought at the forefront as the solution for improving fisheries management (Beddington et al. 2007, Costello et al. 2008, Berkes 2009, Gutiérrez et al. 2011, Deacon 2012). However, theoretical works and empirical evidences have demonstrated that right based management does not constitute a panacea (Clark, 2010, Thebaud et al. 2012, Melnychuk et al. 2012). Co-management by delegating a part of management tasks to user-organizations can substantially reduce transactions by decreasing monitoring and control of activity (Van Hoof, 2009). Furthermore, co-management can increase the legitimacy of regulations and social norms (Jentoft 1998, Nielsen 2003).
2.2 Uncertainty in fishery management

Large uncertainty is common in most fisheries management activities. To embrace uncertainties, fishery management can be viewed as an adaptive management cycle (Figure 3, Walters 1986, Fulton et al. 2011) where a central fishery agency collects information supporting decisions on regulations on annual or longer periods. Uncertainty emerges at each step of the management cycle and can act to undermine effective fishery management (Fulton et al. 2011). Previous surveys classified uncertainties related to the resource dynamics, assessment and management procedure and propose best practices to address those uncertainties (Figure 3, Hilborn & Peterman 1996; Charles 1998, Regan et al. 2002, Harwood & Stocks 2003, Peterman 2004, Hill et al. 2007, Fulton et al. 2011, Link et al. 2012). Seven sources of uncertainties (sometimes called error) that are important sources of risk in fisheries management have been identified: uncertainties associated with environment conditions, observations, model,
socio-economic conditions, parameters, decisions and behaviours (adapted from Hilborn & Peterman 1996, Figure 3).

2.2.1 Environmental conditions uncertainty

A major source of uncertainty in fishery systems stems from the inherent unpredictability of the resource and ecosystem dynamics (Glaser et al. 2014, Planque 2015). In his seminal work on ecosystem resilience, Holling (1973) identified that complex interactions (feedback mechanisms), stochastic and non-linear processes are part of the restricting features of numerical modeling used for predictions. Without the will to be exhaustive, environmental uncertainties encompass all spatio-temporal variations in species and community abundance, distributions and interactions, changes in life traits, periodic variability of environmental conditions or shifts in productivity regimes (Link et al. 2012). For example, a typical concern in fishery management is the definition of the stock recruitment relationship which is highly dependent on environmental conditions and subject to random fluctuations (e.g. Fromentin et al. 2014).

2.2.2 Observational uncertainty

Uncertainty in observations arises from imperfect methods of observation and from sampling error\(^4\). Such observation uncertainty leads to parameters estimation (or inference) errors (i.e. imprecision, mis-specified parameter distributions and biased parameter estimates) and structural errors (e.g. mis-specified migratory pattern and stock composition). For example, the lack of fisheries-independent indices is a common situation for highly migratory species (abundance indices relied mainly on catch per unit effort, CPUE, Maunder & Punt 2004, Lynch et al. 2012). The logistical challenges of data collection in such fishery are huge. Several sampling methods are available such as tagging, larval and acoustic surveys which can provide abundance indices, but they are constrained by high costs resulting in restricted spatial coverage (Leroy et al. 2015). However, new methods take advantage of specific behavior of tuna species, aerial surveys of tuna school counts and acoustic tagging surveys associated with fish aggregating devices (FADs) are getting close to be a reliable solution to overcome this

\(^4\) Sampling error can be defined as the statistical differences between a sample of individuals and the population.
issue (Bauer et al. 2015, Capello et al. 2016). Mis-reporting of catch which is related to illegal, unreported and unregulated (IUU) fishing is also a challenge for management of highly migratory species (e.g. Fromentin et al. 2014).

2.2.3 Model and parameter uncertainty

Model and parameter uncertainties are the upshot of an incomplete, and potentially misleading, representation of system dynamics (Hill 2007). Models are only abstractions and there still be uncertainty about whether a given model structure (also called structural uncertainty) is an appropriate representation of the system being studied. Alternative model structures result in multiple model formulations that can achieve the same level of fit to data (Lehuta et al. 2016). Model uncertainty can have a large impact on achieving management objectives (Punt 2008). For example, even with the advent of the EBFM, most of the models used in stock assessment are based on single-species age-structured population dynamics, ignoring important ecological interdependencies. Furthermore, assessment models such as Virtual Population Analysis (VPA5) are very sensitive to several assumptions about key biological dynamics such as the natural mortality (Jiao et al. 2012) and selectivity patterns (Brooks et al. 2010).

2.2.4 Economical, political and social uncertainty

Uncertainty in economic, political and social conditions results from market fluctuations which affect species price, as well as in fixed and variable costs of fishing effort. Such variations affect expected profits and consequently the short-term dynamic behavior of fishing fleets (Salas & Gaertner 2004). Consequently, the magnitude of catches might vary in the short-term, affecting the population abundance. For example, in case of substitutable resources on global market such as tuna species, modification in both local and international political conditions and decisions (e.g. TAC in RFMOs) may also constitute a source of uncertainty by altering prices and therefore economic incentives (Sun et al. 2015, Guillotreau et al. 2017, Sun et al. 2017).

5 e.g. statistical VPA used in the International Commission for the Conservation of Atlantic Tunas (ICCAT), Porch (2003).
2.2.5 Decisional uncertainty

Uncertainty in decision, changes in management objectives (resulting from an unpredictable behaviour of the political authority) and the existence of multiple and conflicting objectives constitute an important source of uncertainty (Anderson 1984, Hilborn 2007). Political, social and economic pressures can alter management decisions and lead to ignoring scientific advice claiming the argument of uncertainty in the scientific advice (Rosenberg 2003, Delaney et al. 2007, Rosenberg 2007, Fromentin et al. 2014). For example quota reductions may not be implemented (e.g. Fromentin et al. 2014, Piet et al. 2010, Villasante et al. 2010, O’Leary et al. 2011). In international shared fisheries, strategic interactions play also a crucial role in the determination of common management leading to cooperation between states through international arrangements and institutions (e.g. RFMOs). Compared to domestic fisheries, international fisheries are subject to management difficulties mainly because of a lack of cooperation between states (Munro 2004, McWhinnie 2009, Teh & Sumaila 2015).

2.2.6 Behavioural uncertainty

Uncertainty in the behaviour of resource users is the consequence of complex interactions between economic and social drivers which can lead fishers to act as free-rider and undermine the intent of management actions (Fulton et al. 2011). Behaviour of fishers concerning their spatio-temporal allocation of fishing effort to different métiers, and the reliability of catch and effort data reported, can change in an unexpected way as a response of management regulations (Salas & Gaertner 2004, Vermard et al. 2012). Mis-alignment between managers and users objectives has been claimed as the main factor driven the uncertainty in fishers’ behaviour (Grafton et al. 2006). Divergence of management intentions and response of resource users often leads to complex management regulations based on an accumulation of input controls (i.e. control of fishing effort, qualified of ‘band-aids’ approach, Hilborn et al. 2004). Uncertainty in the behavior of resource users could be also the consequence of a lack of control or an inadequate enforcement policy (Fulton et al. 2011). For example, IUU fishing can emerge because of lack of control or and inadequate policy can be designed if there is no a direct

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6 Shared fisheries refer to transboundary, straddling and highly migratory stocks.
7 Fisheries contained within one exclusive economic zone (EEZ).
8 Métier means a combination of a gear, a target or group of target species.
link between the management lever (e.g. effort), indicator (e.g. catch) and objective (e.g. constrained levels of fishing mortality, Fulton et al. 2011).

Figure 3: Schematic diagram of the rule-based adaptive management cycle and sources of uncertainties that can undermine fisheries management (adapted from Fulton et al 2011).

3 Effect of uncertainties on optimal fishery management: Does precautionary management prevail in face of uncertainties?

3.1 Optimal fishery management problem

Uncertainty is a central concern in fishery management, as described previously complex simulation frameworks have been developed integrating ecological, economic and social aspects to assess the robustness of HCRs on different kinds of uncertainty. However, this approach does not allow deriving formal management rules. Feedback
solutions through the application of optimal control theory extensively used in fishery economics studies have the ability to translate biological or ecological indicators (e.g. stock) into harvest advice. The so-called ‘bang-bang’ or ‘constant-escapement’ management policy finds its origin in the seminal work on feedback solutions made by Clark & Munro (1975) in which the present value of the economic rent of the resource is maximised by bringing the stock to an optimal level as quickly as possible. The optimal escapement⁹ level resulting from the well-known golden rule of capital accumulation is defined at the point where the internal rate of return of the stock is equal to the social rate of discount (Clark & Munro 1975). Nevertheless, to achieve an efficient bang-bang control, management’s policy mechanisms must respond promptly and accurately especially in presence of uncertainties (Roughgarden & Smith 1996). Before discussing the impact of uncertainty on the optimal policy, let’s introduce the modeling framework of a management problem with a single decision maker.

A typical discrete¹⁰ optimal dynamic management problem is defined as a social planner, a hypothetical fishery manager who could be a corporation, a cooperative, a government agency, or a regulatory body, someone who owns the rights to the exploitation of the fish stock and which seeks to maximise the expected net present value of the resource stock¹¹. The manager decides in each period the level of a control variable (e.g. TAC) to adjust the state variable (e.g. stock of fish). This decision is based on the current period value function (e.g. profits from fishing) and future values which are down-weighted using a discount factor. The state transition function depends on the current state and control variables which ensure the Markov property. The manager’s problem can be set as:

\[
\max_{(y_t)} \mathbb{E} \left[ \sum_{t=0}^{\infty} \delta^t \pi(x_t, y_t, \epsilon_t^f, \theta_t^f) \right]
\]

Subject to:

\[x_{t+1} = f(x_t, y_t, \epsilon_t^f, \theta_t^f)\]

Where \(\pi(x_t, y_t, \epsilon_t^f, \theta_t^f)\) is the objective function (value function) and \(f(x_t, y_t, \epsilon_t^f, \theta_t^f)\) the state transition function from period \(t\) to \(t+1\). Each function depends on a set of variables, the state variable \(x_t\) (i.e. the stock) and control variable \(y_t\) (i.e. the yield). The

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⁹ Escapement level refers to the stock level after harvesting.
¹⁰ We only illustrate he discrete case which is sufficient to illustrate the principles involved.
¹¹ We only focus our review on models grounded in subjective expected utility theory (SEU, see Shaw & Woodward 2008).
vectors of stochastic terms $\epsilon_t=(\epsilon_t^p, \epsilon_t^f)$ applied on the objective function (e.g. stochastic prices) or the transition function (e.g. stochastic shocks to the resource stock), vectors of parameters $\theta_t=(\theta_t^p, \theta_t^f)$ relating to the state transition and objective functions. Finally, $\delta$ represents the discount factor.

Those kinds of Markov decision process (Puterman 2004) are generally solved using stochastic dynamic programming techniques (Marescot et al. 2013). As highlighted in Deroba & Bence (2008), stochastic dynamic programming is an efficient method for defining an HCR which best meets the specified objective over a long term period. HCRs can be derived both analytical and numerical, but because of their complexities most fishery applications are numerical (e.g. in a deterministic framework Sandal & Steinsman 1997, Grafton et al. 2000, Arnason et al. 2004). The computational cost of such technique is high in face of the so called issue of “the curse of dimensionality” arising from searching over a wide range of policy strategy (Marescot et al. 2013).

Trade-offs between biological, economic realism and model complexity have limited most fisheries applications to surplus production model. However recent studies have tackled the resolution of optimal strategy in more complex settings such as the age-structured model (e.g. Tahvonen et al. 2017). This field of studies departs from simulation-based evaluation of HCRs which consider complex modeling approach evaluating the trade-offs between several indicators (e.g. studies involving MSEs).

Since the seminal work of Reed (1979), economic literatures have undertaken to study the effect of different classes of abstracted uncertainty related to the previous classification on optimal resource management policy. In the following section, we will discuss the relative impacts of different classes of uncertainty on the optimal policy related to the dynamic management which has been exposed. However, as pointed out by Holland & Herrera (2009) findings and resulting recommendations from bioeconomic models relying on optimal control theory (which found their basis in the Bellman’s principle of optimality, Bellman 1957) are ambiguous or conflicting in many cases. Model (structural) uncertainty relating to biological or economic assumptions has been found to qualitatively and quantitatively affect the optimal policy.

To extract consistent and salient features of optimal policy we disregard in this section the literature using complex model integrating into their model, age structuration (e.g. Tahvonen et al. 2017), spatial processes (e.g. Costello & Polasky 2008), multispecies interactions (e.g. Poudel & Sandal 2015) or comparison of different regulation tools (fee
versus quotas, e.g. Weitzman 2002). We focus our analysis on risk neutral profit maximization objective.\footnote{Or yield maximisation which is equivalent to the profit maximization objective when profit is a linear in harvest. Furthermore, we focus on risk neutral framework and we leave the consideration about risk aversion utility function to integrate precautionary principles (Gollier et al. 2000, Chevé & Congar 2003).}

3.2 Uncertainty and precautionary management

3.2.1 Qualitative optimal policy

McGough et al. (2009) provided a useful analytical solution of a general stochastic fishery model on which we will stand to review the effects of uncertainties on optimal policy. They concluded that the constant escapement policy is optimal under the following specific structural assumptions: i) stochastic shocks affecting the stock (growth) are independently and identically distributed (i.i.d.), ii) demand is perfectly elastic, iii) objective implies risk neutrality and iv) marginal harvest costs are independent of the quantity harvested (i.e. Schaefer’s production function). Relaxing one of these conditions should imply that the constant escapement policy is not optimal. They demonstrated that functional assumption (linear or non-linear in state variable, harvest) made on the objective function (profit function) alter the optimality of the constant escapement policy. When profit exhibit a non-linear dependence on harvest, the optimal policy swift toward a biomass-based rule smoothing harvest in order to decrease the magnitude of the price reduction (downward slopping demand) or decrease the magnitude of the cost augmentation (Cobb Douglas’ type production function). Otherwise, considering a white noise (i.i.d. shocks on growth) does not affect qualitatively the optimal policy, but they showed that allowing correlated environmental shocks affecting the growth of the resource modify the optimal policy. The size of the resource left loses its value at the expense of the size of the environmental shock which provides useful information to predict future growth of the resource.

The constant escapement control rule is a specific policy. Catch and fishing mortality\footnote{Per capita mortality rate.} can also be used to define HCRs. The constant escapement rule involves taking all biomass over some specified target level. The constant catch rule consists to harvest the same biomass each year (or period) and leads to high fishing mortality when the
biomass is at low level\(^{14}\), while the constant fishing mortality maintains the same fishing mortality regardless of stock abundance (see supplementary materials, Appendix A). From that basic HCRs, different variants have been implemented, adding more flexibility related to the biomass level, to address the different weakness, such as depensatory effects which can cause resource collapse.

We take advantage of the review of harvest policies produced by Deroba & Bence (2008) to classify optimal found in the literature in 5 classes corresponding to common control rules: i) constant escapement, ii) constant catch, iii) constant fishing mortality, iv) biomass-based catch and v) biomass-based fishing mortality which could be assigned to shock-based policy described in the theoretical result of McGough et al. (2009). In their review, Deroba & Bence (2008) referred mainly on simulation-based studies which analyse the performance of common HCRs relative to different objective functions\(^{15}\). While Deroba & Bence (2008) include complex modeling framework, the general qualitative findings of McGough et al. (2009) are in line with their observations (see supplementary materials, Appendix B). However, the integration of the state (observation) uncertainty about the size of resource seems to alter the optimality of the constant escapement policy and favor a constant fishing mortality policy.

Therefore, based on these criteria, we reviewed the applications of optimal control theory on fishery management to disentangle the qualitative effects of different classes of uncertainty (Table 1 and Table 2). We compare optimal policy in the structural assumptions setting define by McGough et al. (2009) by confronting what kind of control rule is optimal and if greater level of uncertainty leads to more precautionary\(^{16}\) policy as it expected under the scientific obligations to precautionary approaches.

### 3.2.2 Environmental conditions uncertainty - stochastic growth

#### 3.2.2.1 Independent and identically distributed shocks

In surplus production biomass model, random fluctuations affecting the growth of the stock are a stylised representation of the stochasticity observed in the recruitment, productivity (i.e. carrying capacity) or mortality of the stock driven by environmental

\(^{14}\) Constant catch rule is defined as a depensatory policy (i.e. density independent).

\(^{15}\) We only keep the result based on the profit or yield maximization objective which can be linked to the decomposition of McGough et al. (2009).

\(^{16}\) Precautionary means that uncertainty causes managers to choose less intensive harvest and maintain higher stock.
conditions. Since the seminal work of Reed (1979), several authors have confirmed that introducing stochastic growth (i.e. multiplicative i.i.d shocks in discrete setting or a Wiener process in continuous setting) does not affect the optimality of the constant escapement (CE) policy (Parma 1990, Sethi et al. 2005, Nostbakken 2008, Kapaun & Quass 2013). However, as McGough et al. (2009) highlight the structural assumptions behind this result are very restrictive. If the objective function does not respect the linearity condition in harvest, the optimal policy is no longer the constant escapement (Pindyck 1984, MacDonald 2002, Kugarajh et al. 2006, Nostbakken 2008, Sarkar 2009; Kapaun & Quass 2013 and Kvamsdal et al. 2016). Under the non-linearity assumption, the optimal HCR vary with the resource size and fit a biomass-based catch (BBC) type rule defined by Deroba & Bence (2008).

Furthermore, increasing uncertainty surrounding the growth of the resource has a different impact in term of caution if we consider linear or a non-linear objective function. Nonetheless, quantitative results show only a small absolute difference. Optimal feedback policies do not seem to be strongly affected by stochastic environmental uncertainties. In the linear setting, increasing the uncertainty (variance of the stochastic shocks) leads to an ambiguously more cautious harvest which in turn preserves the resource level to higher level. When profits are non-linear in harvest the resulting cautious of HCR is ambiguous. McDonald et al. (2002), Kugarajh et al. (2006) and Kvamsdal et al. (2016) found that increasing uncertainty has the same effect that increasing the discount rate in the deterministic case especially at low stock level. The resulting optimal HCR is, therefore, more aggressive when uncertainty is high and resource is scarce. However, their logistic growth model which includes a specific depensation response creates an incentive to fish down the resource when the stock falls below the critical depensation level. In such case, the stock will be unable to recover. When the depensation assumption is relaxed, Sarkar et al. (2009) found that the optimal harvest (HCR) size is a decreasing function of the growth uncertainty. Pindyck (1984) has generalized the condition in which uncertainty lead to more or less cautious harvesting behaviour when stochasticity is included in a non-linear model. Growth fluctuations reduce the value of the stock, and because their variance is an increasing function of the stock level, there is an incentive to reduce the stock level by harvesting faster. Growth fluctuations also increase in average harvesting costs and create an incentive to increase harvest rate. If we consider a fixed harvest rate, the expected
growth rate of the stock decreased which in turn reduces the harvest rate. Therefore, Pindyck concludes that the effect of uncertainty on the feedback control rule is indeterminate. Kapaun & Quass (2013) came to a similar conclusion in a discrete setting assuming a convex cost function and infinitely elastic demand. They demonstrated that the optimal HCR could be higher or lower than in the deterministic setting.

A special case of non-linear objective function concerns convex profits. This situation typically involves schooling fisheries which face concave cost functions. When fish presents schooling behaviours, as long as fishermen have the ability to locate the schools harvest does not depend on the size of the resource. This structural assumption yields incentives to fish down the stock at low level increasing the risk of collapse. Furthermore, this assumption turns the HCR into a pulse-fishing type which induces to harvest a lot above a threshold and then let the stock growth (Maroto & Moran 2008, Maroto et al. 2012). Da Rocha et al. (2014) investigated the effect of growth uncertainty when increasing returns are considering. They confirmed that convex profits conduct to pulse fishing, but increasing growth uncertainty tends to fit a constant escapement policy.

Overcapacity is widely recognized as a major problem affecting world fisheries. Even in a regulated fishery, overcapacity in fishing fleets in response to (temporarily or cyclical) positive rents is a major impediment to achieving economically productive fisheries (Beddington et al. 2007). Most of the studies ignore the cost of investing in fishing vessels by considering the capital as perfectly malleable. Introducing costly capital adjustment turns the optimal policy into a biomass-based catch type. When the objective function is linear in harvest, uncertainty in growth leads in most case to a more precautionary harvest of the resource (e.g. Charles and Munroe 1985). However, when stocks are fast growing and capital are low cost, investment in large fleet which offers the opportunity to take advantage of positive recruitments events (positive shocks), becomes a reliable strategy. This result holds even if we consider the objective function to be non-linear in harvest (Poudel et al. 2015). Costly capital adjustment can also be linked to policy adjustment¹⁸ (e.g. TAC adjustment). When a resource fluctuates randomly, biomass-based or constant escapement HCR increases variability in catch to

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¹⁷ Overcapacity can result from several sources such as periodic fluctuation of fish abundance (e.g. Fréon et al. 2008), use of subsidies (e.g. Clark et al. 2004), fluctuation of variable costs (e.g. fuel price) or directly fish price which affect the profitability of the fishery (e.g. Sumaila et al. 2008). The high profitability of the initial phase of a developing fishery is typical case of overcapitalisation.

¹⁸ Transaction costs associated with revisiting past policy decisions.
reflect environmental variation (Deroba & Bence 2008). A trade-off between more or less responsive approaches to environmental variations which can lead to more or less precautionary harvest depends on the linearity assumption of the objective function and the forms of policy costs (Boettiger et al. 2016, Ryan et al. 2017).

3.2.2.2 Correlated and cyclical variations

Considering that environmental fluctuations are serially uncorrelated is a strong assumption. Many observations showed that recruitment is serially correlated induced by environmental signals (e.g. Koster 2005). Furthermore, growth rates of fish stocks have been shown to be non-stationary. Cyclical environmental variations over large range of temporal scales independently of fishing activity have been shown to induce fluctuations of fish stock. For example, several studies have shown the influence of large scale climatic variations such as the El Nino Southern Oscillation (e.g. Lehodey et al. 1997) or long term trend in physical factors such as the temperature (e.g. Ravier & Fromentin 2004).

McGough et al. (2009) demonstrated that when environmental fluctuations are correlated or cyclical are considered the optimal policy becomes sensitive to environmental shocks which fit a biomass-based fishing mortality (BBF) HCR. This result is in line with studies which include correlated or cyclical variations of fish stock growth (e.g. Parma 1990, Walters & Parma 1996, Singh et al. 2006 and Carson et al. 2009). When fluctuations are cyclical, the optimal HCR followed closely environment cycles with lower escapement when conditions are poor and higher when conditions are good (Parma 1990, Walters & Parma 1996 and Carson et al. 2009). This investment behavior taking advantage of good environmental condition to invest in the resource reinforces recruitment fluctuations. Singh et al. (2006) found close results with a model included simultaneously correlated random stock growth and costly capital adjustment with a non-linear objective function. Under these assumptions, they showed that optimal HCR implies to build up the fleet when environmental conditions are good (positive serial correlation) in anticipation of higher future catch levels and decrease fleet when conditions are poor.
<table>
<thead>
<tr>
<th>Surplus Production Model</th>
<th>Objective function: Maximize Profit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Malleable Capital/Policy</td>
</tr>
<tr>
<td></td>
<td>Linear objective function in harvest†</td>
</tr>
<tr>
<td>No uncertainty</td>
<td>CE</td>
</tr>
<tr>
<td>Growth uncertainty (i.i.d shocks)</td>
<td>CE</td>
</tr>
<tr>
<td>Growth uncertainty (correlated &amp; cyclical variations)</td>
<td>BBF</td>
</tr>
<tr>
<td>Growth uncertainty (regime shift - endogeneous)</td>
<td>BBC</td>
</tr>
<tr>
<td>Growth uncertainty (regime shift - exogeneous)</td>
<td>CE</td>
</tr>
<tr>
<td>Price uncertainty (i.i.d. shocks)</td>
<td>BBC</td>
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<tr>
<td>Price uncertainty (correlated variations)</td>
<td>-</td>
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<tr>
<td>Growth uncertainty (correlated variations)</td>
<td>CE</td>
</tr>
<tr>
<td>* Price uncertainty</td>
<td></td>
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<tr>
<td>Growth uncertainty (regime shift - endogeneous * i.i.d. shocks)</td>
<td>BBC</td>
</tr>
<tr>
<td>Growth uncertainty (regime shift - exogeneous * i.i.d shocks)</td>
<td>CE</td>
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<tr>
<td>Parameter uncertainty</td>
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<tr>
<td>Stock size observation Uncertainty</td>
<td>BBC</td>
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<tr>
<td>Stock size observation * Growth Uncertainty (i.i.d shocks)</td>
<td>BBC</td>
</tr>
<tr>
<td>Regime shift uncertainty</td>
<td>BBC</td>
</tr>
</tbody>
</table>

CE: Constant Escapement policy
BBC: Biomass-based catch policy
BBF: Biomass-based fishing mortality policy
† Infinitely elastic demand associated with Schaefer's type production function or yield maximization.
‡ Downward slopping demand or/and Cobb Douglas' type production function non-linear in harvest.
\[\] More precautionary optimal policy
\[\] Less precautionary optimal policy
\[\] Ambiguous effect or no effect
### Table 2: References used for the construction of Table 1.

<table>
<thead>
<tr>
<th>Surplus Production Model</th>
<th>Objective function: Maximize Profit</th>
<th>Malleable Capital</th>
<th>Costly Capital Adjustment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Linear objective function in harvest†</td>
<td>Non-linear objective function in harvest†</td>
<td>Linear objective function in harvest†</td>
</tr>
<tr>
<td>Growth uncertainty (i.i.d shocks)</td>
<td>Reed (1979); Parma (1990); Sethi et al. (2005); Nostbakken (2008); Kapaun &amp; Quass (2013); Da Rocha et al. (2014)</td>
<td>Pindyck (1984); MacDonald (2002); Kugarajh (2006); Nostbakken (2008); Sarkar (2009); Kapaun &amp; Quass (2013); Da Rocha et al. (2014); Kvamsdal et al. (2016)</td>
<td>Charles &amp; Munro (1985)</td>
</tr>
<tr>
<td>Parameter uncertainty</td>
<td>-</td>
<td>-</td>
<td>-</td>
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<tr>
<td>Growth uncertainty (regime shift - endogeneous)</td>
<td>Polasky et al. (2011); Baggio &amp; Fackler (2016)</td>
<td>-</td>
<td>Ren &amp; Poaksy (2014)</td>
</tr>
<tr>
<td>Growth uncertainty (regime shift - exogeneous)</td>
<td>Reed (1988); Polasky et al. (2011); Baggio &amp; Fackler (2016)</td>
<td>-</td>
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</tr>
<tr>
<td>Price uncertainty (correlated variations)</td>
<td>-</td>
<td>-</td>
<td>Kvamsdal et al. (2016)</td>
</tr>
<tr>
<td>Growth uncertainty (multiplicative i.i.d) * Price uncertainty (correlated variations)</td>
<td>Nostbakken (2006)</td>
<td>-</td>
<td>Kvamsdal et al. (2016)</td>
</tr>
<tr>
<td>Growth uncertainty (regime shift - endogeneous * multiplicative i.i.d)</td>
<td>Baggio &amp; Fackler (2016)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Growth uncertainty (regime shift - exogeneous * multiplicative i.i.d)</td>
<td>Baggio &amp; Fackler (2016)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Observational (State) Uncertainty</td>
<td>Stock size observation uncertainty</td>
<td>Sethi et al. (2005)</td>
<td>Clark &amp; Kirkwood (1986); Costello et al. (2001); Sethi et al. (2005); Memarzadeh &amp; Boettiger (2018)</td>
</tr>
<tr>
<td>Stock size observation uncertainty * Growth Uncertainty (i.i.d shocks)</td>
<td>-</td>
<td>Clark et al. (1979)</td>
<td>-</td>
</tr>
<tr>
<td>Regime shift uncertainty</td>
<td>Baggio &amp; Fackler (2016)</td>
<td>-</td>
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</table>

† Infinitely elastic demand associated with Schaefer's type production function or yield maximization.
† Downward slopping demand or/and Cobb Douglas' type production function non-linear in harvest.
3.2.2.3 Regime shifts

Complex interaction and dynamic in fishery systems may induce sudden and drastic switch between contrasting stable states (Scheffer et al. 2001, Folke et al. 2004). Exogenous environmental shocks and fishing activity may trigger a regime shift from high to low productive regimes or irreversible collapse of populations (review in Jiao 2009 and Kraberg et al. 2011). Catastrophic shifts such as fishery collapses have been mainly attributed to overfishing as a result of economic factors and mismanagement, but environmental stochasticity associated with depensatory mechanism may also be a cause of fisheries collapse (Mullon et al. 2005).

Regime shifts pose difficult challenges for management (Crépin et al. 2012) which depend whether the dominant factors are exogenously and/or endogenously determined as well as on their severity and irreversibility (catastrophic consequences or shift in productivity). The severity criterion appears to be less significant in the determination of the precautionary of the optimal HCR. Therefore, we dissociate studies on the basis of the likelihood of the shift (change in the stock growth function) is exogenous or a function of management actions (e.g. TACs).

Reed (1988) seminal work applied a general surplus production model with a linear objective function in harvest and stochastic exogenous and endogenous irreversible regime shift (catastrophic collapse consequences). Uncertain exogenous shift reduces the future value of the resource which gives incentives to harvest the resource in the current period resulting in more aggressive HCR. However, endogenously driven shifts result in more precautionary harvest which depends on how the shifting probability increases as resource level decreases (density-dependent effect) compared to the density-independent nature of the hazard rate function (density-independent effect).

When the population is able to recover after collapse (reversible shift), the resulting HCR becomes more aggressive because of the reduction of the density-dependent effect. Polasky et al. (2011) generalized these results considering two kinds of shifts: catastrophic collapse or change in system dynamic (reduced growth). Their findings confirmed Reed’s outcomes, when the risk is endogenous the cautious of the resulting HCR depends on the severity of the consequence of the shift which gives more weight to the density-independent effect. If the shift is reversible or implies non-catastrophic consequence, the resulting HCR is more cautious. On the contrary, when the shift is
irreversible and lead to stock collapse the resulting HCR is ambiguous depending on which of the opposite density-dependent and independent effects dominate. Ren & Polasky (2014) examined the optimal management problem with a general utility function rather than a linear function. They demonstrated that the shape of the utility function considerably affects the optimal HCR which may become more or less precautionary depending on the relative magnitudes of two kinds of effects acting in opposite directions. Concomitantly, a regime shift lowers the future profit from the fishery which reduces the profitability of the investment in the resource. Finally, Baggio & Fackler (2016) extended the previous model by considering stochastic shocks (i.i.d.) and non-catastrophic reversible shifts affecting growth of the resource. Their numerical analysis confirmed the analytical results from Polasky et al. (2011) emphasising the influence of growth stochasticity on the cautious of the optimal HCR. They also showed that the endogenous switching probability changes the optimal policy to a biomass-based catch type with a far more precautionary strategy. In summary, the degree of contrast and resilience (reversibility between states) as well as volatility of the resource fluctuations has important impact on optimal policy.

### 3.2.3 Economical, political and social uncertainty - Stochastic price

Uncertainties related to economic conditions have been limited to market fluctuations affecting fish price (Nostbakken 2006, Kvamsdal et al. 2016). Price uncertainty has been found to play only a minor role in the determination of the optimal HCR. However, the optimal policy is no longer a constant escapement. Kvamsdal et al. (2016) described a smooth harvest policy as a function of stock size and price with a non-linear objective function. Additionally, although price uncertainty has only a minor effect, volatility in price leads to relatively more cautious harvest which buffers the increasing price effect with the scarcity of the resource.

### 3.2.4 Observational uncertainty - Uncertain states

Perfect information has been assumed in most studies, however, fishery management relies on indirect observations of fish stocks which are subject to high level of uncertainties. Additionally, assessments methods are imperfect and subject to many sources of bias. Relaxing the perfect observation assumption change considerably the
optimal HCRs and no longer fit Markov decision process framework needed to employ standard stochastic dynamic programming method (Fackler & Pacifi 2014). Clark & Kirkwood (1986) and Sethi et al. (2005) tackled the stock measurement uncertainty problem and showed that the optimal HCR is less conservative than the deterministic solution. Moreover, they found that the optimal policy becomes sensitive to stock size (biomass-based catch policy) when measurement errors are introduced. In the case where multiple uncertainties are confronted, measurement uncertainty has the largest impact on the determination of the optimal HCR. Memarzadeh & Boettiger (2018) argued that these counterintuitive results are supported by means of a simplification which ensures that the transition probability between states is independent of all previous states. They demonstrated through the implementation of a partially observed Markov decision process\(^{19}\) approach which relaxed the full observability assumption of the system’s state that more conservative policy is optimal. While state uncertainties concern primarily the size of the resource, in more complex setting such as regime shift dynamics, the current regime may not be directly observed. Using a partially a partially observed Markov decision approach Baggio & Fackler (2014) showed that policy adjustment depends on the weight of belief in a given regime. Additionally, optimal policy tends to be more or less precautionary depending on the belief state. Past information are determinant in the definition the optimal policy, thus anticipating future conditions may also affect the optimal HCR. Costello et al. (2001) investigated the impacts of growth fluctuations shocks (i.i.d.) when an uncertain forecast of environmental shocks is available. When new information is available, the optimal escapement is no longer constant but varies with the shocks prevision and increases substantially the profits.

### 3.2.5 Model and parameter uncertainty

Structural uncertainty arises when a system is imperfectly understood and represented (Williams 2011). As we discuss previously, the choice of optimal HCR depends critically on structural assumptions. The selection of an objective function and appropriate uncertainties which represent the system determined the class and the precautionary of the optimal HCR. The central objective in adaptive management is learning, which

\(^{19}\) Extension of Markov decision process in which unobservable state variables are replaced by a belief distribution and are updating with observable variables using Bayes rule (Fackler & Pacifi 2014).
should occur through the adjustments of decision making allowing by new information (Walters 1986, Williams 2011). Model and parameter uncertainties can be addressed by new modeling frameworks which extend the standard Markov decision process using Bayes rule. Unknown parameters or functional forms of the system are replaced by belief distributions updating through time and new information gathered (Fackler 2014, Fackler & Pacifi 2014, Williams 2016, LaRiviere et al. 2017). Memarzadeh & Boettiger (2018) are among the first implementations of adaptive management to renewable resource management introducing model, parameters and observation uncertainties. This promising framework should be a serious candidate to compete with simulation-based approaches such as MSE. However, such approaches still need to select pertinent structural assumptions and uncertainties to include as potential candidate to characterize the system.

Along with the development of modeling methods to address adaptive management, more complex model such as stochastic age-structured model has been studied. Bioeconomic studies surveyed have been criticised for being too simple to sustain management guidelines. Trade-offs between simple and more complex models such as age-structured are central when we evaluate the cost-benefits of using models for management which in turn reduce ease of learning and communication. However only few studies have undertaken to study uncertainties effect in age structured model (Holden & Conrad 2015, Tahvonen et al. 2017). They found that such as for surplus biomass model, the addition of random recruitment fluctuations (i.i.d. shocks) does not affect strongly the optimal HCR.

### 3.3 Decisional uncertainty- the case of shared fisheries management

Our review builds on the studies where decision making relied on a unique hypothetical fishery manager who could be a corporation, a cooperative, a government agency, or a regulatory body. However, many fish stocks are not solely distributed within a single exclusive economic zone (EEZ). Thus, the assumption of a single manager or a cooperative organization holds the responsibility of the decision making is no longer acceptable. Shared fish stocks (Munro et al. 2004, Munro 2007) are a special case which causes particular strategic management problems (McWhinnie 2009). Optimal management studies leave aside the question of how stakeholders’ strategic considerations are influenced by uncertainties. Two kinds of uncertainties arise in social
dilemmas such as shared fisheries, social and environmental uncertainty (van Dijk et al. 2004). When we consider a group of stakeholders on which relies a common decision, social uncertainty refers to the individual uncertainty about what their fellow group members will decide. Whereas, environmental uncertainty relates to the characteristic of the dilemma which defines the fishery system, the number of stakeholders involved and also uncertainties related to fishery management previously introduced. A central question in shared fisheries is, therefore, would interaction between social and environmental uncertainty lead to more precautionary or to more aggressive management. The economics of shared fisheries is anchored on game theory as the management of internationally shared fish stocks involves the strategic interaction between several countries. Several approaches have been used useful to understand cooperation in such context, but two main strands of game literature applying to shared fisheries can be considered, cooperative and non-cooperative dynamic or coalition games (reviews in Hannesson 2011, Miller et al. 2013, Pintasssilgo et al. 2015). Non-cooperative games involve competition between stakeholders in which only self-enforcing (e.g. through threats) cooperation are possible, while cooperative games, a priori, suppose that cooperative behaviours are enforced through external binding agreements (e.g. International Fisheries Agreements, IFA). Early game theory studies showed that competitive behaviours lead to the well-known the tragedy of the commons (Hardin 1968), while a joint exploitation of the resources is equivalent to the optimal management under the sole manager hypothesis (Munro 1979). However, only a few studies integrated uncertainty or incomplete information in the analysis of strategic interaction in shared fisheries. Stochastic models provide key information to studies anticipate how shocks and potential regime shifts in the system may affect the cooperative solution and its stability compared to the sole ownership theoretical case. In various settings included growth (recruitment), migration fluctuations, imperfect monitoring or potential regime shifts, several works have shown ambiguous results of

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20 Social dilemma refers to a situation where a group members experience a conflict between their personal interests and the interests of the group to which they belong.
21 Imperfect information can concern player actions, e.g. monitoring of harvests (Laukkanen 2003, Tarui et al. 2008) or the state of the system (Laukkanen 2003).
22 Stochastic models concern growth (recruitment) uncertainty in fish-war game type (Antoniadou et al. 2013, Diekert & Nieminem 2017) or in sequential game (Laukkanen 2003), the migration pattern of fish stock under climate change in fish-wars game (McKelvey et al. 2003), potential regime shifts in productivity or collapse which are exogenous (Fesselmeyer & Santugini 2013, Sakamoto 2014, Miller & Nkuiya 2016), or endogenous (Sakamoto 2014, Miller & Nkuiya 2016) in fish-wars game.
uncertainty depending on the structural assumptions of the model and the solution framework. Strategic interaction between countries harvesting shared stocks in a context of uncertainty is a fast-growing strand of the game theory literature and requires a specific analysis that we are leaving for further discussions.

4 Conclusion

This article explores several forms of uncertainty in economic optimal fishery management which have only been tackled partially or through the lens of simulation-based approaches in previous surveys (e.g. Deroba & Bence 2008, Holland & Herrera 2009, Liu et al. 2016, LaRiviere et al. 2017). Harvest policies have become a standard framework in fishery management. The definition of a management strategy which is based on the knowledge of the system ensures that the rules for how harvest will vary are foreseeable to all stakeholders. Bioeconomic literature brings important insights to tackle fishery management with HCRs for different forms of uncertainty. This review provides guidelines on which control rules is optimal and if the objective of maximizing the economic return of the fishery lead to more or less precautionary outcomes.

The constant escapement policy is rather an exception than the rules. Non-constant economic returns and uncertainty with the exception of independent and identically distributed random fluctuations have been shown as the main determinant of the class of the optimal policy. Escapement is, therefore, a function of the current stock, and harvests are smoothed over time to balance its effects on prices, harvesting costs and the future stock. While correlated shocks and cyclical variation turns the optimal escapement into a function of the current shock. Furthermore, when the system is threatened by a potential regime which his triggered independently of manager actions (i.e exogenous) the constant escapement policy remains optimal.

The common consideration that adding uncertainty should lead toward more precautionary harvest is also questioning. Results are ambiguous depending on the interaction between structural assumptions and type of uncertainty considered. In the case of complex dynamic involving regime shift, the threat of a potential disastrous shift affects the cautious of the resulting optimal policy. When an endogenous shift is present optimal management involves precautionary actions that reduce the likelihood of regime shift. With a potential shift whose occurrence is independent to management
actions, the severity and irreversibility of the shift determines the cautious of the
management. When the regime shift affects the productivity of the resource but does not
cause stock collapse, optimal management is unaffected by the potential for regime shift.
However, once the shift has occurred, the control rule is adjusted to fit the new
productivity. On the contrary, when the shift implies a disastrous collapse, the resulting
control rule is more aggressive to accumulate profits prior to potential destruction.

We have restrained the candidate models in our review to single species fisheries. Such
simple framework already leads to complex optimal policy and ambiguous results.
However, bioeconomic feedback solutions have been extended to more complex models
involving trophic relationship and population structured in age or stage. Such complex
models offer the possibility to evaluate the optimal control rule in the context of
ecosystem-based fisheries management and to extend the scope of feedback solution
which has only been relevant so far for stylized representation of the fishery system.
Along with the increasing complexity of models, the development of Markov decision
process to tackle unknown structure or unobserved states through learning process
offers the possibility to fully address structural uncertainty into a single framework. This
promising development should offer an alternative to management strategy evaluation
in the assessment of HCRs for different model and parameter assumptions to fully
implement adaptive management.
5 References


Caddy, J. F., & Seijo, J. C. (2005). This is more difficult than we thought! The responsibility of scientists, managers and stakeholders to mitigate the unsustainability of marine fisheries. *Philosophical Transactions of the Royal Society B: Biological Sciences, 360*(1453), 59-75.


Appendix A. Basic control rules and how fishing mortality (ratio) generally changes with biomass for each type (from Deroba & Bence, 2008).
Appendix B. Optimal harvest policy under different structural assumptions of profits and uncertainty (adapted from Deroba & Bence 2008 and McGough et al. 2009).

<table>
<thead>
<tr>
<th>Surplus Production Model</th>
<th>Objective function: Maximize Profit</th>
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<tr>
<td></td>
<td>Linear objective function</td>
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<td>in harvest†</td>
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<td></td>
<td>Non-linear objective function</td>
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<td></td>
<td>in harvest‡</td>
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<td>No uncertainty</td>
<td>CE</td>
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<td>BBC</td>
</tr>
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<td>CE</td>
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<tr>
<td>Growth correlated shocks</td>
<td>BBC &amp; BBF</td>
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<tr>
<td>Growth correlated shocks</td>
<td>BBF</td>
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</tbody>
</table>

CE: Constant Escapement policy
BBC: Biomass-based catch policy
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†Infinitely elastic demand associated with Schaefer’s type production function or yield maximization.
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