Center for Behavior, Institutions and the Environment

CBIE Working Paper Series

#CBIE-2018-002

How does knowledge infrastructure mobilization influence the safe operating space of regulated exploited ecosystems?

Jean-Denis Mathias
IRSTEA, 9 avenue Blaise Pascal, CS 20085, 63178 Aubire, France

John M. Anderies
School of Sustainability and School of Human Evolution and Social Change
Arizona State University, P.O. Box 875502, Tempe, AZ 85287-5502

Marco A. Janssen
School of Sustainability
Arizona State University, P.O. Box 875502, Tempe, AZ 85287-5502

February 16, 2018

The Center for Behavior, Institutions and the Environment is a research center located within the Biosocial Complexity Initiative at ASU. CBIE can be found on the internet at: http://cbie.asu.edu. CBIE can be reached via email at cbie@asu.edu.

How does knowledge infrastructure mobilization influence the safe operating space of regulated exploited ecosystems?

Jean-Denis Mathias[a], John M. Anderies[b], Marco A. Janssen[c],

[a]IRSTEA, 9 avenue Blaise Pascal, CS 20085, 63178 Aubire, France;
[b]School of Sustainability and School of Human Evolution and Social Change
Arizona State University, P.O. Box 875502, Tempe, AZ 85287-5502;
[c]School of Sustainability
Arizona State University, P.O. Box 875502, Tempe, AZ 85287-5502;

Corresponding author:
Jean-Denis Mathias
IRSTEA, Laboratoire dIngnierie pour les Systmes Complexes
jean-denis.mathias@irstea.fr

Abstract:
Managing and regulating exploited ecosystems is a critical issue because of uncertainties, non-linear dynamics, and time delays. Decision-makers often have to act before critical times to avoid the collapse of ecosystems using imperfect knowledge. Adaptive management may help managers tackle such issues. However, because the knowledge infrastructure required for adaptive management may be mobilized in several ways, we study how the following typology of knowledge and its use may impact the safe operating space of exploited ecosystems: 1) knowledge of the past based on a time series distorted by measurement errors; 2) knowledge of the current systems dynamics based on the representativeness of the decision makers mental models of the exploited ecosystem; iii) knowledge of future events based on decision-makers likelihood estimates of extreme events based on modeling infrastructure (models and experts to interpret them) they have at their disposal. We consider different adaptive management strategies of a general regulated exploited ecosystem model and we characterize the robustness of these strategies to imperfect knowledge. Our results show that even with significant mobilized knowledge and optimal strategies, imperfect knowledge may still shrink the safe operating space of the system leading to the collapse of the system. However, and perhaps more interestingly, we also show that in some cases imperfect knowledge may unexpectedly increase the safe operating space by suggesting cautious strategies. Beyond the quantitative results, we focus on the importance of understanding the subtleties of how adaptive knowledge mobilization and knowledge infrastructure affect the robustness of exploited ecosystems.

Keywords:

How does knowledge infrastructure mobilization influence the safe operating space of regulated exploited ecosystems?

Jean-Denis Mathias [1], John M. Anderies [2,3,4], and Marco A. Janssen [2,4]

[1]IRSTEA, Laboratoire d'Ingénierie pour les Systémes Complexes, 9 avenue Blaise Pascal, CS 20085, 63178 Aubière, France

[2]School of Sustainability, Arizona State University, United States

[3]School of Human Evolution and Social Change, Arizona State University, United States

[4]Center for Behavior, Institutions and the Environment, Arizona State University, United States

Key Points:

- We have built a typology of knowledge used for regulating uncertain exploited ecosystem.
- According to the mobilized and available knowledge, we consider several stylized adaptive management strategies.
- These strategies are more or less robust to imperfect knowledge and may broadly impact the safe operating space of regulated exploited ecosystems.

Corresponding author: Jean-Denis Mathias, `jean-denis.mathias@irstea.fr`

Abstract

Managing and regulating exploited ecosystems is a critical issue because of uncertainties, non-linear dynamics, and time delays. Decision-makers often have to act before critical times to avoid the collapse of ecosystems using imperfect knowledge. Adaptive management may help managers tackle such issues. However, because the knowledge infrastructure required for adaptive management may be mobilized in several ways, we study how the following typology of knowledge and its use may impact the safe operating space of exploited ecosystems: 1) *knowledge of the past* based on a time series distorted by *measurement errors*; 2) *knowledge of the current systems' dynamics* based on the *representativeness* of the decision-makers' mental models of the exploited ecosystem; iii) *knowledge of future events* based on decision-makers' *likelihood estimates* of extreme events based on modeling infrastructure (models and experts to interpret them) they have at their disposal. We consider different adaptive management strategies of a general regulated exploited ecosystem model and we characterize the robustness of these strategies to imperfect knowledge. Our results show that even with significant mobilized knowledge and optimal strategies, imperfect knowledge may still shrink the safe operating space of the system leading to the collapse of the system. However, and perhaps more interestingly, we also show that in some cases imperfect knowledge may unexpectedly increase the safe operating space by suggesting cautious strategies. Beyond the quantitative results, we focus on the importance of understanding the subtleties of how adaptive knowledge mobilization and knowledge infrastructure affect the robustness of exploited ecosystems.

1 Introduction

Managers of exploited ecosystems are continually struggling with sustaining resource exploitation while addressing the need to conserve the underlying ecosystems that support it. One solution relies on adaptive management that enables decision-makers to balance these needs in a dynamical way based on the state of the exploited ecosystem. This concept of adaptive management was developed in the 1980s [*Milliman et al.*, 1987; *Walters*, 1986] for fisheries and was then picked up by scholars for managing a diversity of ecosystems [*Millar et al.*, 2007; *Pahl-Wostl*, 2007; *Bohnet*, 2010] in the face of uncertainties and hazards. However, there is continued debate regarding the effective implementation of adaptive management in practice *McLain and Lee* [1996]; *Walters* [1997]. These debates focus on learning processes [*Pahl-Wostl*, 2009a], how knowledge capital grows, and how available knowledge is mobilized by stakeholders [*Bohnet*, 2010; *Anderies et al.*, 2016; *Frischmann*, 2005]. Here we focus on the broader question of the role that human infrastructure (knowledge and decision-making skills embodied in people) and knowledge infrastructure (stock of stored knowledge and the infrastructures that create, communicate, and maintain it such as sensors, IT systems, organizations, etc.) play in adaptive management.

Based on several existing stylized management strategies, we propose a typology of knowledge (based on characteristics of available knowledge infrastructure) and managers (based on how they use knowledge in the decision-making process). Because of the complexity and diversity of the technical, economic, and social processes involved, the creation, curation, and use of knowledge is necessarily imperfect. This is a fundamental issue that all resource managers and decision-makers must face [*Rogers et al.*, 2000; *Yokomizo et al.*, 2014]. Therefore, once we have classified several stylized adaptive management strategies according to our typology, we analyze their robustness to imperfect knowledge.

In addition, our analysis contributes to the refinement of the practical application of robustness concepts in the context of exploited ecosystems [*Anderies et al.*, 2007; *Anderies and Janssen*, 2013; *Anderies et al.*, 2013]. There are many options for quantifying robustness such as, for example, sensitivity of performance measures or characterization of the worst case [*Rodriguez et al.*, 2011]. Many studies are based on pathway-based robustness that are not completely compatible with the concept of adaptive management which relies on real-time knowledge of the system. Therefore, instead of thinking in terms of pathways, we use a set-based indicator. The concept of safe operating space (SOS) [*Rockström et al.*, 2009; *Carpenter et al.*, 2015, 2017] seems particularly appealing in our case: we identify a suitable set of solutions that can be accessed through adaptive management and use the size of the SOS for characterizing the robustness of stylized adaptive strategies to imperfect knowledge.

In order to illustrate these concepts, we use a general model of a regulated exploited ecosystem based on the work of Clark et al. [*Clark*, 1973; *Clark and Gordon*, 1975]. We compare the size of the SOS for each stylized strategy in the spirit of the recent work of [*Carpenter et al.*, 2015]. Finally, we test the robustness of the strategies in the case of imperfect knowledge before discussing new insights in terms of the management of knowledge infrastructure.

2 A general model of regulated exploited ecosystems

2.1 Unregulated exploited ecosystem

Many models of exploited ecosystems have been developed based on variations inspired by the general model studied by Clark [*Clark*, 1973] to explore the impacts of human actions on ecosystems:

$$\frac{dx}{dt} = F(x) - Y(x) \tag{1}$$

Where x is the state (e.g., biomass) and $F(x)$ represents the regenerative dynamics of a natural resource system. $Y(x)$ represents human impacts on the natural system. Many studies have analyzed variations of this model system in terms of optimal or robust management under different assumptions about uncertainty, and the forms of $F(x)$ and $Y(x)$. Some messages of this work are relevant to knowledge infrastructure: there are inherent trade-offs associated with how knowledge is used to build robustness to certain classes of shocks [*Anderies et al.*, 2007], suppressing variance can shrink the SOS [*Carpenter et al.*, 2015], and depending on whether uncertainty is endogenous or exogenous, it may induce precautionary or aggressive management decisions [*Polasky et al.*, 2011].

For clarity, for $F(x)$ we choose the widely used logistic function (with a growth rate r) that takes into account the carrying capacity K of the system and a minimum size of the population α such that survival is impossible [e.g., *Clark*, 1973] (due to predation or Allee effects for instance):

$$F(x) = r(K - x)(x - \alpha). \tag{2}$$

Note that considering $\alpha = 0$ leads to a logistic growth function without natural collapse. Having a natural collapse for $x < \alpha$ does not change the results in what follows. The exploitation function $Y(x)$ is proportional to human resource extraction effort e:

$$Y(x, e) = ex(t) \tag{3}$$

where we have scaled e to dispense with the usual constant of proportionality, i.e., set the "catchability/extractibility" coefficient to 1. This model has been broadly studied in the literature (especially in the case of α=0). According to the value of effort e, we can have either 0, 1 or 2 equilibria, i.e., the net recruitment compensates the removal due to exploitation. When the exploitation rate exceeds net recruitment, we have an overexploitation of the system (see the orange part on Figure 1a, in the case of e=0.35). If the effort e is constant, overexploitation will lead to the collapse of the ecosystem. However, if we consider an adaptive management of the effort, i.e., we can change the effort value e over time according to the state of the exploited ecosystem, the problem becomes much more difficult to address. For instance, under what conditions can the system recover from overexploitation? What are the economic implications? These questions require that we consider the net revenue π for various levels of exploitation, classically expressed as follows:

$$\pi = pY(x, e) - ce \tag{4}$$

where p represents the price per unit of biomass and c the cost of effort. Bioeconomic treatments of this problem typically explore policies (time paths of $e(t)$) that maximize some functional of $\pi(t)$, e.g., the (expected) discounted net present value of value flow of $\pi(t)$. These treatments typically make rather restrictive assumptions about the knowledge infrastructure at the disposal of managers, distributional issues, utility structures, etc. Our objective here is to relax these assumptions as much as possible and explore how various strategies to deploy knowledge infrastructure impact the capacity of the system to deliver valued flows over time.

As such, we suppose that the objective of the governing body (we are not concerned here with problems of governance and collective action) is to ensure a minimum net revenue $\pi^{\min}$ per unit effort:

$$px - c \geq \pi^{\min} \Leftrightarrow x \geq \frac{c + \pi^{\min}}{p} \tag{5}$$

This is a condition on the per-unit effort profit flowing from the resource and can be interpreted as the governing body wishing to maintain minimum livelihood standards for resource users. If $\pi^{\min} > 0$, management action pushes the system away from the open access bioeconomic equilibrium to a new more preferable equilibrium, $x_{ev} = \frac{c+\pi^{\min}}{p}$. This latter equation constitutes the economic constraint of our exploited ecosystem. We also consider a minimum value of the effort ($e^{\min}$) (exploitation cannot be fully stopped), which constitutes a socio-political constraint. This general model of exploited ecosystems exhibits three types of equilibria (see Figures 1a and 1b)

- "sustainable equilibria": the system is profitable for the user and the ecosystem doesn't collapse;
- "ecological equilibria": the system doesn't collapse but it is not profitable for stakeholders;
- "tipping points": unstable equilibria (that can be described by both ecological tipping points and sustainability tipping points).

The combination of these equilibria and the objectives of the user—i.e., not to collapse and to be minimally profitable—enables us to define the following sets (Figure 1b):

- a set from where the system collapses because of overexploitation (golden area, right side). The exploitation $Y(x)$ is too high relative to the net recruitment $F(x)$, yielding $Y(x) > F(x)$;
- a set from where the system collapses because of its ecological properties. For $x < \alpha$, the population is not large enough in order to survive (because of biological/predation issues);
- an unprofitable set without the collapse of the system (blue area). This set corresponds to the basin of attraction of the ecological equilibria. The effort is not sufficient in order to be profitable;
- a transitory unsustainable set (yellow area, narrow horizontal sliver): the exploited ecosystem is not profitable yet but the ecological dynamics will naturally increase the biomass making the ecosystem profitable in the long-term (if the effort is held constant while the ecosystem recovers);
- a sustainable set (green area) defined as the safe operating space (SOS) of the exploited ecosystem: in this set, the exploited ecosystem will converge to the sustainable equilibria. The SOS is the basin of attraction of the sustainable equilibria.

2.2 Regulation for mitigating overexploitation

Most stocks of European fisheries are overfished [*Froese et al.*, 2011] leading to international fishery agreements. These agreements rely on objectives based on the maximum sustainable yield (MSY). However this policy view relies on a static objective that may ignore sustainable dynamical pathways: allowing overexploitation in the short-term may enable the system to be sustainable in the long-term whereas constraining the system to reach a precautionary target biomass (such as 90% of the MSY biomass) in the short-term may not comply with socio-economic constraints of the system in the long-term. Let's consider the following "open access" dynamics of the effort e:

$$\frac{de}{dt} = \beta e(px - c)(1 - e). \tag{6}$$

Here, the effort e will increase until the biomass x decreases towards c/p at a rate determined by the coefficient β or e reaches a maximum level of 1 (everyone in the fishery is fishing). From an ecological point of view, two situations are possible according to the value of c/p: 1) c/p is high: the system is not very profitable and exploitation will stop before the collapse of the system (the open access equilibrium effort level is in the SOS); 2) c/p is low yielding a very profitable exploited ecosystem in which users tend toward an exploitation level such that the system will collapse even if users stop exploitation of the system based on Equation (5). The second case characterizes potential overexploitation and requires regulation.

To capture the notion of regulation rules mathematically, consider the following controlled dynamics of the effort e:

$$\frac{de}{dt} = \beta e(px - c - a(t))(1 - e) \tag{7}$$

where $a(t) \in [0, a_{max}]$ is the control and can be interpreted as a user fee of some sort such as an annual licensing fee.

As such, our modelled decision-makers aim at choosing the right value of $a(t)$ based on the dynamics of the ecosystem and exploitation level. To illustrate the subtle interactions between stock and effort dynamics associated with choices of $a(t)$, Figure 1-c represents the phase diagram of the regulated ecosystem dynamics ($a(t) = a_{\max}$) with a trajectory (in green) as well as a trajectory of the unregulated ecosystem ($a(t) = 0$). The regulated trajectory is also represented on Figure 1-d. Two main insights may be extracted from this graphic. First, there is a delay in terms of effort adaptation according to current biomass (Figure 1d) yielding a risk of: overexploitation (point A), underexploitation (point C) or stock collapse (point B). This time delay is mainly due to the nature of the regulation that acts as an integral controller. In order to avoid stock collapse, decision-makers have to avoid ecosystem dynamics with a low biomass (like point B). The second insight relates to the delay in effort adaptation: what might be viewed as a conservative strategy of imposing maximum fees ($a = a_{\max}$) is not the most effective management strategy to avoid collapse because of this time delay. For instance, on Figure 1c, from the starting point, the system will go through point B with maximum fees imposed. For limiting the risk of stock collapse, it is better to 1) have no regulation from the starting point to point D, 2) recognize that regulation has little effect on the dynamics from point D to point E; 3) impose maximum fees from point E on. Therefore, the best strategy requires switching between regulation and no regulation according to the state of the ecosystem.

In the deterministic case just discussed, the program for decreasing/increasing the tax $a(t)$ over time is relatively intuitive. However the uncertain case faced by managers in the real world, devising strategies to stay in the safe operating space is much more difficult. For instance, consider adding a stochastic process $U(t)$ (e.g., white noise) in Equation 8:

$$\frac{dx}{dt} = F(x) - Y(x) + U(t) \tag{8}$$

First, we recall that such a system will be sustainable at an infinite time horizon with probability zero if $U(t)$ has infinite support (which is the case in practice). Therefore, to define the SOS in the stochastic case it is important to introduce the time horizon of interest, denoted T hereafter. Our goal, therefore, is to calculate the probability of maintaining the sustainability of the system from time zero to T by complying with the economic and socio-political constraints and avoiding collapse of the stock.

2.3 Mobilizing knowledge infrastructure

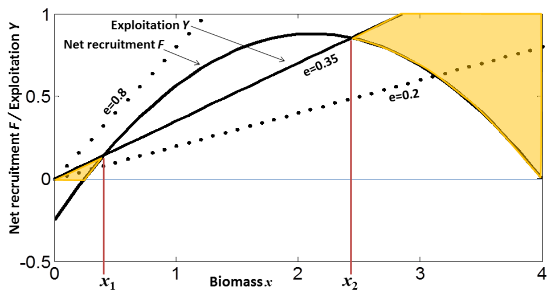
Good decisions require the injection of knowledge into the decision-making process: bad decisions may result from good decisions based on wrong (or incomplete) knowledge. However, having full and perfect knowledge is a holy grail for managers that seems unrealistic in practice due to the volume of required knowledge, i.e., time series, biological and economic processes, hazards etc. This assumption of full knowledge access seems less questionable in the case of industrial production: production lines are typically well controlled with reliable knowledge infrastructure based on the technological deployment of reliable systems (based on sensors, new materials etc.). In the case of natural resources, the question of full knowledge access is much more complex. Managers have to mobilize knowledge infrastructure including people, organizations, technology, and a science establishment to gather, interpret, and act on knowledge [*Frischmann*, 2005]. Therefore, how does the process of knowledge infrastructure mobilization influence the sustainability of exploited ecosystems? How does imperfect knowledge impact the system? The answers to these questions clearly depend on the implementation of the management strategy.

3 Adaptive management of exploited ecosystems

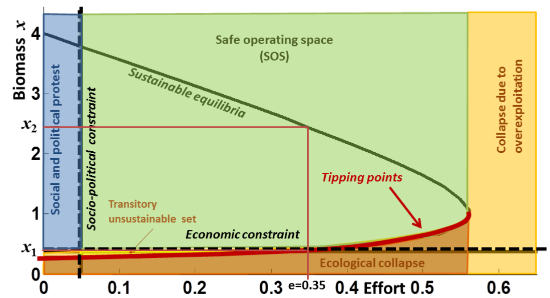
3.1 Stylized adaptive strategies

Various adaptive management strategies may effectively keep an exploited ecosystem within its safe operating space. However, they may come at very different costs and levels of complexity. For example, early warning approaches (based on variance for instance) involve efficient measures against uncertainties and avoiding tipping points [*Lenton et al.*, 2008; *Scheffer et al.*, 2009; *Dakos et al.*, 2008, 2012] while backwards techniques enable managers to take into account the dynamics of the system [*Rougé et al.*, 2013; *Rougé et al.*, 2014; *Rougé et al.*, 2015; *Brias et al.*, 2015]. Here we highlight the impact of various adaptive management strategies on system collapse. For this purpose, we consider five types of regulation functions $a(t)$ (more details are available in SI, specifically regarding the control maps of each manager). The regulation functions are listed in order of increasing complexity and, with it, implementation costs:

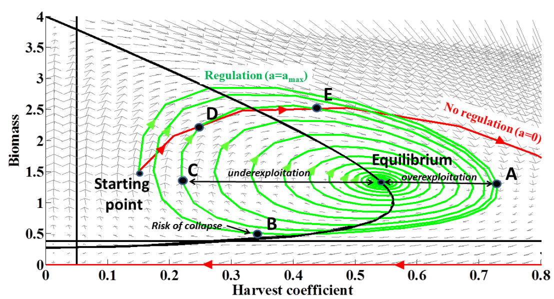
- **The "Annual License Fee" (ALF) manager** regulates the ecosystem through a fixed annual license fee, which is the same for all users, independent of their effort levels. In what follows, this annual license fee equals $a_{\max}$. This option is the cheapest relative to the following strategies in terms of mobilizing knowledge infrastructure because it only requires basic infrastructure for listing users, collecting payments, and license monitoring.
- **The "Flat Tax" (FT) manager** proportionally adapts the value of $a(t)$ according to the effort e: $a(t) = \gamma_1 e + \gamma_2$. This option is more expensive than the previous one—it requires monitoring of effort, collecting of tax, and may also require monitoring of the exploited system to choose the tax.
- **The "Early Warnings" (EW) manager** monitors variance of the system for preventing failures due to uncertainties (he uses knowledge about time series) [*Scheffer et al.*, 2009]. If the short-term variance is low, there is no tax ($a = 0$), if the short-term variance is high, the tax is maximum ($a = a_{\max}$). Controlling or assessing surrogates of stock variance may be a less expensive alternative to direct measurement of variance.



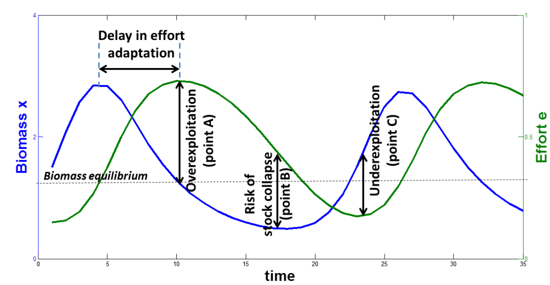
a - Net recruitment $F(x)$ and exploitation function $Y(x)$ according to biomass.



b - Equilibria and associated sets in the case of constant exploitation



c - Effect of regulation on the dynamics of the ecosystem



d - Effect of effort adaptation on the ecosystem dynamics

Figure 1. Managing exploited ecosystem. Decision-makers aim at assessing sustainable strategies that enable them to exploit the ecosystem without its collapse. Figure 1a recalls the trade-off between the net recruitment and the exploitation function. Such a figure has been broadly used for studying overexploitation and equilibrium. Considering an economic constraint yields new equilibria with a corresponding set as shown on Figure 1b (see the main text). Introducing effort dynamics may change the dynamics (Figure 1c) especially if there is a delay in terms of effort adaptation according to available biomass (Figure 1d) yielding a risk of: overexploitation (point A), underexploitation (point C) or stock collapse (point B). In order to avoid stock collapse, decision-makers have to avoid ecosystem dynamics with a low biomass. However, imposing maximum fees ($a = a_{\max}$) is not the optimal management strategy because of this time delay. For instance, on Figure 1c, from the starting point, the system will go through point B with maximum fees. For limiting the risk of stock collapse (at point B), it is better to 1) have no regulation until point D, 2) recognize that regulation policy has little effect on the dynamics from point D to point E; 3) to have maximum fees from point E on.

- **The "Maximum Sustainable Yield" (MSY) manager** aims at keeping the system close to the maximum sustainable yield (MSY). This manager is concerned more about biological overexploitation than economic overexploitation since MSY is never economically optimal—it is always above the economically optimal stock level. MSY is supported by a stable population size, denoted x^{MSY}. Below the x^{MSY}, there is no tax ($a = 0$), above the x^{MSY} the tax is maximum ($a = a_{\max}$). Note that a "maximum economic yield" will produce similar results with the difference that the MEY manager is more conservative (the MEY is below the MSY). This option is even more expensive; it requires whole departments to do stock surveys, build stock-recruitment models, scientists to interpret data, etc. as well as collect tax.
- **The "Optimal Adaptive Effort" (OAE) manager** takes decisions based on assessment of uncertainties, knowledge of the dynamics of the system, and time series. The control is optimized to avoid failure of the exploited ecosystem [*Rougé et al.*, 2013]. The value of $a(t)$ is adaptive and depends on the current state of the system and is chosen to maximize the probability of sustaining the exploited ecosystem to a given time horizon T. This option is the most expensive because it requires a perfect knowledge infrastructure: soft-human made infrastructure for regulation processes, hard-human infrastructure for monitoring the biological system (through sensors for instance), etc.

The purpose of our analysis is to compare these strategies and the effect of the regulation $a(t)$ on the SOS. When managers consider the probability of sustainability at a given time horizon T as their criteria, they need full knowledge of the exploited ecosystem, and more specifically, knowledge on the probabilistic distribution of uncertain events. However, EW managers only need a time series for making decisions. These five types of management show the trade-off between the expectations of decision-makers and the knowledge they need for achieving these expectations.

3.2 Typology of knowledge

According to [*Holling*, 1978; *Walters*, 1986], active learning enables managers to change and adapt policy in response to past events and present states of the exploited ecosystem. According to the different management strategies defined above, different types of knowledge may be mobilized (see Table 1). We propose the following typology of knowledge that is used in the decision-making process (see Figure 2):

- *Knowing the past* based on time series $(x(t), x(t-1), x(t-2), ...)$ (denoted as knowledge K_1). We suppose that decision makers use this information in their decision process. It requires a monitoring of the system. It is necessary to define what the relevant measurements are and what the monitoring frequency is, yielding investment and maintenance in monitoring infrastructure (sensors, people, etc.).
- *Knowing current ecological dynamics F* (denoted as knowledge K_2). Interactions within the exploited ecosystem are assessed (social and ecological interactions). Interactions between the exploited ecosystem and the decision makers as well as the exogenous drivers (such as climate change or inherent variability) are also known. It requires experts in several interacting areas (climate scientists, biologists).
- *Knowledge of future events* based on the properties of uncertainties U (denoted as knowledge K_3) such as the probability distribution of drivers is used during the decision process. Standard and extreme events are characterized from data or from expertise (from climate scientists to mathematicians).
- *Knowing exploitation levels* based on the users' declaration (denoted as knowledge K_4): managers aim at assessing how the ecosystem is exploited. As K_1, it requires investment in monitoring the exploitation of the system.

The proposed typology mixes the object-based knowledge (times series, events, dynamics) and time-based knowledge (past, present, future). We acknowledge that a more developed typology may be considered by crossing object-based knowledge and time-based knowledge. This can be particularly true if learning processes are well established along with "object-object," "time-time" or "object-time" relationships. However, in our analysis we restrict our attention to the typology composed of these four categories to keep the problem tractable. Indeed, assessing these four categories of knowledge is already challenging in practice: many technical and social processes may yield biases in knowledge assessment such as the following:

- *Measurement errors* (also known as observation errors) on time series, affecting K_1. Measurement errors in time series [*S. R. Carpenter*, 1994] may cause substantial difficulties in the understanding of the exploited ecosystem [*Ives et al.*, 2003]. Many

Manager	**Regulation**	**Knowledge**	**Adaptation**	**Control**	**Relative cost**
Annual Licence Fee (ALF)	Defining a constant Annual Licence Fee	-	-	a(t)=cst	$
Flat tax	Flat tax or admittance fees	K4	K4	$a(t) = \gamma_1 e(t) + \gamma_2$	$ $
Early-Warnings	Limiting short-term variance of the ecosystem biomass	K1	K1	$a(t) = 0$ if $\mathbb{V}(x(t)) < cst$; $a(t) = a_{\max}$ if $\mathbb{V}(x(t)) > cst$	$ $
MSY	MSY policy	K1, K2	K1	$a(t) = 0$ if $x(t) > x^{MSY}$; $a(t) = a_{\max}$ if $x(t) < x^{MSY}$	$ $ $
Optimal Adaptive Effort	Defining optimal policy according to the state of the ecosystem	K1, K2, K3, K4	K1, K2, K3, K4	$\max_{a(t)} \mathbb{P}^s(T), \forall t$	$ $ $ $

Table 1. Objectives used in the decision-making process for different management strategies.

methods exist in order to limit this measurement error in the time series [*Ives et al.*, 2003] but such errors inevitably persist in the assessment of the time series in the exploited ecosystem.

- *Representativeness* of interactions affecting K_2. Representing socio-ecological systems and their complexity remains a critical issue [*Forrester et al.*, 2014] that can be a significant barrier to producing useful models [*Walters*, 1997]. If the representativeness is perfect, interactions are representative of the reality. However, measurement errors (involving calibration errors), biases, beliefs, and values may affect how the system is perceived [*Tversky and Kahneman*, 1974]. Such cognitive biases are complex and evolved over time. In what follows, we neglect the evolution of cognitive biases and we only test the influence of a wrong representation on the system. For instance, if the actual carrying capacity, K, is 5, how the system is affected if the manager believes that K=8?
- *Likelihood* of extreme events affecting K_3. Globalization and anthropogenic pressures yield a diverse and broad set of hazards that may affect the SOS of the exploited ecosystem. Such hazards (especially tail distributions) are difficult to model and to predict due to non-linearities and multiple interactions. Moreover, there is a natural tendancy to underestimate the frequency of extreme events because the knowledge associated to these extreme events remains limited [*Plag et al.*, 2015]. The likelihood of events corresponds to the ability to correctly predict events, e.g., the probability distribution. For instance, underestimating the likelihood of extreme events can be catastrophic for the system, while overestimating the likelihood of extreme events may yield useless precautions. As representativeness, the mental representation of likelihood may evolve over time according to past events and learning. Here, we slightly change the standard deviation of uncertainties $U(t)$. In other terms, how is the system affected if the manager underestimates (or overestimates) the likelihood of extreme events?
- *Errors* in exploitation declaration affecting K_4. "Errors" include false declaration as well as unconscious error, caused by administration complexity or other exogenous processes.

In our framework, measurement errors, likelihood, errors in declarations, and representativeness can be viewed as knowledge filters that can evolve over time according to learning processes (see Figure 2). These four processes (measurement errors, representativeness, like-

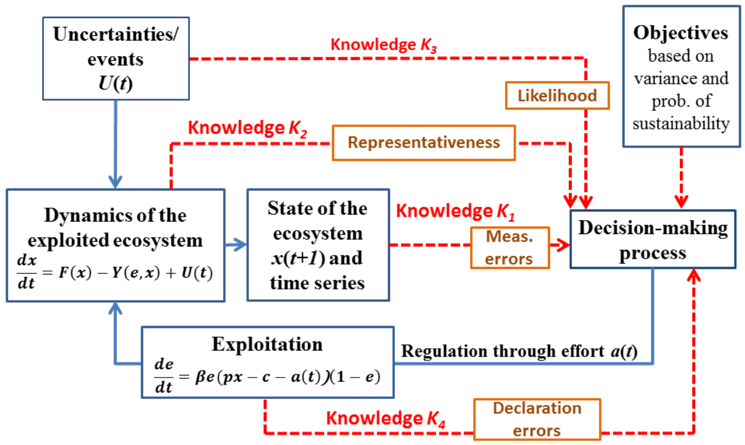


Figure 2. Decision-making process of regulated exploited ecosystem through the lens of the proposed knowledge typology.

lihood, errors in declaration) are naturally dependent. For instance, measurement errors first affect the quality of time series but if time series are used for calibrating the model, the representativeness of the model will be diminished. In what follows, we will test simple cases in order to explore how relationships between different knowledge types and their biases may broadly impact ecosystem management. For instance, is it better to have accurate knowledge based on poor representativeness or approximate knowledge based on a good representativeness of the system? The answer to such questions clearly depends on the adaptive management strategy decided by managers. In what follows, we explore such interactions between knowledge mobilization and management strategies.

4 How is the safe operating space impacted by adaptive management in the case of perfect knowledge?

In order to compare the influence of different management strategies on the safe operating space (SOS), we define the SOS as the set of system states for which the probability of complying with economic, ecological, and socio-political constraints during the time horizon T is above a predefined threshold as done in [*Carpenter et al.*, 2015]. Indeed, the SOS approach does not require any particular conditions on the trajectories of the exploited ecosystem, as long as the exploited ecosystem stays in the SOS [*Carpenter et al.*, 2015]. Further, rather than managing for a single, optimal state, decision makers have to manage the exploited ecosystem within a range of acceptable outcomes while avoiding irreversible negative effects and keeping flexibility in their decision-making process [*Johnson*, 1999]. The SOS is defined by the set of initial states with a sustainability probability higher than 0.9. Figure 3 shows the SOS according to initial biomass and effort (with 1000 simulations, see SI).

Our results show that adaptive management (like OAE manager) of the system enables decision-makers to enlarge the SOS as we would expect; when more knowledge is mobilized, SOS is larger. The OAE manager exhibits the largest SOS and constitutes our reference manager: she knows everything and effectively uses her knowledge. Her strategy results in decreasing the number and amplitude of cycles experienced by the system as it converges toward the stable equilibrium). In order to reach the equilibrium faster, the following are the main components of the strategy (see SI for more details): 1) decreasing the tax in areas of state space with low biomass and low effort and 2) increasing tax in other areas. The most interesting aspect of this strategy is decreasing the tax at low biomass and allowing more effort. This sort of non-intuitive action results from fully incorporating the non linear ecological dynamics: this action will reduce the amplitude of system overshoot (and thus the probability of exiting the SOS) at a later time.

The MSY manager uses a similar strategy in the sense that the biomass level is used for increasing/decreasing the tax (according to MSY). But MSY decision-making is static and does not take into account the dynamics of the ecosystem (especially the equilibrium cycle convergence) and the effort level. The flat tax manager takes into account the effort level in her strategy but does not consider the biomass level, yielding unsafe exploitation. The ALF manager does not account the biomass nor the effort level. Finally, the EW manager adapts his strategy according to the biomass variance and does not take into account the effort level. Note that if the EW manager is very cautious (for instance, he is sensitive to very small changes), his results will converge to the ALF manager.

5 Robustness to imperfect knowledge

In this analysis, we suppose that there are biases in knowledge assessment to explore how the system evolves when managers mobilize imperfect knowledge of the ecosystem. **In what follows, we consider imperfect knowledge in the decision-making process of managers, that may potentially affect the SOS. Note that the SOS remains the same when the imperfect knowledge is not used by managers.** For instance, we consider four cases:

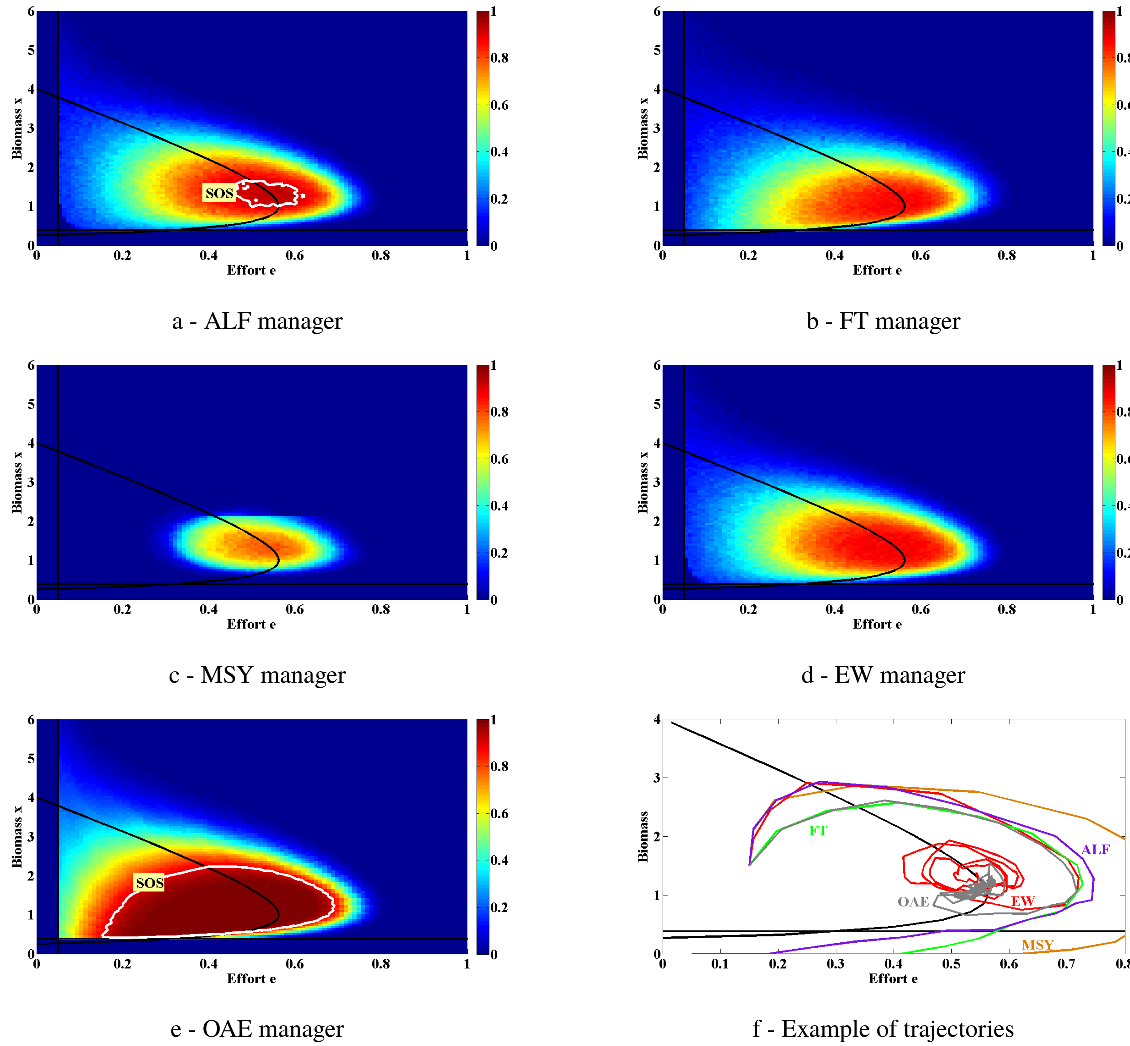


Figure 3. Safe operating space of the different managers (during 100 time steps). The SOS is described by the probability of sustainability higher than 0.9.

- Imperfect knowledge of type K_1. We suppose that managers overestimate the biomass $x(t)$. This impacts the decisions of all managers except the ALF and the "flat tax" manager who never changes her strategies according to the biomass (see Table 1). Interestingly, the size of the SOS of adaptive managers decreases more relative to the non-adaptive strategy if the biomass overestimation is too significant. In this case, a non-adaptive strategy (such as ALF strategy) may be better than adaptive strategy (such as an OAE strategy) based on an overestimation of the biomass. On the other hand, the SOS of EW-based management is surprisingly increased (see SI for more details). Indeed, overestimation of the biomass artificially increases the short-term variance and leads to more cautious strategies: they make cautious decisions because early warnings are artificially created by the biomass overestimation.
- Imperfect knowledge of type K_2. We suppose that managers over/underestimate the carrying capacity K resulting in an incorrect representation (reduced representativeness) of the system. Our analysis (see SI) shows that overestimation 1) may be catastrophic for OAE manager (no SOS) due to the fact that dynamics cross tipping points whereas managers believe the system is in a "safe" zone; 2) may yield positive effects for the MSY manager who makes cautious decisions because of overestimation.
- Imperfect knowledge of type K_3: we suppose that managers underestimate the frequency of extreme events. Knowledge of type K_3 hardly impacts OAE managers very little in our case because of the trade-off between under/overestimation of K_3 and the dynamics of the exploited ecosystem.
- Imperfect knowledge of type K_4: we suppose that managers underestimate the exploitation of the ecosystem. Knowledge of type K_4 impacts the OAE and the flat tax managers. It decreases the SOS of OAE but increases the SOS of the FT manager. The FT manager overestimates the exploitation yielding stringent strategies in terms of tax.

Table 2 sums up the best strategies according to imperfect knowledge of each type. Results show that there is no panacea—in terms of management strategies—that is universally robust to imperfect knowledge.

Imperfect knowledge	**Underestimation (-50%)**	**Perfect estimation**	**Overestimation (+50%)**
K_1 (time series)	OAE/ALF/MSY	OAE	EW/ALF
K_2 (ecosystem)	ALF/OAE	OAE	ALF/MSY
K_3 (uncertainties)	OAE	OAE	OAE
K_4 (effort)	ALF	OAE	FT

Table 2. Robustness of the safe operating space according to imperfect knowledge: best management strategies are reported according to each imperfect knowledge. K- and σ-parameters as well times series and effort e are multiplied by a coefficient (yielding more or less over/underestimations) in the decision-making process. But the dynamics are calculated with the real ones.

6 Discussion and policy implications

Here we proposed to compare different management strategies and to analyze them according to how they perform vis à vis a given knowledge typology. The more aggressive deployment of knowledge (in our terminology, more sophisticated knowledge infrastructure and management strategies) correlates with a larger SOS, except when the knowledge is imperfect. In this latter case, the use of imperfect knowledge can be catastrophic when agents act in a feedback loop with incorrect information. However, results also show that in some cases, imperfect knowledge may involve unexpected cautious strategies that enlarge the SOS. These results suggest some of the difficulties involved with integrating the right level knowledge in the decision-making process despite the general importance of learning processes and knowledge on the successful management of ecosystems [*Berkes*, 2009]. However, we can suggest some useful insights based on our analysis:

- **Using a diversity of adaptive strategies**. As shown in Table 2, there is no panacea in terms of management strategies that faces imperfect knowledge. This suggests that managers have to estimate the cost-benefit ratio of a better characterization of knowledge: they have to evaluate if the expected gains provided by a strategy based on a full (and perfect) knowledge will counterbalance the costs of knowledge assessment, especially compared to strategies whose resources are saved from the simplicity of the control, with low possibility of being wrong. Learning how to navigate this portfolio of adaptive strategies is therefore of critical importance.

- **Identifying (un-)safe zones**. One key issue of choosing a strategy with the right level of knowledge is identifying relatively safe and unsafe zones. Indeed, switching between lower and higher cost controls may be a cost effective approach especially in safe zones. As it is unnecessary to over-monitor safe areas, decision-makers have to estimate when it is necessary to assess more knowledge in order to avoid falling in zones with a non-adapted level of required knowledge.
- **Using adaptive learning**. Beyond improving models and data acquisition in order to develop a robust strategy, managers may also focus on learning about safe and unsafe zones and how to combine relatively simple (efficient in terms of the knowledge infrastructure required) strategies that perform well in each into a "piecewise adapted" controller based on a knowledge typology such as the one we have explored here. A critical issue is the use of adaptive learning in order to assess the two-way relationship between people and their social-ecological environment [*Davidson-Hunt and Berkes*, 2003].

By using a diversity of adaptive-based strategies and adaptive learning, stakeholders may mobilize the right knowledge at the right time. It will therefore reduce the probability of collapse of the system by coping with emerging and inevitable hazards that drive socio-ecological systems.

These results underline the necessity as well as the difficulty of assessing and integrating knowledge within the management of socio-ecological systems. It is not straightforward in practice and remains a critical issue [*Bohnet*, 2010] that may involve a diversity of social and institutional processes such as multi-level learning [*Pahl-Wostl*, 2009b]. Mobilizing the right knowledge at the right time also requires the management of acquired knowledge. We argue that knowledge management used in organizational approaches [*Alavi and Leidner*, 2001; *Hansen et al.*, 1999] may improve regulation of exploited ecosystem. Our conceptual approach based on a knowledge typology and robustness may help highlight the importance of a given knowledge according to a given state of the system and to a given strategy.

In a more general way, our results show the importance of knowledge infrastructure and knowledge commons. Although knowledge infrastructure is not a traditional infrastructure [*Frischmann*, 2005], it remains of prime of importance for managing exploited ecosystems [*Anderies et al.*, 2016] and should be clearly highlighted in the system in order to produce the knowledge required for adaptive management.

References

Alavi, M., and D. Leidner (2001), Review: Knowledge management and knowledge management systems: Conceptual foundations and research issues, *MIS Quarterly: Management Information Systems*, *25*(1), 107–136, cited By 0.

Anderies, J., M. Janssen, and E. Schlager (2016), Institutions and the performance of coupled infrastructure systems, *International journal of the commons*, *10*, 495–516.

Anderies, J. M., and M. A. Janssen (2013), Robustness of social-ecological systems: Implications for public policy, *Policy Studies Journal*, *41*(3), 513–536, doi:10.1111/psj.12027.

Anderies, J. M., A. A. Rodriguez, M. A. Janssen, and O. Cifdaloz (2007), Panaceas, uncertainty, and the robust control framework in sustainability science, *Proceedings of the National Academy of Sciences*, *104*(39), 15,194–15,199, doi:10.1073/pnas.0702655104.

Anderies, J. M., C. Folke, B. Walker, and E. Ostrom (2013), Aligning key concepts for global change policy: robustness, resilience, and sustainability., *Ecology and Society*, *18*(2).

Berkes, F. (2009), Evolution of co-management: role of knowledge generation, bridging organizations and social learning, *Journal of environmental management*, *90*, 1692–1702.

Bohnet, I. (2010), Integrating social and ecological knowledge for planning sustainable land- and sea-scapes: Experiences from the great barrier reef region, australia, *Landscape Ecology*, *25*(8), 1201–1218.

Brias, A., J.-D. Mathias, and G. Deffuant (2015), Accelerating viability kernel computation with cuda architecture : application to bycatch fishery management, *Computational management Science*, p. submitted.

Carpenter, S. R., W. A. Brock, C. Folke, E. H. van Nes, and M. Scheffer (2015), Allowing variance may enlarge the safe operating space for exploited ecosystems, *Proceedings of the National Academy of Sciences of the United States of America*, *112*(46), 14,384–14,389.

Carpenter, S. R., W. A. Brock, G. J. A. Hansen, J. F. Hansen, J. M. Hennessy, D. A. Isermann, E. J. Pedersen, K. M. Perales, A. L. Rypel, G. G. Sass, T. D. Tunney, and M. J. Vander Zanden (2017), Defining a safe operating space for inland recreational fisheries, *Fish and Fisheries*, *18*(6), 1150–1160, doi:10.1111/faf.12230.

Clark, C. (1973), The economics of overexploitation, *Science*, *181*(4100), 630–634.

Clark, C., and R. Gordon (1975), The economics of fishing and modern capital theory: a simplified approach, *Journal of environmental economics and management*, *2*, 92–106.

Dakos, V., M. Scheffer, E. Van Nes, V. Brovkin, V. Petoukhov, and H. Held (2008), Slowing down as an early warning signal for abrupt climate change, *Proceedings of the National Academy of Sciences of the United States of America*, *105*(38), 14,308–14,312, doi: 10.1073/pnas.0802430105, cited By 244.

Dakos, V., S. Carpenter, W. Brock, A. Ellison, V. Guttal, A. Ives, S. K??fi, V. Livina, D. Seekell, E. van Nes, and M. Scheffer (2012), Methods for detecting early warnings of critical transitions in time series illustrated using simulated ecological data, *PLoS ONE*, *7*(7), doi:10.1371/journal.pone.0041010, cited By 110.

Davidson-Hunt, I., and F. Berkes (2003), Learning as you journey: Anishinaabe perception of social-ecological environments and adaptive learning, *Conservation Ecology*, *8*(1), 5.

Forrester, J., R. Greaves, H. Noble, and R. Taylor (2014), Modeling social-ecological problems in coastal ecosystems: A case study, *Complexity*, *19*(6), 73–82.

Frischmann, B. (2005), An economic theory of infrastructure and commons management, *Minnesota Law Review*, *89*, 917–1030.

Froese, R., T. A. Branch, A. Proel??, M. Quaas, K. Sainsbury, and C. Zimmermann (2011), Generic harvest control rules for european fisheries, *Fish and Fisheries*, *12*(3), 340–351.

Hansen, M., N. Nohria, and T. Tierney (1999), What's your strategy for managing knowledge?, *Harvard business review*, *77*(2), 106–116, 187, cited By 0.

Holling, C. (1978), *Adaptive environmental assessment and management.*, London: John Wiley and Sons.

Ives, A., B. Dennis, K. Cottingham, and S. Carpenter (2003), Estimating community stability and ecological interactions from time-series data, *Ecological Monographs*, *73*(2), 301–330.

Johnson, B. (1999), The role of adaptive management as an operational approach for resource management agencies, *Conservation Ecology*, *3*(2), xix–xx.

Lenton, T., H. Held, E. Kriegler, J. Hall, W. Lucht, S. Rahmstorf, and H. Schellnhuber (2008), Tipping elements in the earth's climate system, *Proceedings of the National Academy of Sciences of the United States of America*, *105*(6), 1786–1793, doi: 10.1073/pnas.0705414105, cited By 905.

McLain, R., and R. Lee (1996), Adaptive management: Promises and pitfalls, *Environmental Management*, *20*(4), 437–448.

Millar, C. I., N. L. Stephenson, and S. L. Stephens (2007), Climate change and forests of the future: Managing in the face of uncertainty, *Ecological Applications*, *17*(8), 2145–2151, doi:10.1890/06-1715.1.

Milliman, S., A. Grima, and C. Walters (1987), Policy making within an adaptive management framework, with an application to lake trout (salvelinus namaycush) management, *Canadian journal of fisheries and aquatic sciences*, *44*, 425 – 430.

Pahl-Wostl, C. (2007), Transitions towards adaptive management of water facing climate and global change, *Water Resources Management*, *21*(1), 49–62, doi:10.1007/s11269-006-9040-4, cited By 373.

Pahl-Wostl, C. (2009a), A conceptual framework for analysing adaptive capacity and multi-level learning processes in resource governance regimes, *Global Environmental Change*, *19*, 354–365.

Pahl-Wostl, C. (2009b), A conceptual framework for analysing adaptive capacity and multi-level learning processes in resource governance regimes, *Global Environmental Change*, *19*(3), 354–365, doi:10.1016/j.gloenvcha.2009.06.001, cited By 0.

Plag, H.-P., S. Brocklebank, D. Brosnan, P. Campus, S. Cloetingh, S. Jules-Plag, and S. Stein (2015), Extreme geohazards - reducing the disaster risk and increasing resilience, *Tech. rep.*, European Science Foundation.

Polasky, S., A. De Zeeuw, and F. Wagener (2011), Optimal management with potential regime shifts, *Journal of Environmental Economics and management*, *62*(2), 229–240.

Rockström, J., W. Steffen, K. Noone, ??sa Persson, F. S. I. Chapin, E. Lambin, T. M. Lenton, M. Scheffer, C. Folke, H. J. Schellnhuber, B. Nykvist, C. A. de Wit, T. Hughes, S. van der Leeuw, H. Rodhe, S. S??rlin, P. K. Snyder, R. Costanza, U. Svedin, M. Falkenmark, L. Karlberg, R. W. Corell, V. J. Fabry, J. Hansen, B. Walker, D. Liverman, K. Richardson, P. Crutzen, and J. Foley (2009), Planetary boundaries: Exploring the safe operating space for humanity, *Ecology and Society*, *14*(2), art.32, doi:10.1126/science.1259855.

Rodriguez, A. A., O. Cifdaloz, J. M. Anderies, M. A. Janssen, and J. Dickeson (2011), Confronting management challenges in highly uncertain natural resource systems: a robustness–vulnerability trade-off approach, *Environmental Modeling & Assessment*, *16*(1), 15–36, doi:10.1007/s10666-010-9229-z.

Rogers, K., D. Roux, and H. Biggs (2000), Challenges for catchment management agencies: Lessons from bureaucracies, business and resource management, *Water SA*, *26*(4), 505–511, cited By 53.

Rougé, C., J.-D. Mathias, and G. Deffuant (2013), Extending the viability theory framework of resilience to uncertain dynamics, and application to lake eutrophication, *Ecological Indicators*, *29*, 420–433.

Rougé, C., J.-D. Mathias, and G. Deffuant (2014), Relevance of control theory to design and maintenance problems in time-variant reliability: The case of stochastic viability, *Reliability Engineering & System Safety*, *132*, 250 – 260.

Rougé, C., J.-D. Mathias, and G. Deffuant (2015), Vulnerability: From the conceptual to the operational using a dynamical system perspective, *Environmental Modelling and Software*, *73*, 218 – 230, doi:j.envsoft.2015.07.018.

S. R. Carpenter, C. A. S., K. L. Cottingham (1994), Fitting predator-prey models to time series with observation errors, *Ecology*, *75*(5), 1254–1264.

Scheffer, M., J. Bascompte, W. A. Brock, V. Brovkin, S. R. Carpenter, V. Dakos, H. Held, E. H. van Nes, M. Rietkerk, and G. Sugihara (2009), Early-warning signals for critical transitions, *Nature*, *461*(7260), 53–59.

Tversky, A., and D. Kahneman (1974), Judgment under uncertainty: Heuristics and biases, *Science*, *185*(4157), 1124–1131, doi:10.1126/science.185.4157.1124.

Walters, C. (1986), *Adaptive management of renewable resources.*, New-York: McGraw Hill.

Walters, C. (1997), Challenges in adaptive management of riparian and coastal ecosystems, *Conservation Ecology*, *1*(2), 1.

Yokomizo, H., S. Coutts, and H. Possingham (2014), Decision science for effective management of populations subject to stochasticity and imperfect knowledge, *Population Ecology*, *56*(1), 41–53, doi:10.1007/s10144-013-0421-2, cited By 6.

A: Supporting Information: How does knowledge infrastructure mobilization influence the safe operating space of regulated exploited ecosystems?

A.1 Managing a harvest population

The biomass dynamics follow:

$$\frac{dx}{dt} = r(K - x)(x - \alpha) - e(t)x(t) + w(t) \tag{A.1}$$

Symbols are logistic growth parameters $r = 0.25$ and $K = 4$, sigmoid predation consumption coefficient $\alpha = 0.25$. $w(t)$ is a white noise process with a standard deviation equal to 0.075.

The effort dynamics $e(t)$ writes:

$$\frac{de}{dt} = \beta e(px - c - a(t))(1 - e) \tag{A.2}$$

with $\beta = 0.075, c = 1.5$, $p = 4.5$. $a(t) \in [0, a_{max}]$ is the control with $a_{\max} = 4.5$. The term $(1 - e)$ is used in order to have an upper limit of the effort equal to 1. We set the minimum effort $e^{\min}$ to 0.05 and $\pi^{\min}$ to 0.2. In what follows, 1000 simulations were used for assessing the probability of sustainability of the system. The time horizon is equal to 100 time step.

A.2 Adaptive strategies

A.2.1 Optimal Adaptive Effort Manager

OAE manager adapts the control $a(t)$ according to time series in order to maximize the probability of sustainability. This problem can be solved by dynamic programming. Let's consider a time of interest T. We consider the probability of sustainability $\mathbb{P}^s(T, x)$ at time T. If biomass x is lower than a threshold $\pi^{\min}$ or the effort lower than $e^{\min}$, the system is considered as failed. Then we use the following backwards technique (dynamic programing):

$$\forall t \in [1, T], \mathbb{P}^s(t, x(t)) = \max_{a(t)} \sum \mathbb{P}(f(x(t), a(t)))\mathbb{P}^s(t + 1, f(x(t), a(t))) \tag{A.3}$$

Finally we have access to the strategy $a(0), a(1), \ldots, a(T)$ that maximizes the probability of sustainability $\mathbb{P}^s(0, x)$.

A.2.2 Admittance Fee Licence Manager

AFL manager always imposes a constant fee $a(t) = a_{\max}, \forall t$.

A.2.3 Flat Tax Manager

FT manager always imposes $a(t)$ as follows:

$$a(t) = a_{\max} \frac{e(t) - e_{\min}}{e^{FT} - e_{\min}} \tag{A.4}$$

e^{FT} constitutes a normative issue: the effort for which the fee $a(t)$ reaches the maximum fee $a_{\max}$. Here, we arbitrary choose $e^{FT} = 0.7$. Note that the choice of this value doesn't qualitatively change the results.

A.2.4 Early Warnings Manager

"'Early warnings"' manager adapts regulation $a(t)$ according to short-term variance of times series $V(x(t-10), ..., x(t))$. Then according to a threshold γ, following rules are used:

- if $V(x(t-10), ..., x(t)) > \gamma$, $a(t) = a_{\max}$;
- if $V(x(t-10), ..., x(t)) < \gamma$, $a(t) = 0$

In the simulations, we choose $\gamma = 0.0025$ in such a way that it characterizes the collapse of the system (variance increases when the system collapses). Note that other sophisticated indicators may be used based on knowledge K_3.

A.2.5 MSY Manager

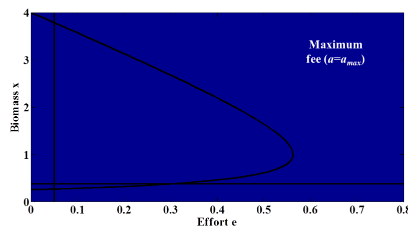
MSY manager adapts regulation $a(t)$ according to biomass and the MSY:

- if $x(t) < x^{MSY}$, $a(t) = a_{\max}$;
- if $x(t) > x^{MSY}$, $a(t) = 0$

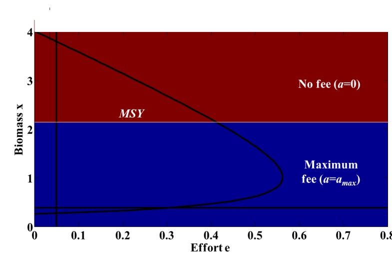
Here, x^{MSY} equals to 2.125.

A.3 Control maps

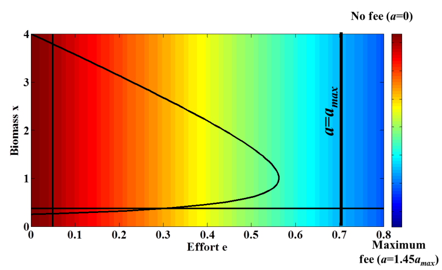
Figure A.1 represents the map of controls for the different managers. In the case of OAE manager, optimal strategy consists in: no regulation when the biomass and the effort are low and regulation elsewhere. These results echo comments of Figures 1c and 1d. Note that any controls leads to a probability of sustainability of 0 when the effort is too high, explaining that optimization give unstable results on the right hand (with 1000 simulations).



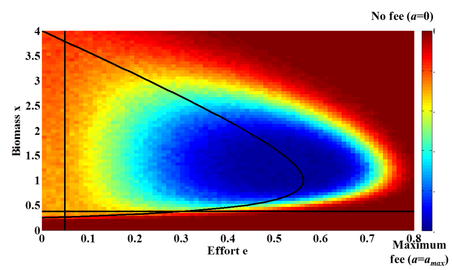
a - ALF manager



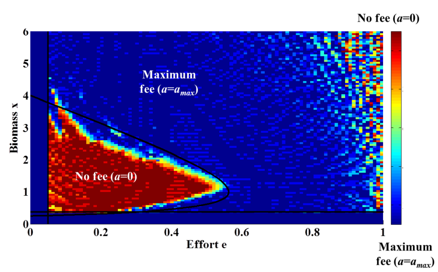
b - MSY manager,



c - FT manager



d - EW manager,



d - OAE manager

Figure A.1. Control maps for the different managers. Note that for the EW manager, it corresponds to the mean value of the control according to the state of the system and for t=50 (control maps are qualtitatively the same over time)

A.4 Sensitivity of SOS to imperfect knowledge

A.5 Introduction

Knowledges are under or overestimated by decreasing or increasing (50%) the following data:

- time series $x(t)$ for knowledge k_1;
- the carrying capacity K for knowledge K_2;
- the standard deviation σ for knowledge K_3;
- the effort e for knowledge K_4.

A.5.1 Imperfect knowledge K_1

OAE, MSY and EW managers use knowledge K_1 in their decision-making process. Hereafter, the SOS of these managers according to knowledge K_1 (Figure 5).

A.5.2 Imperfect knowledge K_2

OAE and MSY managers use knowledge K_2 in their decision-making process. Hereafter, the SOS of these managers according to knowledge K_2 (Figure 6).

A.5.3 Imperfect knowledge K_3

Only OAE manager uses knowledge K_3 in their decision-making process. Hereafter, the SOS of this manager according to knowledge K_3 (Figure 7).

A.5.4 Imperfect knowledge K_4

Only OAE and FT managers use knowledge K_4 in their decision-making process. Hereafter, the SOS of these managers according to knowledge K_3 (Figure 8).

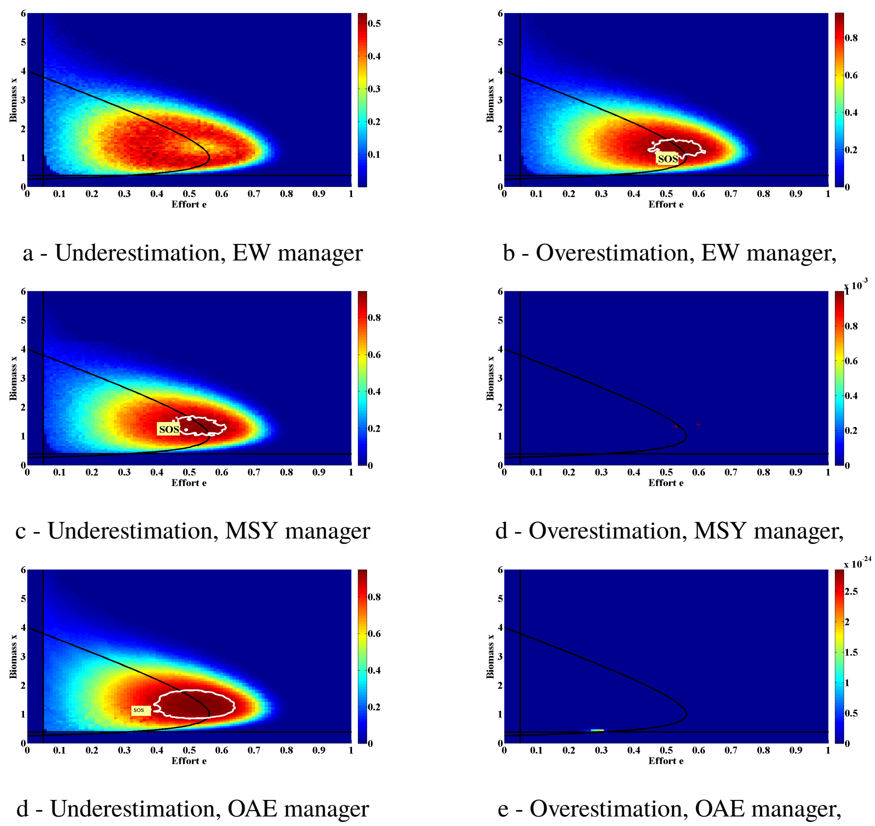
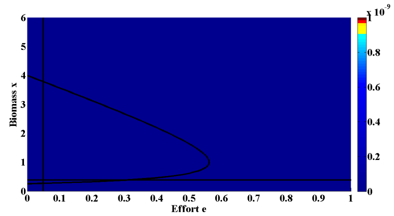
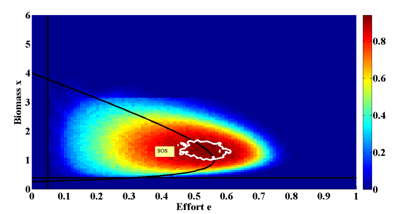


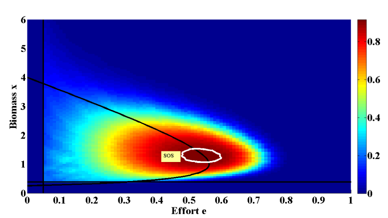
Figure A.2. Robustness of the safe operating space according to imperfect knowledge K_1. Times series are multiplied by a coefficient (yielding more or less over/underestimations) in the decision-making process. But the dynamics are calculated with the real ones.



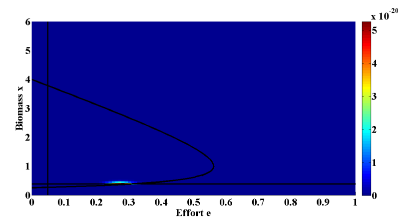
a - Underestimation, MSY manager



b - Overestimation, MSY manager,

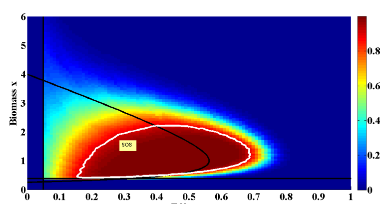


c - Underestimation, OAE manager

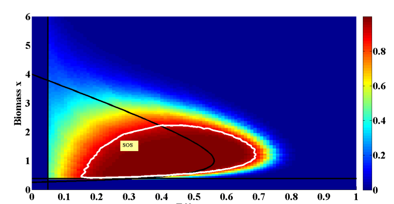


d - Overestimation, OAE manager,

Figure A.3. Robustness of the safe operating space according to imperfect knowledge K_2. K-parameter is multiplied by a coefficient (yielding more or less over/underestimations) in the decision-making process. But the dynamics are calculated with the real ones.

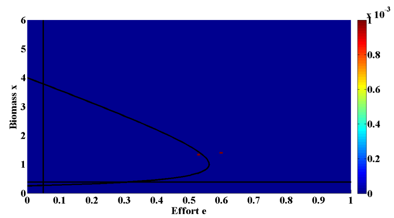


a - Underestimation, OAE manager

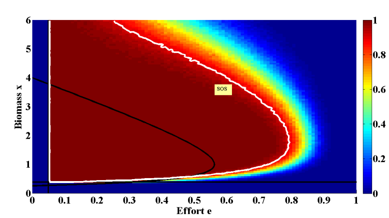


b - Overestimation, OAE manager,

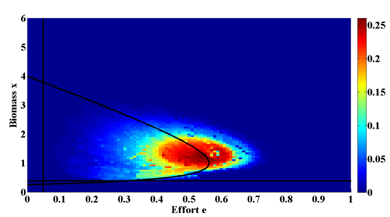
Figure A.4. Robustness of the safe operating space according to imperfect knowledge K_3. σ-parameter is multiplied by a coefficient (yielding more or less over/underestimations) in the decision-making process. But the dynamics are calculated with the real ones.



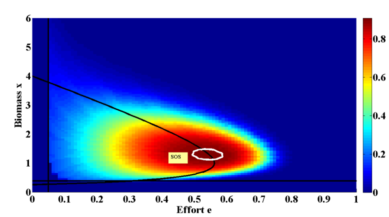
a - Underestimation, FT manager



b - Overestimation, FT manager,



c - Underestimation, OAE manager



d - Overestimation, OAE manager,

Figure A.5. Robustness of the safe operating space according to imperfect knowledge K_4. Effort e is multiplied by a coefficient (yielding more or less over/underestimations) in the decision-making process. But the dynamics are calculated with the real ones.

Acknowledgments

The lead author, JD Mathias, would like to thank the French National Research Agency (project VIRGO, ANR-16-CE03-0003-01 grant) for their financial support.