Resolving the measurement uncertainty paradox in ecological management

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Abstract

Ecological management and decision-making typically focus on uncertainty about the future, but surprisingly little is known about how to account for uncertainty of the present: that is, the realities of having only partial or imperfect measurements. Our primary paradigms for handling decisions under uncertainty – the precautionary principle and optimal control – have so far given contradictory results. This paradox is best illustrated in the example of fisheries management, where many ideas that guide thinking about ecological decision making were first developed. We find that simplistic optimal control approaches have repeatedly concluded that a manager should increase catch quotas when faced with greater uncertainty about the fish biomass. Current best practices take a more precautionary approach, decreasing catch quotas by a fixed amount to account for uncertainty. Using comparisons to both simulated and historical catch data, we find that neither approach is sufficient to avoid stock collapses under moderate observational uncertainty. Using partially observed Markov decision process (POMDP) methods, we demonstrate how this paradox arises from flaws in the standard theory, which contributes to over-exploitation of fisheries and increased probability of economic and ecological collapse. In contrast, we find POMDP-based management avoids such over-exploitation while also generating higher economic value. These results have significant implications for how we handle uncertainty in both fisheries and ecological management more generally.

Key words: POMDP, measurement uncertainty, decision theory, fisheries, conservation

Imperfect information is ubiquitous in ecological management and conservation decision making. While the pressing concerns of global change have put the spotlight on forecasting, i.e. the uncertainty of the future (e.g. Petchey et al. 2015), management decisions must also contend with uncertainty of the present: How many fish are in the sea today? What regions harbor the most fragile biodiversity? How do we make use of a rapidly expanding but opportunistically collected data, such as in citizen science efforts, which may involve strong sampling biases? Much of our focus in dealing with uncertainty has been through the lens of statistical approaches to model fitting. The rise of approaches such as Hierarchical Bayesian Modeling have given us sophisticated tools to reflect uncertainty in our data and uncertainty in our knowledge of mechanisms and parameters in our models (Ellison 2004). But estimating a model is not the same as making a decision, particularly when a model leaves us with considerable uncertainty about current and future states. A model can only provide the rules of the chess board. It is the role of decision theory to provide us with a strategy.

Decision theory has a long history in the ecological literature (e.g Schaefer 1954; Walters and Hilborn 1978; Clark 1990; Shea 1998; Polasky et al. 2011) which has sometimes been overshadowed by recent emphasis on model fitting. While in principle a model will be updated throughout the decision process (as we will discuss), it is convenient to think of the model as "given," estimated, with uncertainty, using the best available methods. The goal of a decision theory is not maximize some abstract notion of model fit (least squares, likelihood, etc), but a more practical notion of utility (happiness, economic value, or any combination of stakeholder objectives, see Halpern et al. (2013)). Approaches for decision making under uncertainty in ecological systems can be divided into two camps: (1) those based upon "optimal control" solutions, and usually favored by natural resource economists, and (2) those based in heuristic methods such as scenario planning, resilience thinking, and precautionary rules of thumb, more commonly found in both ecological literature and actual practice (Fischer et al. 2009; Polasky et al. 2011). While researchers have recognized the need to unify the transparent and quantitative algorithmic approach of optimal control with the greater complexity and uncertainty of real ecosystems that is acknowledged by heuristic methods, computational barriers to doing so have stymied this progress. We illustrate how the limitations of these approaches have manifested in the example of fisheries management, and present a new approach that can combine the reality of measurement uncertainty and the rigor of optimization to resolve a long-standing paradox and suggest a more robust approach to management.

The challenge of making decisions under uncertainty is not unique to fisheries. Optimal control-based decision methods which assume perfect measurements are applied to a wide range of population and ecosystem management issues, including fire ecology (Richards et al. 1999), invasive species (Shea 1998; Blackwood et al. 2010), disease outbreaks (Shea et al. 2014; Li et al. 2017), and protecting biodiversity (Dee et al. 2017; Iacona et al. 2017), and in common textbooks and reviews (Mangel 1985; Clark 1990; Marescot et al. 2013). Yet fisheries conservation and management has long been both a crucible and proving ground for the theory of ecological management more generally, including topics such as adaptive management (Walters and Hilborn 1978), ecosystem-based management (Levin and Lubchenco 2008) and resilience thinking (Holling 1973; May 1977), while also giving rise to the sub-discipline of resource economics (Gordon and Press 1954; Schaefer 1954; Beverton and Holt 1957), thanks to its global relevance, long history, and readily available data. Despite the generality of the models and issue of measurement uncertainty considered here, any application must be grounded in both the history and context of the particular decision problem. In light of this, we begin with a brief background on existing decision theory approaches common in fisheries management.

In this paper, we examine three strategies to managing a natural population, such as a fishery, under such uncertainty. This problem has a long history in both theory and practice, where seemingly innocuous simplifying assumptions have led to a deep paradox in how managers should respond to uncertainty. The precautionary principle (Kriebel et al. 2001) would seem to suggest that the greater the uncertainty in our models, the more cautious we should be in management policies. Yet a well-known mathematical proof by Reed (1979) established that under quite general conditions, the optimal strategy under uncertainty is no different than under no uncertainty at all. Attempts to resolve this have since only deepened this paradox, arguing that adding additional sources of uncertainty, such as imperfect measurements, should lead to optimal harvest that increases with greater uncertainty (e.g. Clark and Kirkwood 1986; Sethi et al. 2005). Meanwhile, much of actual practice has (perhaps fortunately, as we shall see) ignored these results in favor of a more heuristic application of the precautionary principle. Here, we show that this paradox can be resolved by uncovering previous shortcuts and tackling the optimal management problem head-on, which we can solve thanks to the computational efficiency of sophisticated algorithms developed more recently in the field of robotics. This approach allows us to reject this paradox largely in favor of the precautionary principle. Further, our comparisons show that widely recognized existing approaches in both theory and practice are not by themselves sufficient to manage a population under substantial uncertainty over the long term, but our recently borrowed approach from robotics literature can under identical conditions sustain both higher biomass and higher economic yields than those approaches. This conclusion has important implications not only for fisheries but ecosystem more broadly: First, our results highlight that measurement error must be accounted for in both the decision process itself, and not merely in the estimation of model. Second, these results underscore the opportunity to learn from engineering fields such as robotics when faced with complex and uncertain decisions that we have previously dismissed as intractable.

The Decision Problem

We consider the management problem of setting catch quotas for a marine fishery in the face of imperfect information about the current stock size and uncertainty about future recruitment. We seek to determine the sequence of actions h_t for $t \in [1, ...\infty]$ that maximize the net present value (discounted sum of all future profits) of the fishery. We will denote the discount rate γ. For simplicity we will once again follow classic theory and assume a fixed price for fish, (equivalently, measuring our value in units of discounted fish rather than discounted dollars). Each year, the manager also obtains an estimate y_t of the true x_t stock size subject to some measurement uncertainty ξ_t

$$y_t = \xi_t x_t \tag{1}$$

For simplicity, we will assume measurement uncertainty is normally distributed with standard deviation σ_m, $\xi \sim \mathcal{N}(1, \sigma_m)$. Given an estimated population model along with this (uncertain) measurement of the stock size, the manager must choose the set of a harvest quotas $\{h_t\}$ for $t \in [0, 1, \infty]$ that maximizes expected long term utility of the stock:

$$\max_{\{h_t\}} \mathbb{E} \left\{ \sum_{t=0}^{\infty} \gamma^t \cdot U(x_t, h_t) \right\} \tag{2}$$

For convenience of presentation, we will assume this utility is simply equal to the harvest itself.

$$U(x_t, h_t) = \min(h_t, x_t) \tag{3}$$

where the min function ensures no additional reward for attempting to harvest more than the entire stock. In economic terms, this corresponds to a fixed price per fish caught, with no proportional cost on effort required to do so, but the results do not depend on this assumption, as existing analyses have previously established (Reed 1979). Using this form allows a more direct comparison to approaches such as maximum sustainable yield (MSY) which do not include an economic model but merely maximize long-term catch. In principle, utility could also reflect ecosystem services or other intrinsic values for fish left in the sea and not merely the market for consumption (Halpern et al. 2013).

The solution to this decision problem is conditional on a population model for the underlying ecological process, describing the probability that the system moves to state x_{t+1} given that it was in state x_t and the manager selected a harvest h_t, which we discuss below. Such a model would typically be estimated and parameterized from available data, often (but not necessarily) using a hierarchical Bayesian approach that acknowledges the existence of uncertainty in both measurements and process (e.g. see Dichmont et al. 2016 for a discussion of how uncertainties are frequently included in stock assessment models). However, accounting for measurement uncertainty when going from data to model does not mean we have also accounted for this uncertainty when going from model to decision. For example, a harvest decision policy based upon maximum sustainable yield simply depends on the stock size which maximizes the expected growth rate of the model. Measurement uncertainty in model estimation can indeed influence the position of that maximum, but as we shall see, that strategy is only optimal in the absence of any uncertainty.

There is one further subtlety arising in this seemingly simple problem statement that we must address. Given our discrete-time formulation of the recruitment process, it is necessary to decide if the measurement y_t happens before or after harvest h_t: that is do we: measure, recruit, harvest, or measure, harvest, recruit? Following convention in the optimal control literature (e.g. Reed 1979; Clark 1990; Sethi et al. 2005), we will assume the latter; measurement occurs immediately before harvest, followed by recruitment. This assumption has occasionally been reversed to introduce some additional uncertainty from stochastic recruitment immediately prior to setting the harvest quota (e.g. Clark and Kirkwood 1986; Weitzman 2002), which appears to mimic uncertainty in measurements but does not allow uncertainty to accumulate since the measurement step still occurs without error.

The optimal strategy must think not only about the next year, but rather considers the sequence of all future actions h_t, under all possible realizations of the underlying model. This strategy must also acknowledge that the manager will receive new information each year, and may need to modify actions accordingly. It is this ability of the decision problem to think ahead that allows it to tolerate short-term costs (e.g. reduced harvests in the current season) for larger future payoffs. When Eq (1) is ignored, such optimal control problems are known as Markov Decision Processes or MDPs. These are more commonly referred to in the ecological literature by their solution method of Stochastic Dynamic Programming (SDP; Marescot et al. 2013), and widely used in both ecological management and animal behavior (Mangel 1985; Mangel and Clark 1988). The addition of measurement uncertainty in Eq (1) turns this problem into a Partially Observed Markov Decision Process (POMDP), for which solution methods have not been widely available for large problems until more recently. We discuss these decision methods in more detail below.

Population model

To facilitate tractability and interpretation, we will focus on the well-studied Gordon-Schaefer model (Gordon and Press 1954; Schaefer 1954) of logistic population growth (stock recruitment),

$$x_{t+1} = \varepsilon_t (x_t - h_t) r \left(1 - \frac{(x_t - h_t)}{K}\right) \tag{4}$$

where x_t is the current stock size, h_t the harvest chosen that year, with parameters r giving the individual growth rate, and K the carrying capacity and ε representing stochastic recruitment in a variable environment. We have written this in terms of $x_t - h_t$ to underscore that we assume the convention of observe, harvest, recruit. We will assume for simplicity $\varepsilon \sim \mathcal{N}(1, \sigma_g)$. This and similar models are widely used in large scale analyses across diverse stocks (e.g. (Costello et al. 2016; Britten et al. 2017)), and form the basis for much of bioeconomic theory (Clark 1990). As such, it will be easier to compare our results against intuition and classic theory, and avoid the possibility of differences arising only because of some particular subtle assumption hidden in a more complex model.

It is important to remember that all three decision methods we compare here will use this same model as given. In the case of numerical simulations, we will simply pick reasonable fixed parameter values for the model above. To illustrate the application to empirical data, we will first estimate these parameters using a hierarchical Markov Chain Monte Carlo (MCMC), and then use the resulting estimates to drive all three decision models. As such, the details of how the model is estimated are immaterial to the differences in performance between these decision methods. In all cases, the model is considered fixed. Technically, it would be possible to re-estimate the model parameters given each new observation during the decision process. Adaptations of the decision processes we consider here include this possibility for learning about the model during the decisions. Some include the possibility of taking knowingly bad actions, like suddenly increasing harvest rates, to improve learning over parameters. We investigate these in subsequent work (Memarzadeh and Boettiger 2018). For better comparison with established theory, here, the model is considered fixed. In the case of the simulations, the model is known without error (though still stochastic in nature), such that additional observations cannot improve the parameter estimates in any event. Despite that obvious simplification, we shall illustrate how existing decision methods fail to account for measurement uncertainty appropriately. Even with these simple models, decisions are complex, and knowing the rules of the game is not the same as knowing how to win.

Current Theory and Practice

Gordon and Press (1954) and Schaefer (1954) independently showed that the maximum sustainable yield is achieved by reducing the stock to the population to the size at which it obtains the maximum growth rate. This stock size is known as Biomass at Maximum Sustainable Yield, B_{MSY}. For the Gordon-Schaefer model (and many others), this is achieved at $B_{MSY} = K/2$. They observed that fishing at a *constant yield* (that is, an individual fish mortality, F, such that harvest $H = F \cdot B$) of $F_{MSY} := \frac{H_{MSY}}{B_{MSY}}$) will eventually lead to a population that converges to the biomass B_{MSY} and produces the maximum sustainable harvest, $H_{MSY} = rK/4$ in this model. From here, theory and practice diverge.

This *constant yield* (constant mortality) solution thus corresponds to an equilibrium analysis which does not solve the time-dependent optimization problem above. In particular, this maximum sustainable yield (MSY) strategy will not be optimal whenever the stock is away from B_{MSY}. Clark (1973) demonstrated (assuming no uncertainty in measurement or stochasticity in population dynamics) that the optimal time-dependent strategy is not one of constant yield, but rather of *constant escapement*. We will return to this approach in a moment.

Uncertainty in Practice: MSY & TAC

Maximum Sustainable Yield (MSY) remains the basis of international law (including the UN, IWC, IATTC, ICCAT, ICNAF; Mace (2001)) and a familiar standard of management in terrestrial ecosystems as well as aquatic (Clark 1990). Critics have for some time observed the limitations of harvesting at MSY in face of uncertainty in stock sizes and population dynamics (Larkin 1977; Botsford et al. 1997). Many US fisheries reflect this uncertainty through a series of adjustments that effectively reduce the target fishing mortality level to reflect this uncertainty. Typically, a stock assessment model provides a best estimate of B_{MSY} and corresponding mortality F_{MSY} is used to define the stock Over-Fishing Limit, (OFL). Based on this, a somewhat lower level is set as the Allowable Biological Catch (ABC), reflecting uncertainty in the stock assessment. To reflect possible uncertainty between reported and actual catch, the ABC may be reduced further to define the Total Allowable Catch, (TAC), which forms the basic unit of management for many such fisheries. To reflect this process, our analysis will also consider policies in which the harvest quota is set at 80% of the level expected under the MSY policy: $H_{TAC}(t) = 0.8 \cdot F_{MSY} \cdot B_t$, for a biomass estimated at $B(t)$ in year t. To distinguish this approach from MSY, we will refer to this approach as a TAC policy. This more closely represents a heuristic (e.g. Hilborn 2010) or resilience-based approach (sensu Fischer et al. 2009) than an optimization-based policy. Importantly, this approach shares the fundamentally stationary assumptions of an MSY policy by defining a constant mortality rather than a dynamic policy. Thus, despite being more cautious overall and generating lower economic yield than a constant escapement policy, TAC policies continue to harvest at non-zero rates even if a stock falls below B_{MSY}, while the constant escapement policy does not.

It is important to note that actual management strategies are quite diverse. Our focus on comparisons TAC, MSY, and Constant Escapement (CE) reflects only the subset of current practices. Another increasingly common approach to address uncertainty in both process and models is known as Management Strategy Evaluation (MSE, Smith 1994; Dorner et al. 2009; Bunnefeld et al. 2011; Punt et al. 2016). MSE performs forward simulations under a suite of pre-selected candidate strategies to determine which strategy achieves the best expected outcomes. Crucially, by limiting the analysis to a suite of candidate strategies over a finite number of replicate simulations, this approach is able to accommodate substantially greater complexity and uncertainty than has been possible with more formal optimal control approaches we discuss below. Optimal control solutions rely on dynamic programming to consider all possible strategies (all possible sequences of harvest under all possible realizations of stock dynamics). As such, MSE can be viewed as an approximation to the optimal control solutions considered below, a notion that has been formalized in the literature on approximate dynamic programming (Nicol and Chadès 2011). Future work may be able to leverage the forward-simulation approach used in MSE to extend the POMDP methods introduced here to yet more complex dynamics.

Optimal management

So far, attempts to provide a more formal basis for managing uncertainty than the heuristic adjustment of catch limits described above have largely foundered in a series of paradoxes. Without uncertainty, the theoretical policies are quite intuitive: The result derived by Clark (1973) for an optimal dynamic strategy to replace the equilibrium solution of MSY can be summarized as: If the stock is most productive at B_{MSY}, then obtain B_{MSY} as quickly as possible. Thus, at any level below B_{MSY}, the economically optimal thing to do is to completely shut down the fishery, while above this stock, harvests greater than H_{MSY} will be needed to bring the stock back to B_{MSY}. (This intuition must be adjusted slightly in the case of economic discounting of future profits, but is otherwise quite general, see Clark (1990)). This strategy is known as *constant escapement* (CE), since a constant sock size B_{MSY} escapes harvest each year. Because CE and MSY converge to the *same long-term biomass and same long-term average yield*, CE can appear to be merely a more formal justification for MSY. However, in practice the two approaches are very different: because natural populations fluctuate year-to-year, under CE, a different harvest quota must be set each year to achieve the constant escapement. Because CE is derived as the economic optimum (assuming perfect measurements), it is sometimes referred to as Maximum Economic Yield, (MEY; Burgess et al. 2018), or as Rights Based Fisheries Management (RBFM, Costello et al. 2016).

In the face of a naturally fluctuating population, previous arguments made by Gordon and Press (1954); Schaefer (1954) or Clark (1973) no longer hold. As noted above, the optimal harvest of a population under a model such as the stochastic Gordon Schaefer, Eq (4), is an example of a Markov Decision Problem (MDP) which must be solved with stochastic dynamic programming. Thanks to a mathematical proof provided by Reed (1979), fisheries managers have largely been able to bi-pass such computational effort. However, this convenient result also opened the door to paradox of uncertainty that has persisted in ecological management for the past four decades.

Reed's Paradox: $S = D$

Reed (1979) proved that, under sufficiently general assumptions, the optimal escapement S for a population under stochastic growth, is identical to Clark (1973)'s optimal escapement D for a deterministic population, $S = D = B_{MSY}$. This surprising result suggests that in going from a world where a manager has perfect knowledge of absolutely everything into a scenario where the manager faces considerable uncertainty about the future state of the world, no additional precaution is needed.

Clark's Paradox

Clark and Kirkwood (1986) was among the first attempts to resolve Reed's Paradox. Clark and Kirkwood (1986) (quite correctly, as we will see), identified the crux of Reed's Paradox as the absence of measurement uncertainty:

> An important tacit assumption in Reed's analysis, as in the other works referred to above, is that the recruitment level X is known accurately prior to the harvest decision, [. . .] In the case of fishery resources, the stock level X is almost never known very accurately, owing to the difficulty of observing fish in their natural environment.

Clark and Kirkwood (1986) were unable to solve the resulting problem exactly, but had to adopt an almost equally troublesome assumption:

> For reasons of tractability, we shall adopt the simplifying assumption that the escapement level S, is known exactly at the end of that period. (The mathematical difficulty of the problem increases markedly if this assumption is relaxed.)

Unfortunately, this "simplifying assumption" serves to squash most of the measurement error, and their results instead only deepened the paradox, finding policies that become even *less* cautious as uncertainty increases:

> [Our] results appear to contradict the conventional wisdom of renewable resource management, under which high uncertainty would call for increased caution in the setting of quotas.

Relying on a quite different but still flawed assumption nearly two decades later, Sethi et al. (2005) largely confirm Clark's Paradox, which they likewise observed with some concern:

> It may seem counter-intuitive that a measurement error causes lower expected escapements below the deterministic fishery closure threshold.

Despite these notes of caution, both Clark and Kirkwood (1986) and Sethi et al. (2005) ultimately attempt to rationalize this counter-intuitive conclusion rather than reject it. Intuitively, uncertainty in the population growth model (stochasticity) or measurement error, would seem to justify harvesting fewer fish. Instead, existing optimal control theory has presented only the paradoxical results that uncertainty either should not matter at all, or that we should increase rather than decrease harvests in response to increased uncertainty. Numerous other attempts have been made to resolve this paradox through alternative assumptions, the most common being to assume from the outset to look only for 'constant-escapement' type policies (Ludwig and Walters 1981; Roughgarden and Smith 1996; Engen et al. 1997; Moxnes 2003). Owing to the "mathematical difficulty" Clark first observed, none have attempted a direct solution which we will present here.

In practice, TAC-managed fisheries are more common that CE-managed fisheries, at least in the United States. CE-based regulation is limited primarily to salmon, species for which population estimates may be more precise and thus closer to Reed's assumption. We are not aware of any fishery that has put Clark's Paradox into practice, harvesting more in response to increased uncertainty. As we shall illustrate, this is fortunate; though approaches that properly account for both forms of uncertainty can perform even better.

POMDPs: An optimal treatment of measurement uncertainty

Why does the introduction of measurement uncertainty make the decision problem so much harder? Consider the thought experiment of managing a fish stock where in each of the previous four years stock assessments have put the population size at, say, 51, 54, 49, 51, (say, measured in percent of carrying capacity, K). Under a constant escapement target of 50, the harvest quota would be 1, 4, 0, 1, respectively. Note that this control rule depends only on the measurement for the year in question, which is assumed to be measured without error. If we then measure a stock size of 75, an assumption that this measurement is made without error would justify the sudden increase to a quota of 25. Yet if we admit the possibility of measurement error, this sudden bump starts to look very suspicious in light of all the previous observations. Perfect measurements let us exploit the Markov property of the model – the most recent measurement tells us all we need to know. In contrast, the introduction of measurement uncertainty breaks this Markovian assumption: a rational decision maker would suspect this 75 to be an over-estimate based on prior observations. Under imperfect observations introduced by Eq (1), we no longer have a Markov Decision Process (MDP) over the observed state space. Rather, we have a Partially Observed Markov Decision Process (POMDP). A POMDP policy cannot be expressed as a policy function at all (much less as policy function with a single constant-escapement target, as much previous work has assumed). Instead, a POMDP policy can be thought of as depending not only on the most recent observation, but the recent observation combined with a *prior belief* about what state the system is in, which itself is determined by all past observations. In this manner, the POMDP can consider how much weight to give the most recent observation based on how it compares to prior beliefs.

Algorithmic innovations from the robotics community have now made it possible to numerically solve non-trivial POMDP problems. The need to consider all past observations becomes particularly demanding given the forward-looking nature of a decision problem. Not only must we consider all possible sequences of future actions over all possible sequences of future states, but we must add to that all possible sequences of future measurements. The computational complexity involved has historically limited POMDP applications to contexts with only a handful of possible states and actions (e.g. Chadès et al. 2008, 2011; Fackler and Haight 2014; Fackler and Pacifici 2014), insufficient to capture fisheries models appropriately. Meanwhile, methods to solve decision problems with imperfect information have advanced steadily in the field of robotics and artificial intelligence. Almost contemporaneous with Reed's work, papers by Smallwood and Sondik (1973) and Sondik (1978) laid mathematical foundations for algorithms that could efficiently solve POMDP problems (e.g. Kaelbling et al. 1998; Pineau et al. 2003). More recently, driven by demands in areas such as autonomous vehicle decision making, newer point-based approximation algorithms such as SARSOP (Kurniawati et al. 2008) have made it possible to solve POMDPs with 100s of states and actions. We have adapted this algorithm for application to the fisheries context, and provide an efficient implementation as a preliminary R package (Boettiger et al. 2018) which can be used to replicate and further explore results presented here. Details of the analysis presented here including annotated code to reproduce and further explore all of the following results are provided in the supplementary material.

Precise definitions of both the (fully observed) MDPs and POMDPs (not to be confused with Markov Process Models and Hidden Markov Process Models – methods for which estimate the model but do not involve the feedback of any decision process) in an ecological context can be found in Williams (2011), or in classic work from the engineering and robotics community (e.g. Smallwood and Sondik 1973; Sondik 1978). For convenience, we summarize the POMDP definition and common notation here. The POMDP problem is posed identically to that of the MDP problem, with the addition of an observation process The POMDP problem for fisheries question considered here can be summarized as follows:

- Transition process (state equation): $T(x_t, x_{t+1}, a_t)$: the probability that a system is in state x_{t+1} at time $t+1$ given that it began in state x_t at time t and the manager took action a_t. In our context, this relationship is given by the Gordon-Schaefer stock recruitment function f with normally distributed growth uncertainty $x_{t+1} \sim \mathcal{N}(f(x_t, a_t), \sigma_g)$, truncated at zero to exclude negative population sizes. The action a_t represents the harvest quota set for the fishery. Attempting to implement a quota the exceeds the true population size results in collapse of the fishery. As Clark and Kirkwood (1986) eloquently argues, assuming that extinction is impossible regardless of fishing intensity would unreasonably bias the decision problem.

- Observation function: $O(x_t, y_t, a_{t-1})$ the probability of observing state y_t given a system in state x_t. In principle, the action chosen can influence the precision of the observation. In our case, we simply assume normally distributed errors around the true state, $y_t \sim \mathcal{N}(x_t, \sigma_m)$, truncated at zero to exclude negative population sizes.

- Utility function: $U(x_t, a_t)$, the utility received at time t for taking action a_t, given that the system is in state x_t. For simplicity of analysis, we will simply set the utility to be equal to the harvested stock: $U(x_t, a_t) = \min(x_t, a_t)$, indicating that realized harvest cannot be negative. This choice ensures that in the case of no uncertainty ($\sigma_g = \sigma_m = 0$), the optimal solution matches that expected under a simple MSY calculation. More realistic utility functions may include diminishing returns with increasing harvest (supply and demand effects), and the cost of fishing, both of which act to suppress large harvests. By focusing on a simple utility we can be sure that our comparison to MSY is driven by the treatment of uncertainty rather than merely differing economic assumptions.

The optimization problem is to select the action a_t that will maximize the net present utility over all time. Future utility may be discounted by a factor γ, so that a value V in t year is valued at $\gamma^t V$ today. Numerically, each of these functions are defined over a discrete set of possible states, observations, and actions, and can thus be represented as a collection of matrices or tensors.

Simulations

We consider the average fish biomass across 100 replicate simulations of the same stock dynamics (Eq 4) under three different management strategies: constant escapement (CE), total allowable catch (TAC; equal to 80% MSY), and partially observed Markov decision process (POMDP) management. Each suite of simulations is considered under three sequentially higher measurement error regimes, from $\sigma_m = 0$ (no measurement errors), $\sigma_m = 0.1$ (low error), and $\sigma_m = 0.15$ (moderate error), as indicated, while stochastic recruitment (environmental noise) is set to a moderate $\sigma_g = 0.15$. Empirical estimates of measurement error in stock sizes vary widely, with estimates often dependent upon methodological assumptions. Early estimates

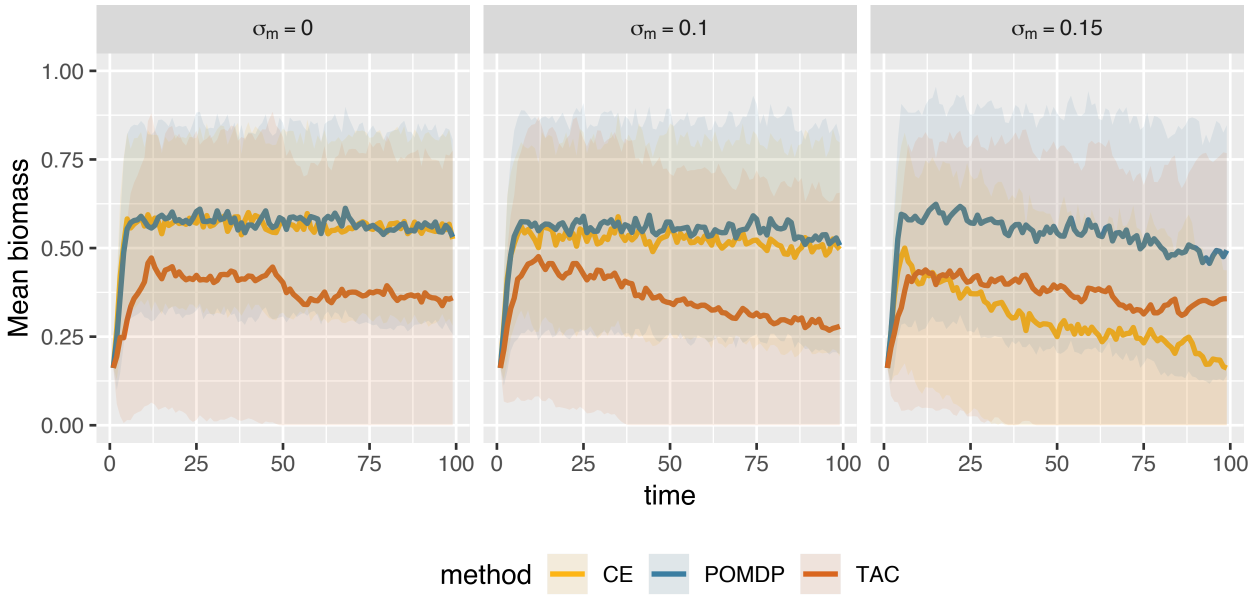

Figure 1: Average fish biomass under different management strategies under increasing levels of measurement uncertainty. Each plot the mean stock size over time across 100 replicate simulations under each policy: constant escapement (CE), Total allowable catch (TAC = 80% MSY), and the proposed partially observed Markov decision process (POMDP) method. Standard deviation from the mean across replicate simulations is shown as faint colored bands, indicating significant variation due to stochasticity between individual replicates. Measurement error increases as a normal distribution with standard deviation 0, 0.1, or 0.15, as indicated at the top of the panel. Environmental stochasticity is fixed a standard deviation of 0.15 in each panel. Carrying capacity K normalized to 1, r = 0.75. Additional environmental noise levels and comparison to MSY rather than TAC can be found in the supplementary material.

have put possible error as high as 50% (Clark and Kirkwood 1986) and more recent analyses have suggested an average of closer to 36%, though with cases that may be much higher (Ralston et al. 2011). Consequently, range between 0 to 15% provides a probably conservative estimate of typical uncertainty ranges, which we show is nevertheless large enough to drive substantially negative ecological and economic outcomes under management strategies that do not appropriately account for that error over the long run.

Results

In the absence of either environmental noise or measurement error POMDP, CE, and MSY would converge to stock at the B_{MSY}, while TAC would maintain the stock at a slightly higher level (see Supplemental material, Figure S1). The introduction of stochastic growth has a significant negative impact on the TAC strategy, with a mean biomass significantly lower than B_{MSY} (first panel, Figure 1; this impact is even more severe for MSY, see Figure S2). Without measurement error, the CE and POMDP strategies are nearly identical with both approximately maintaining the stock at B_{MSY} despite the significant environmental stochasticity. As measurement error increases in the subsequent panels, CE and TAC strategies perform

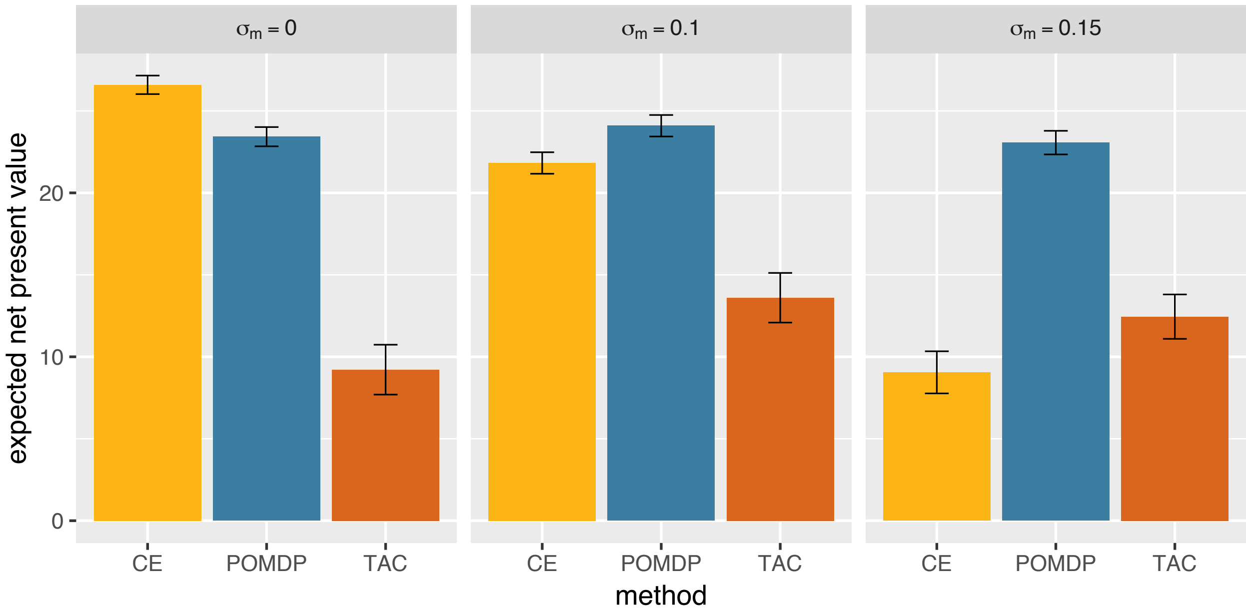

Figure 2: Expected net present value of the fishery across strategies under increasing levels of measurement error σ_m. Net present value is the sum of all future harvests discounted over time and averaged across 100 replicates simulations under each strategy, assuming discount factor $\gamma = 0.95$, as shown in Figure 1. The value under constant escapement (CE) is optimal when measurements are perfect but decreases rapidly with increasing measurement error. The more cautious TAC is not economically optimal but largely unimpacted by increasing error, while POMDP attains consistently high economic yield despite the increasing uncertainty.

increasingly poorly, while the POMDP continues to maintain the average stock close to B_{MSY}. Notably, CE is significantly more impacted by measurement uncertainty than TAC, with CE averaging even lower biomass than TAC under moderate measurement uncertainty. These results confirm that the precautionary approach represented by the TAC does indeed prove more robust to the problem of measurement error than the optimization solution represented by CE, but is less robust to environmental error. Many of the replicate simulations under CE experience complete stock extinction under large measurement error, owing to the arbitrarily large harvests permitted by the "bang-bang" nature of the CE policy. In contrast, the POMDP approach successfully handles both sources of uncertainty, maintaining higher stocks, near B_{MSY} level, and producing the highest yield.

This pattern in management success in ecological terms (the relatively recovery and maintenance of fish biomass) is also borne out in terms of economic performance. We find the mean net present value (averaging across replicates and discounting future profits by the discount factor $\gamma = 0.95$) for these same simulations at increasing levels of measurement uncertainty (Figure 2). As before, environmental stochasticity is set at $\sigma_g = 0.15$. In the absence of measurement uncertainty, constant escapement (CE) is optimal (as per Reed (1979)), while the heuristic caution built into the total allowable catch (TAC) strategy (at 80% MSY) results

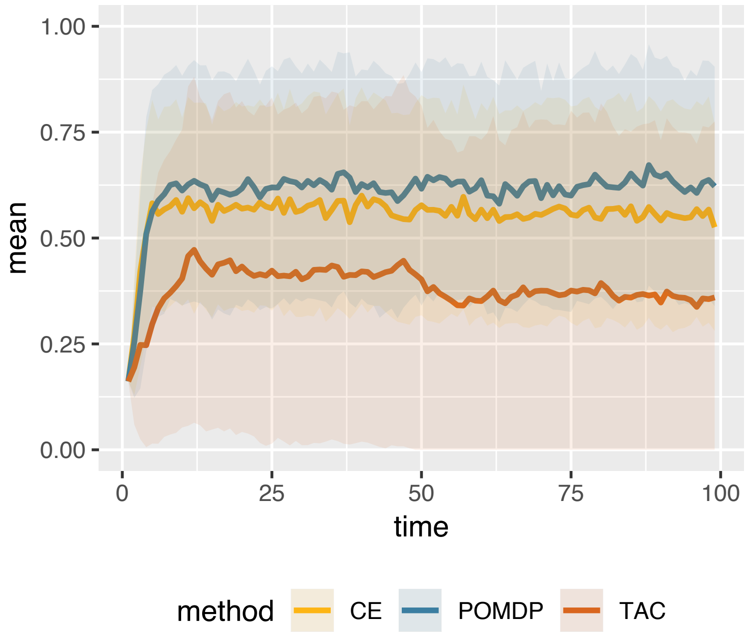

Figure 3: Average fish biomass when the POMDP strategy assumes a high level of measurement uncertainty, while simulations reflect perfect measurements. Despite this overestimation, biomass under POMDP strategy closely tracks the optimal biomass under CE in the absence of measurement error. Solid lines indicate averages over 100 simulations, colored bands indicate +/- one standard deviation.

in a sub-optimal economic yield. The presence of stochasticity in recruitment ($\sigma_g = 0.15$), also contributes to the reduction in yield under TAC. Though CE is quite robust to the environmental stochasticity level, this strategy proves very sensitive to increasing measurement error, showing sharp declines in economic value, falling below the TAC economic value at $\sigma_m = 0.15$. Though the risk of stock collapse does increase with increasing measurement error under TAC (as seen by the mean declines in Figure 1), these have little impact on the economic value due to the discount rate. A smaller discount rate would penalize unlikely but not improbable collapses more, since a significant amount of time is required to realize those rare events. Supplemental Figure S3 summarizes these economic trends across different noise values σ_g and includes comparison to a simple MSY policy. In contrast to the declining economic performance of CE and the consistently sub-optimal economic yield for TAC, the POMDP strategy continues to generate economic yields at approximately the optimal level (as attained by CE in the absence of measurement error) despite the increasingly uncertain measurements. This demonstrates that the reduced risk of stock collapse and higher average stock biomass attained by the POMDP strategy in the presence of high measurement error, Figure 1 is not the result of a trivial reduction in harvesting under all circumstances, but rather, evidence of a more nuanced strategy that manages to account for the uncertainty in measurement while maintaining a reasonable harvest.

The POMDP strategy is also robust to overestimation of the level of measurement uncertainty. In the simulation results shown in Figures 1 and 2, we have assumed that the level of measurement uncertainty σ_m was known, and saw that ignoring this uncertainty (as the CE policy does) has significant negative impact on ecological and economic outcomes. If the level of measurement uncertainty is not known precisely, *overestimating* the measurement error while using the POMDP strategy provides a precautionary approach that can nevertheless achieve nearly optimal ecological and economic outcomes. Figure 3 summarizes the results of the same simulations as before, but under the scenario in which the POMDP approach assumes a measurement error of $\sigma_m = 0.15$, when in fact all simulated measurements are made without error ($\sigma_m = 0$). This represents an extreme case of overestimating the measurement error. Stochastic growth remains the same as before, $\sigma_g = 0.15$, and simulations under TAC and CE policies are shown for comparison. When measurement error is absent, Reed's proofs hold and the CE strategy is optimal. Figure 3 shows that the POMDP outcomes track almost exactly the CE outcomes despite the misplaced assumption that measurements are quite poor. (As we have already seen, the TAC strategy is insufficiently cautious for this level of stochasticity in recruitment, resulting in over-exploitation and long-term decline). The ability of the POMDP solution to perform nearly optimally even when significantly overestimating the level of measurement uncertainty contrasts sharply to the significant declines from ignoring measurement uncertainty seen in the CE solutions in Figure 1. This demonstrates that while we may not know precisely the level of measurement error, we achieve far better outcomes overestimating measurement uncertainty than underestimating it. This also underscores the observation that POMDP policy is quite robust to the details of the uncertainty. We can get a better understanding for the performance of POMDP in these simulations by looking more closely at how any individual decision under a POMDP strategy compares to the action chosen by the current alternatives.

To better understand the differences in performance of these strategies and resolve the paradox of uncertainty, we must take a closer look at how the specific action recommended by each policy compares given the same observation. Figure 4 shows the action taken by each strategy in response to a measurement of the stock size (biomass estimate). These plots show, for any possible observations, which strategy will attempt to harvest most and which will attempt to harvest least. For comparison purposes, we plot policies both in terms of expected escapement, $S = Y - H$ as is typical in the optimal control literature, (e.g. Reed 1979; Clark and Kirkwood 1986; Sethi et al. 2005), and also directly in terms of the harvest quota H. These plots clearly illustrate the contrast between the constant escapement (CE) strategy and the precautionary Total Allowable Catch (TAC) strategy: CE sets harvest strictly to zero for stocks estimated at biomass below

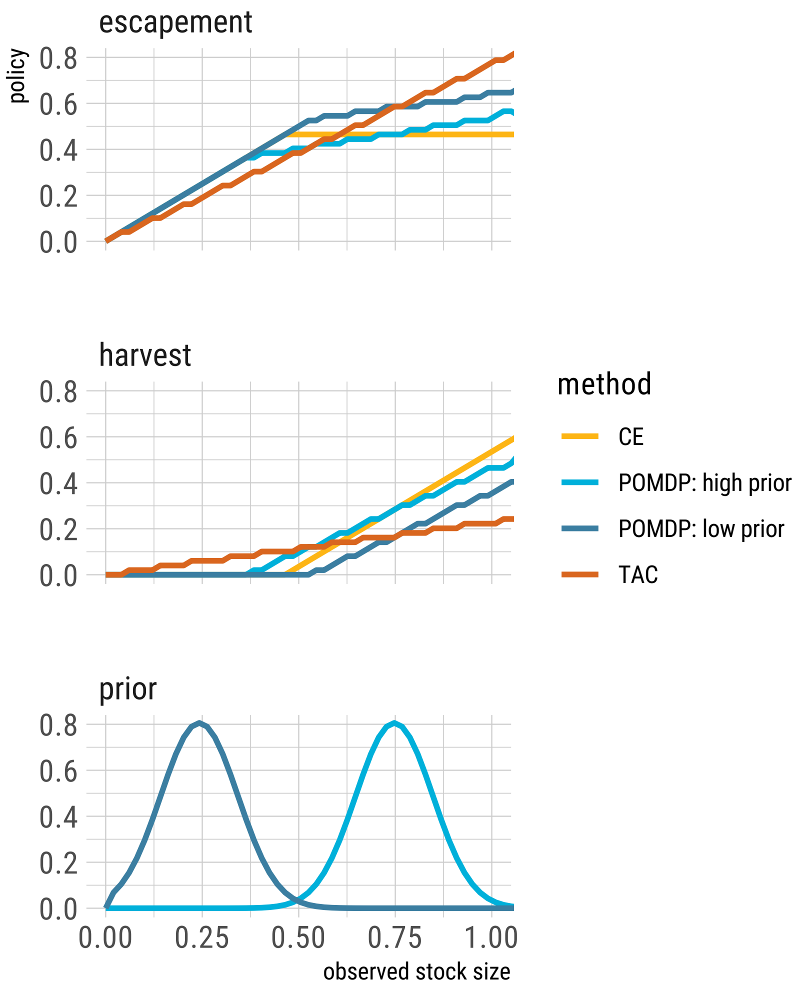

Figure 4: Comparison of the harvest and escapement policies under each strategy as a function of the observed stock size. Escapement refers to the expected fraction of fish left in the sea, $x - h$, while harvest refers to the target catch; two different conventions for plotting the same action. Uniquely, the POMDP policy plot will depend not only on the observed stock size, but also depends on prior information (bottom panel) as determined from any prior observations and actions. Depending on this prior it may harvest less or more than the other policies given an identical observation.

B_{MSY}, while TAC permits a modest harvest of even very small stocks. (Comparable plots with MSY can be found in the Supplemental Material). In principle, the CE policy could depend on σ_g, but as Reed (1979) proved, the constant escapement level with stochasticity is the same as in the deterministic case, S = D, unless the noise level is quite high (comparison plots in Supplemental material.) In contrast to this, our POMDP plots depend very much on both the choice of σ_m and σ_g. If $\sigma_m = 0$, they reduce exactly to the CE solution. Here we show the corresponding policies for POMDP solutions focusing on $\sigma_g = 0.15$ as above, with a modest measurement uncertainty $\sigma_m = 0.1$. Alternate combinations of measurement uncertainty can be found in the appendix but do not change the general pattern. In addition to an explicit dependence on the measurement error, our POMDP solutions depend on another piece of information: any prior observations of the stock size.

Differences in attention to prior beliefs, determined by prior observations, drive the differences between the POMDP strategy and the other strategies and can resolve the uncertainty paradox. While the catch quota under both TAC and CE strategies can be completely determined given the most recent observation of the stock size by using the policy curves shown in Figure 4, this is not the case for the POMDP approach. This fundamental difference is key to understanding the difference in performance and resolving the paradox of uncertainty. The POMDP policy cannot be specified by the most recent observation alone. Instead, the POMDP policy depends on all prior observations, not just the most recent. The reason for this complexity comes from the Markov property. Observations of the state in the perfectly observed system satisfy the Markov property: once we have measured the current biomass exactly, we cannot get any better estimate of the current stock size by studying older measurements. When measurements are uncertain this is no longer the case: intuitively, by comparing the most recent measurement to previous observations we may be able to infer when any given measurement is unusually high or unusually low. POMDP formalizes this intuition by capturing the information from all previous observations into a *prior belief*. This prior belief is updated after every subsequent action and observation in accordance with Bayes Law. The mechanics of this process are well documented in the extensive literature on POMDPs (e.g. Smallwood and Sondik 1973; Sondik 1978; Kurniawati et al. 2008; Williams 2011), but for our purposes it is sufficient to observe how this evolving prior belief serves to continually adjust the POMDP policy. Supplemental Figure S9 (Appendix A) illustrates how the prior belief evolves in response to subsequent observations and actions over the course of an individual simulation.

Figure 4 shows two separate policy curves (in terms of harvest and escapement) for the same POMDP solution given two different prior belief distributions (panel 3, priors). While both priors shown express considerable uncertainty about the precise stock size prior to the most recent observation, the lower prior is centered at a value $\frac{1}{4}K$ stock size, while the high prior is centered at a value of $\frac{3}{4}K$, relative to a (post-harvest, before observation) target size of $B_{MSY} = K/2$. The POMDP policy is determined by the combination of this prior information and the most recent observation, as indicated by the two different POMDP curves for harvest/escapement shown corresponding to the different priors. As with the other policies, the higher the most recent observation (x axis) the higher the POMDP recommended harvest. Yet unlike the alternative strategies, the POMDP solution always reflects the prior information. Consequently, relative to constant escapement (that is, no measurement error), the POMDP with low prior starts harvesting only at higher stock sizes and always harvests less. In contrast under the high prior, the POMDP always harvests at the same or higher level than the constant escapement solution.

A resolution to the paradox.

Herein lies our resolution to the paradox of uncertainty. Previous work created this paradox by suggesting that increased harvest rates (decreased target escapement) would often be the rational response to increased uncertainty. The exact solutions from the POMDP reveal that this is only an accident of the assumptions: it is indeed true that under certain circumstances, harvest levels should increase relative to the case of no uncertainty, but *only when prior knowledge suggests the stock size should be much higher than the most recent estimate would suggest.* In the POMDP solution, all information must be put into its historical (and constantly updated) context. When a measurement roughly matches the expectation of this prior context, Figure 4 shows that the optimal response from POMDP is roughly comparable or slightly more cautious to the harvest under no uncertainty, and not more aggressive as the paradox would suggest. Measurements that exceed expectations are tempered with some skepticism: while the CE solution is willing to meet a high stock measurement with a large harvest, the POMDP solutions increase harvest more cautiously.

This difference between underestimating and overestimating accounts for the poor performance of the CE solution under large measurement uncertainty, where it over-harvests whenever measurements are too large. Even though underestimating is equally likely under the measurement uncertainty model, sooner or later a run of "heads", a sequence of overestimations relative to the true stock, can drive stocks to very low levels where the chance of stock extinction becomes possible. It is precisely this asymmetry: that too much over-harvesting leads to an irreversible state of extinction, while too much under-harvesting is always reversible (modulo some lost revenue) that lay behind Clark's original intuition that there was something fishy about Reed's result that $S = D$: that uncertainty required no extra caution. Constant escapement is particularly susceptible to over-harvesting starting from stock sizes much higher than B_{MSY} since its

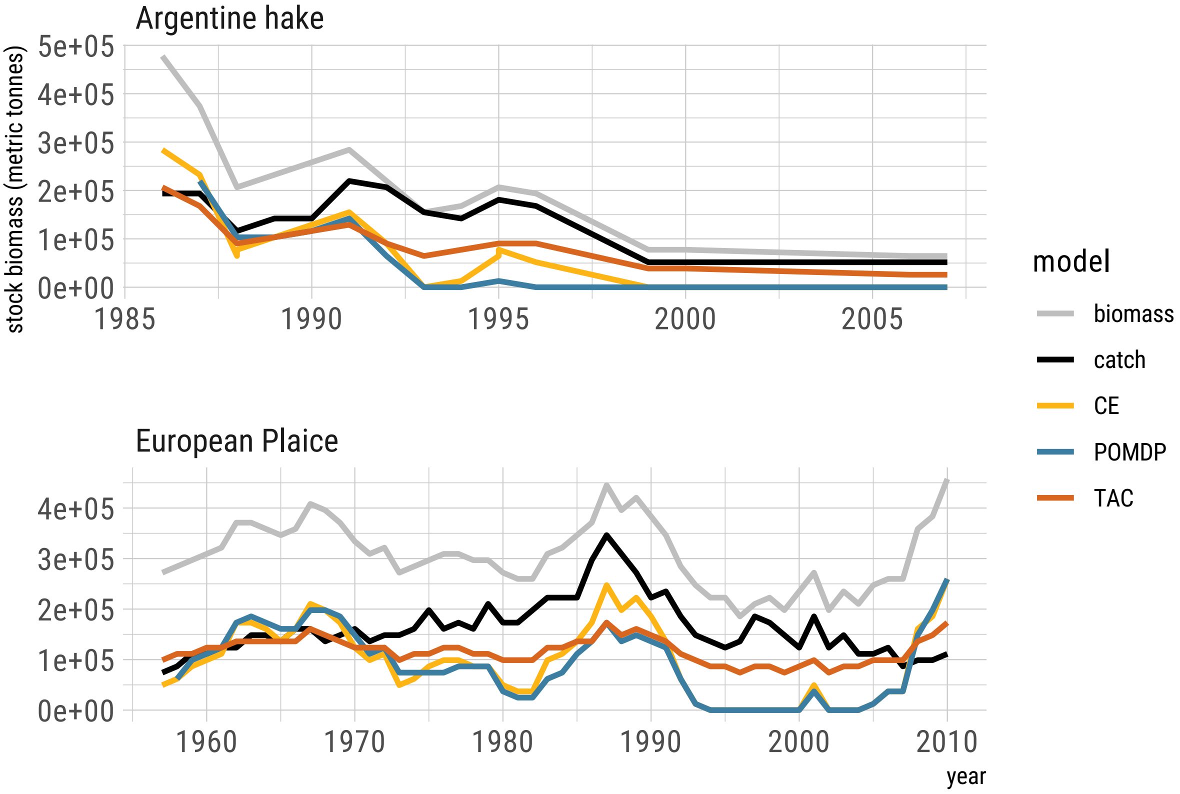

Figure 5: Comparisons of harvest level that would be recommended by policies considered here relative to historical harvest levels in two commercial fish stocks. POMDP solution assumes a measurement error of 10%.

bang-bang optimal solution attempts to bring stocks back to target level as fast as possible. CE is not so vulnerable to collapse from small stock sizes, since it shuts down all harvests once estimates fall below B_{MSY}. Stock collapse under TAC can also be driven by such a string of heads, but is unlikely at high stock sizes since harvest never exceeds H_{MSY}. In both cases, some measurement uncertainty interacts with inherent stochasticity, which provides a continued source of variation to sizes above B_{MSY}, where CE strategy is most vulnerable, and below B_{MSY}, where TAC is most vulnerable.

Historical examples and implementation.

So far we have focused on simulation and an examination of the relative policies under different prior information. Figure 5 compares the harvest level that would have been recommended by each of the strategies we have considered here against the historically observed catch recorded for two commercially fished stocks: Argentine Hake and European Plaice. Historical estimates of biomass and catch are taken from the R.A. Myers Legacy Stock Assessment database (Ricard et al. 2011). Posterior distributions for parameters for the Gordon-Schaefer model are estimated with uncertainty through Markov Chain Monte Carlo using `nimble` (de Valpine et al. 2017) on the historical data, illustrating how this process might be done in more complex models as well (details and code in Supplement, Appendix B). B_{MSY} and corresponding TAC and CE policies are calculated based on posterior mean estimates of the model parameters, along with POMDP solution assuming a 10% measurement error rate. Though measurement error could be estimated directly from the raw data, this would not reflect the true measurement uncertainty arising from the stock assessment process. Each strategy is then compared to historical observations to determine a recommended harvest. As we have seen, the TAC and CE harvest policies are uniquely determined by the observed stock size relative to B_{MSY}, but the POMDP policy must be re-calculated each time step to reflect both the prior observation and prior action.

These historical examples provide another useful lens to compare how the different strategies respond in the face of fluctuations in real data, rather than model simulations. In both stocks, historical catch almost always exceeds that recommended by any of our strategies, falling closer to the MSY value estimated (see Appendix B). In Argentine Hake, the persistent declines result in both POMDP and CE strategies quickly closing down the fishery in an attempt to let the stock recover to a more productive target biomass, while TAC persists with merely a reduced harvest. A small recovery of biomass in 1995 is met by an immediate uptick in harvest under CE, while the POMDP response is more conservative. The example of European Plaice illustrates more volatility in the stock size, revealing further differences in the strategies. Despite this volatility, the TAC level remains relatively level across all five decades, rising or dipping only slightly with changes in stock size. In contrast, the CE harvest tracks this volatility almost exactly. Here, the POMDP solution falls in between these extremes, almost mirroring which-ever of the two policies is more conservative: the POMDP solution matches the dips in harvest taken by CE to allow the stock to recover most quickly, but does not track the doubling of harvests recommended by CE in the mid 1980, increasingly only to the more modest harvest recommended by the TAC policy. Once again, we see that POMDP solution provides a more consistently precautionary policy than either the over-simplified optimal control solution of CE or the more rule-of-thumb approach represented by TAC. Though we have seen that the POMDP solution need not always be more conservative (lower harvest) than these strategies, it makes use of the all prior observations to tune the level of caution appropriately.

Discussion

Using modern algorithms we have been able to both crack the nut of measurement uncertainty in the optimal management of ecological populations such as marine fisheries, debunking a long-standing paradox created by previous literature which has argued that increased measurement uncertainty should be met with equal or larger harvests (e.g. Reed 1979; Clark and Kirkwood 1986; Sethi et al. 2005). By using powerful algorithms developed first in the robotics literature to solve POMDPs (Kurniawati et al. 2008), we have been able to tackle this optimal control problem directly rather than resorting to the simplifying assumptions used in previous work. Our solution confirms the intuition of the precautionary principle in a quantitatively precise form: under most (but not all) conditions, *greater uncertainty results in smaller optimal harvests*. Despite frequently proposing smaller harvests than existing approaches, the POMDP solution achieves higher long-term economic value as well as higher average stock sizes over the long term.

This lesson has clear relevance in the context of fisheries management. Here, practice is already wiser than theory, where the optimal control based on the CE results of Clark (1973) and Reed (1979) is limited to fisheries such as salmon where estimates in stock size may be less significant than in purely marine species. To our knowledge, no fishery has intentionally put the more aggressive harvest solutions of Clark and Kirkwood (1986) and Sethi et al. (2005) into practice. Yet this does not lift the specter of these methods, where CE-based predictions feature prominently in global fisheries analyses as the economically optimal strategy and the fastest route to recovery (Costello et al. 2016; Burgess et al. 2018). Our results raise serious questions about the optimistic forecasts predicted under these CE-based policies. Meanwhile, MSY remains the dominate standard international law (Mace 2001), and many well-managed US fisheries rely on a version of the TAC based precautionary adjustment to MSY to comply with catch limits under Magnuson-Stevens Act. Our results show that these strategies are less sensitive to measurement error, but not immune. Comparisons against more heuristic decision methods are more difficult: management strategy evaluation (MSE; Smith 1994; Punt et al. 2016) will depend on precisely what management scenarios are considered. Under sufficient uncertainty, both the existing optimal and precautionary approaches can lead to declines in biomass and economic returns which could be avoided by POMDP-based management.

This conclusion has important broader implications for ecological management more generally. Decision making under uncertainty is a central challenge for ecology and conservation biology, which frequently pits optimal control based approaches against more heuristic approaches such as resilience thinking, scenario planning, and the precautionary principle (Polasky et al. 2011). With economists frequently favoring the precise, stylized approach of optimal control and ecologists embracing the realities of greater complexity and uncertainty echoed in more heuristic approaches, this division can sometimes appear to pit economic outcomes against ecological objectives. That perspective is echoed in the paradox discussed here, in which economic optimization ignoring uncertainty has argued in cold mathematical logic for a rejection of the precautionary principle. Our results demonstrate that this divide is artificial. With sufficiently powerful algorithms we can go some ways to realizing the call of Fischer et al. (2009) to combine more ecologically realistic assumptions such as measurement error with optimal control approaches in ecological management. Both sides are vindicated in our solution: economic optimization under POMDP does not contradict the precautionary principle, while under POMDP, optimal control can also achieve better ecological outcomes than blunt precautionary rule (i.e. TAC, which reduced all harvests by 20% below MSY target). As Fischer et al. (2009) predicted, unifying optimal control with more resilience-inspired approaches is win-win.

If accounting for measurement uncertainty can resolve previous paradoxes and divides, it also raises additional challenges. The approach discussed here is vulnerable both to the charge of being too simple to be realistic while also being too complicated to be feasible. These issues are as easily recognized in other ecological management contexts, from harvests of wild game or forestry to pest outbreaks, (e.g. Richards et al. 1999; Shea 1998; Blackwood et al. 2010; Shea et al. 2014; Dee et al. 2017; Iacona et al. 2017; Li et al. 2017) as in fisheries, where ecological complexity is invariably high and management capacity invariably limited. We address each of these in turn.

Are the dynamics considered here too simple? Our underlying model is undoubtedly much simpler than many of the age or stage structured models used in modern fisheries management – aspects whose importance to ecological dynamics have been established well beyond fisheries as well. Yet it is critical to bear in mind that this stylized one-dimensional model is used only to compare the relative performance of the different decision strategies considered here (TAC, CE, and POMDP) in order to illustrate the potential importance of uncertainty in measurement. There is little reason to believe CE or TAC would perform better under more complex cases such as age-structured models that only further deviate from the assumptions under which they were derived (e.g. Holden and Conrad 2015). POMDP approaches are in no way incompatible with more complex models, whether that be age structure or even more ambitious non-parametric representations defined directly from data using Gaussian Processes or other machine learning techniques (e.g. Boettiger et al. 2015). Simple models have always served as tools for comparison and intuition, and serve the same illustrative role here.

Is this approach too complex to be feasible? The importance of simple and effective rules of thumb in conservation management has been well documented (e.g. Chadès et al. 2011). Sophisticated and computationally intensive approaches such as POMDP may seem improbable at a time when many areas of natural resource management, even simple, rule-of-thumb based methods struggle to take root. There is no doubt that the solution method needed here is computationally intensive even for the simple model considered here, and will only become more so under greater ecological complexity. Indeed, it was precisely such computational limitations that led to the shortcuts in work such as Clark and Kirkwood (1986), with the ensuing potentially misleading conclusions. While in the following decades ecologists largely turned away from computationally intensive optimization required for even simple models with stochastic dynamic programming, (while continuing to construct ever more complicated hierarchical models), engineers have chipped away at the decision problem to reveal algorithms such as SARSOP that make much larger dynamic programming problems tractable. Yes, we may need even more sophisticated algorithms to accommodate greater ecological complexity, yet we believe such numerical obstacles are no excuse for management by half measures. Rather, our example illustrates how ecologists and managers can learn from and leverage the tools developed in other disciplines to better face the challenges of management in a complex and changing world.

Future directions

Several limitations that have been studied in fully observed (MDP) optimal decision problems, such as parameter uncertainty (e.g. Ludwig and Walters 1982), model uncertainty (Williams 2001; Boettiger et al. 2015) and adaptive management (e.g. Walters and Hilborn 1976) remain largely open challenges for partially observed systems. Future work could extend this analysis to more complex models, such as those with age structure, as (Holden and Conrad 2015) does for the fully observed case. Another limiting assumption common to MDPs and POMDPs is that of stationary dynamics: that the population dynamics equation itself is not changing over time. In reality, forces such as climate change and other forms of environmental variations violate this assumption (Britten et al. 2017). Direct approaches such as Fackler and Pacifici (2014)'s adaptation of Mixed Observability MDP (Ong et al. 2010) do not scale to the number of states and actions considered here. A value of information (VOI) analysis for POMDP (e.g. Johnson and Williams 2015; Memarzadeh and Pozzi 2016), could identify when it is worthwhile to actively reduce measurement error.

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References

Beverton, R., and S. Holt. 1957. On the Dynamics of Exploited Fish Populations. Chapman; Hall, London.

Blackwood, J. C., A. Hastings, and C. Costello. 2010. Cost-effective management of invasive species using linear-quadratic control. Ecological Economics 69:519–527.

Boettiger, C., M. Mangel, and S. Munch. 2015. Avoiding tipping points in fisheries management through Gaussian process dynamic programming. Proceedings of the Royal Society B: Biological Sciences 282:20141631–20141631.

Boettiger, C., J. Ooms, and M. Memarzadeh. 2018. sarsop: Approximate POMDP Planning Software in R, v0.5.0, <https://github.com/boettiger-lab/sarsop>.

Botsford, L. W., J. C. Castilla, and C. Peterson. 1997. The management of fisheries and marine ecosystems. Science 277:509–515.

Britten, G. L., M. Dowd, L. Kanary, and B. Worm. 2017. Extended fisheries recovery timelines in a changing environment. Nature Communications 8:15325.

Bunnefeld, N., E. Hoshino, and E. Milner-Gulland. 2011. Management stratefy evaluation: a powerful tool for conservation? Trends in Ecology and Evolution 26:441–447.

Burgess, M., G. McDermott, B. Owashi, L. Peavey Reeves, T. Clavelle, D. Ovando, B. Wallace, et al. 2018. Protecting marine mammals, turtles, and birds by rebuilding global fisheries. Science 359:1255–1258.

Chadès, I., T. G. Martin, S. Nicol, M. A. Burgman, H. P. Possingham, and Y. M. Buckley. 2011. General rules for managing and surveying networks of pests, diseases, and endangered species. Proceedings of the National Academy of Sciences 108:8323–8.

Chadès, I., E. McDonald-Madden, M. a McCarthy, B. Wintle, M. Linkie, and H. P. Possingham. 2008. When to stop managing or surveying cryptic threatened species. Proceedings of the National Academy of Sciences 105:13936–40.

Clark, C. W. 1973. Profit maximization and the extinction of animal species. Journal of Political Economy 81:950–961.

Clark, C. W. 1990. Mathematical Bioeconomics: The Optimal Management of Renewable Resources, 2nd Edition. Wiley-Interscience.

Clark, C. W., and G. P. Kirkwood. 1986. On uncertain renewable resource stocks: Optimal harvest policies and the value of stock surveys. Journal of Environmental Economics and Management 13:235–244.

Costello, C., D. Ovando, T. Clavelle, C. K. Strauss, R. Hilborn, M. C. Melnychuk, T. A. Branch, et al. 2016. Global fishery prospects under contrasting management regimes. Proceedings of the National Academy of Sciences 113:5125–5129.

Dee, L. E., M. De Lara, C. Costello, and S. D. Gaines. 2017. To what extent can ecosystem services motivate protecting biodiversity? Ecology Letters 20:935–946.

de Valpine, P., D. Turek, C. J. Paciorek, C. Anderson-Bergman, T. Duncan, and R. Bodik. 2017. Programming With Models: Writing Statistical Algorithms for General Model Structures With NIMBLE. Journal of Computational and Graphical Statistics 26:403–413.

Dichmont, C. M., R. A. Deng, A. E. Punt, J. Brodziak, Y.-J. Chang, J. M. Cope, J. N. Ianelli, et al. 2016. A review of stock assessment packages in the united states. Fisheries Research 183:447–460.

Dorner, B., R. M. Peterman, and Z. Su. 2009. Evaluation of performance of alternative management models of Pacific salmon (Oncorhynchus spp.) in the presence of climatic change and outcome uncertainty using Monte Carlo simulations. (R. Hilborn, ed.)Canadian Journal of Fisheries and Aquatic Sciences 66:2199–2221.

Ellison, A. M. 2004. Bayesian inference in ecology. Ecology Letters 7:509–520.

Engen, S., R. Lande, and B. Sæther. 1997. Harvesting strategies for fluctuating populations based on uncertain population estimates. Journal of Theoretical Biology 186:201–212.

Fackler, P., and R. Haight. 2014. Monitoring as a partially observable decision problem. Resource and Energy Economics 37:226–241.

Fackler, P., and K. Pacifici. 2014. Addressing structural and observational uncertainty in resource management. Environmental Management 133:27–36.

Fischer, J., G. D. Peterson, T. a Gardner, L. J. Gordon, I. Fazey, T. Elmqvist, A. Felton, et al. 2009. Integrating resilience thinking and optimisation for conservation. Trends in ecology & evolution 24:549–54.

Gordon, H. S., and C. Press. 1954. The Economic Theory of a Common-Property Resource: The Fishery. Journal of Political Economy 62:124–142.

Halpern, B. S., C. J. Klein, C. J. Brown, M. Beger, H. S. Grantham, S. Mangubhai, M. Ruckelshaus, et al. 2013. Achieving the triple bottom line in the face of inherent trade-offs among social equity, economic return, and conservation. Proceedings of the National Academy of Sciences 110:6229–34.

Hilborn, R. 2010. Pretty Good Yield and exploited fishes. Marine Policy 34:193–196.

Holden, M., and J. Conrad. 2015. Optimal escapement in stage-structured fisheries with environmental stochasticity. Mathematical biosciences 269:76–85.

Holling, C. S. 1973. Resilience and Stability of Ecological Systems. Annual Review of Ecology and Systematics 4:1–23.

Iacona, G. D., H. P. Possingham, and M. Bode. 2017. Waiting can be an optimal conservation strategy, even in a crisis discipline. Proceedings of the National Academy of Sciences 201702111.

Johnson, F. A., and B. K. Williams. 2015. A Decision-Analytic Approach to Adaptive Resource Management. Pages 61–84 *in* C. R. Allen and A. S. Garmestani, eds. Adaptive management of social-ecological systems. Springer Netherlands, Dordrecht.

Kaelbling, L. P., M. L. Littman, and A. R. Cassandra. 1998. Planning and Acting in Partially Observable Stochastic Domains. Artificial Intelligence 101:99–134.

Kriebel, D., J. Tickner, P. Epstein, J. Lemons, R. Levins, E. L. Loechler, M. Quinn, et al. 2001. The precautionary principle in environmental science. Environmental health perspectives 109:871–6.

Kurniawati, H., D. Hsu, and W. S. Lee. 2008. SARSOP : Efficient Point-Based POMDP Planning by Approximating Optimally Reachable Belief Spaces. Proceedings of Robotics: Science and Systems IV.

Larkin, P. a. 1977. An Epitaph for the Concept of Maximum Sustained Yield. Transactions of the American Fisheries Society 106:1–11.

Levin, S. A., and J. Lubchenco. 2008. Resilience, Robustness, and Marine Ecosystem-based Management. BioScience 58:27–32.

Li, S.-L., O. N. Bjørnstad, M. J. Ferrari, R. Mummah, M. C. Runge, C. J. Fonnesbeck, M. J. Tildesley, et al. 2017. Essential information: Uncertainty and optimal control of Ebola outbreaks. Proceedings of the National Academy of Sciences 114:5659–5664.

Ludwig, D., and C. Walters. 1981. Measurement errors and uncertainty in parameter estimates for stock and recruitment. Journal of Canadian Fisheries and Aquatic Sciences 38:711–720.

Ludwig, D., and C. J. Walters. 1982. Optimal harvesting with imprecise parameter estimates. Ecological Modelling 14:273–292.

Mace, P. M. 2001. A new role for MSY in single-species and ecosystem approaches to fisheries stock assessment and management. Fish and Fisheries 2:2–32.

Mangel, M. 1985. Decision and control in uncertain resource systems 255.

Mangel, M., and C. W. Clark. 1988. Dynamic Modeling in Behavioral Ecology. (J. Krebs & T. Clutton-Brock, eds.). Princeton University Press, Princeton.

Marescot, L., G. Chapron, I. Chadès, P. L. Fackler, C. Duchamp, E. Marboutin, and O. Gimenez. 2013. Complex decisions made simple: a primer on stochastic dynamic programming. (R. Freckleton, ed.)Methods in Ecology and Evolution 4:872–884.

May, R. M. 1977. Thresholds and breakpoints in ecosystems with a multiplicity of stable states. Nature 269:471–477.

Memarzadeh, M., and C. Boettiger. 2018. Adaptive management of ecological systems under partial observability. Biological Conservation 224:9–15.

Memarzadeh, M., and M. Pozzi. 2016. Value of information in sequential decision making: component inspection, permanent monitoring and system-level scheduling. Reliability Engineering & System Safety 154:137–151.

Moxnes, E. 2003. Uncertain measurements of renewable resources: approximations, harvesting policies and value of accuracy. Journal of Environmental Economics and Management 45:85–108.

Nicol, S., and I. Chadès. 2011. Beyond stochastic dynamic programming: a heuristic sampling method for optimizing conservation decisions in very large state spaces. Methods in Ecology and Evolution 2:221–228.

Ong, S., S. Png, D. Hsu, and W. Lee. 2010. Planning under uncertainty for robotic tasks with mixed observability. The International Journal of Robotics Research 29:1053–1068.

Petchey, O. L., M. Pontarp, T. M. Massie, S. Kéfi, A. Ozgul, M. Weilenmann, G. M. Palamara, et al. 2015. The ecological forecast horizon, and examples of its uses and determinants. Ecology Letters 18:597–611.

Pineau, J., G. Gordon, and S. Thrun. 2003. Point-based value iteration: An anytime algorithm for POMDPs. IJCAI International Joint Conference on Artificial Intelligence 1025–1030.

Polasky, S., S. R. Carpenter, C. Folke, and B. Keeler. 2011. Decision-making under great uncertainty: environmental management in an era of global change. Trends in Ecology & Evolution 26:398–404.

Punt, A. E., D. S. Butterworth, C. L. de Moor, J. A. A. De Oliveira, and M. Haddon. 2016. Management strategy evaluation: best practices. Fish and Fisheries 17:303–334.

Ralston, S., A. E. Punt, O. Hamel, J. D. Devore, and J. R. Conser. 2011. A meta-analytic approach to quantifying scientific uncertainty in stock assessments. Fishery Bulletin 217–231.

Reed, W. J. 1979. Optimal escapement levels in stochastic and deterministic harvesting models. Journal of Environmental Economics and Management 6:350–363.

Ricard, D., C. Minto, O. Jensen, and J. Baum. 2011. Examining the knowledge base and status of commercially exploited marine species with the RAM Legacy Stock Assessment Database. Fish and Fisheries 13:380–398.

Richards, S. A., H. P. Possingham, and J. Tizard. 1999. Optimal Fire Management for Maintaining Community Diversity. Ecological Applications 9:880–892.

Roughgarden, J. E., and F. Smith. 1996. Why fisheries collapse and what to do about it. Proceedings of the National Academy of Sciences 93:5078–5083.

Schaefer, M. B. 1954. Some aspects of the dynamics of populations important to the management of the commercial marine fisheries. Bulletin of the Inter-American Tropical Tuna Commission 1:27–56.

Sethi, G., C. Costello, A. Fisher, M. Hanemann, and L. Karp. 2005. Fishery management under multiple uncertainty. Journal of Environmental Economics and Management 50:300–318.

Shea, K. 1998. Management of populations in conservation, harvesting and control. Trends in Ecology and Evolution 13:371–375.

Shea, K., M. J. Tildesley, M. C. Runge, C. J. Fonnesbeck, and M. J. Ferrari. 2014. Adaptive Management and the Value of Information: Learning Via Intervention in Epidemiology. PLoS Biology 12:9–12.

Smallwood, R. D., and E. J. Sondik. 1973. The Optimal Control of Partially Observable Markov Processes Over a Finite Horizon. Operations Research 21:1071–1088.

Smith, A. 1994. Management strategy evaluation – the light on the hill. Population dynamics for fisheries management 249–253.

Sondik, E. J. 1978. The Optimal Control of Partially Observable Markov Processes Over the Infinite Horizon : Discounted Costs. Operations Research 26:282–304.

Walters, C. J., and R. Hilborn. 1976. Adaptive Control of Fishing Systems. Journal of the Fisheries Research Board of Canada 33:145–159.

———. 1978. Ecological Optimization and Adaptive Management. Annual Review of Ecology and Systematics 9:157–188.

Weitzman, M. L. 2002. Landing Fees vs Harvest Quotas with Uncertain Fish Stocks. Journal of Environmental Economics and Management 43:325–338.

Williams, B. K. 2001. Uncertainty , learning , and the optimal management of wildlife. Environmental and Ecological Statistics 8:269–288.

———. 2011. Resolving structural uncertainty in natural resources management using POMDP approaches. Ecological Modelling 222:1092–1102.