

Modeling Information in Environmental Decision-Making

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Introduction

Uncertainty abounds in environmental and resource management problems. There is uncertainty about the physical processes themselves, uncertainty about which physical consequences people care about, and uncertainty about the value of the relevant outcomes. Some uncertainty may be expected to diminish with learning over time, but much will remain beyond the time when decisions have to be made. As a result, decision-makers cannot simply wait for uncertainty to go away. Policy needs to anticipate. Decisions must be made *ex ante*.

When evaluating choice under uncertainty, most applied work in environmental and resource economics builds on the well-worn structure of expected utility maximization (the EU model) or subjective expected utility maximization (the SEU model)². There are good reasons for this. For one, it is easy to use. Linearity in probabilities provides a convenient analytical structure that has enabled economists to prove a wide range of useful results. For example, we can clearly define what we mean by an increase in risk, and we can concisely describe how changes in risk will affect optimal decisions (Rothschild and Stiglitz 1970, Arrow 1971).

A second explanation may ultimately be more satisfying—though we as applied economists rarely discuss it. This is the criterion's normative rationale. In economics, the presumptive assumption in normative inquiry is that decisions be consistent with how a "rational" decision maker would act. Rationality is then defined by a set of transparent rules, or axioms, that impose forms of consistency on the decision algorithm. A common example is transitivity: if one prefers *x* to *y* and *y* to *z* then they should also prefer *x* to *z*. Axiomatic rationale offers a strong basis for motivating public policy decisions because the unappealing consequences of violated axioms can be made explicit.

The axiomatic foundations for the EU and SEU models were developed by von Neumann and Morgenstern (1944) and Savage (1954), respectively. It is fair to say that they have been widely—though by no means universally—regarded within our profession as compelling. And though a vigorous strand of inquiry has persisted in questioning the canonical model's justification (for example, Ellsberg 1961 and Kahneman and Tversky 1979), this has not stopped it from becoming the default language for discussing the economics of risk and time. This dominance carries with it the potential for dangerous complacency, especially when policy recommendations follow from potentially misspecified models.

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² The two models imply the same maximization problem, in which expectations are formed through summing probability-weighted outcomes. They differ in their interpretation of probability—for the EU model, probabilities are objectively given, while for the SEU model, they reflect the decision-maker's subjective beliefs.

In this paper, we argue that deviations from the simple setting for which the EU/SEU model was originally intended—and for which it is optimally suited—are more common than is often acknowledged. Indeed, common features of many environmental and resource management problems virtually ensure this. As such, we discuss the consequences of an excessive reliance on the EU/SEU paradigm in formulating policy decisions, and we explore some promising options for moving beyond it, as well as suggesting some other avenues of future research. Our intention is not to provide a comprehensive review of available techniques, nor to work out any particular approach in detail. Rather, we strive to provide a context for thinking about modeling informational issues in environmental decision-making, and to encourage additional research. We do this by pointing out specific ways in which structural components of the workhorse stochastic dynamic optimization framework can be extended or relaxed, and provide an invasive species example (zebra and quagga mussels in aquatic environments) to fix ideas. The paper should be viewed as a complement to Shaw and Woodward (2008) who discuss similar, though not identical, issues.

When the Assumptions Don't Fit

The EU/SEU model works best when the information available for decision-making is well behaved in particular ways. Three deviations from the ideal information structure warrant emphasis for environmental policy decisions. They are shown in Figure 1. *Severity of uncertainty* refers to the extent to which uncertainty can be measured or quantified. A low rating implies that existing data is sufficient for decision makers to confidently assign probabilities, while a high rating implies a situation in which probabilities cannot be uniquely assigned. This distinction has a long history in economics dating back to early contributions by Knight (1921) and Keynes (1921). The *importance of tail events* refers to the importance of high consequence, low probability events in expected utility calculations. As Weitzman has recently shown, so-called “fat tail” distributions have the potential to overwhelm expected utility calculations (Weitzman 2009). Finally, *potential for learning* reflects the extent to which future information flows are important for *ex ante* decisions.

Information structures near the origin in Figure 1 are well behaved in the sense that they offer solid footing for expected utility maximization. In contrast, information structures away from the origin strain the validity of the standard model. Such deviations are important for many environmental and resource management problems because of a common set of physical characteristics that these problems share. These are listed in the first column of Figure 2. Problems that share some or all of these features include climate change mitigation, biodiversity conservation, and invasive species management, just to name a few.³ The links between these physical characteristics and the information structure dimensions in Figure 1 are numerous. For example, novelty implies a situation where scientific knowledge is preliminary and incomplete and thus increases the severity of uncertainty; a long time horizon magnifies uncertainty from all sources; inertia and irreversibilities interact to determine the importance of waiting to learn; and feedbacks increase the importance of tail events by making it hard to rule out probability distributions with fat tails over extreme events (Weitzman 2009, Nordhaus 2011, Roe and Baker 2007).

³ Additional examples can be found in virtually every paper cited herein; however, Table 1 in Shaw and Woodward (2008) provides a nice conceptual overview characterizing the size of probabilities and the potential for ambiguity over them.

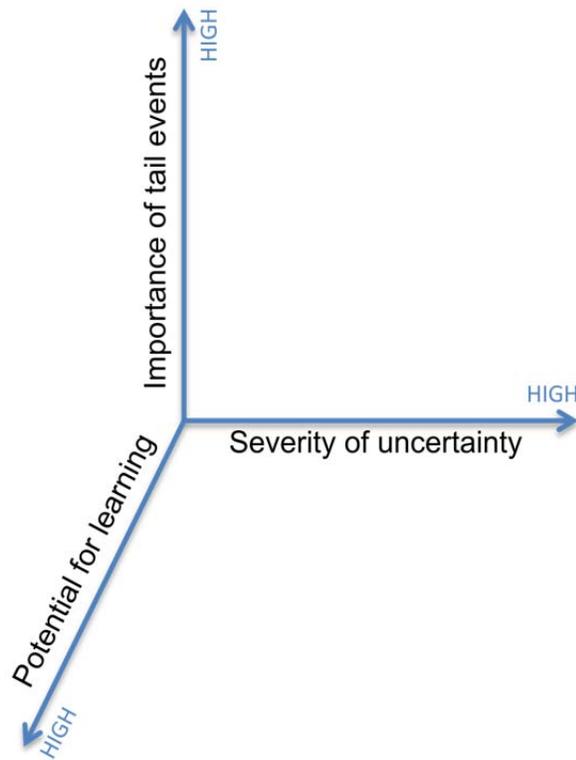


Figure 1: Dimensions of Information in Environmental and Natural Resource Economics Problems

Thus, the relevant information structure for many environmental and resource management problems may deviate from the origin in one or more dimensions in Figure 1. But so what? What if we use the EU/SEU model anyway?

Most importantly, excessive reliance on the EU/SEU model can lead to bad decisions. Consider first a situation where uncertainty is too severe for decision-makers to justifiably specify a unique probability distribution over contending forecasting models. If they persist in using the standard model anyway, they must choose a distribution from among a variety of plausible alternatives. The chosen policy will then perform well—in the *ex ante* sense of balancing expected costs and expected benefits—provided the chosen distribution turns out to be the most appropriate one. But the same policy may perform terribly under another, equally plausible alternative. By forcing policy evaluation into an inappropriate framework, the decision-maker is in effect committing to analytical blinders that understate the true extent of uncertainty. A Bayesian would aggregate probabilities across models with the variance of the aggregate distribution accounting for the dispersion across model alternatives (Brock et al. 2003), but it may still be too much to ask for decision makers to agree on a unique final distribution. A more natural objective when uncertainty is severe is to seek a policy that is in some sense robust across the range of plausible probability distributions, rather than one that performs optimally under a particular distribution while ignoring the implied risks under each of the others.

The consequence of ignoring “fat tailed” probability distributions can be at least as severe. Weitzman (2009) shows that extreme events in the tail of the relevant probability distributions can make an arbitrarily large (i.e., infinite) contribution to the expected utility objective function.

The important takeaway is that the standard practice of ignoring extreme events—predicated on the fact that it is typically difficult or impossible to assign probabilities over them given available data—could lead to arbitrarily bad decisions. Research to better accommodate information about tail events into decision-making is still in its infancy. Nevertheless, it is clear that situations where fat tails cannot be ruled out—most importantly, situations with novelty and feedbacks—warrant pause and concern.

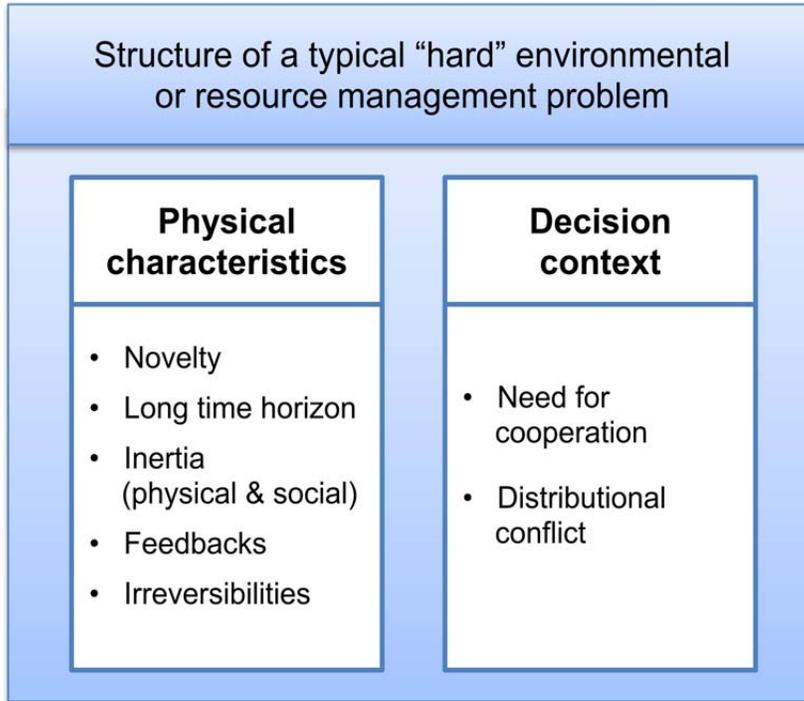


Figure 2: Physical Characteristics and Decision Context of Complex Management Problems

Finally, the consequence of ignoring the dynamic nature of scientific information has been widely discussed; nevertheless, it is still often ignored in applied work. Arrow and Fisher (1974) and Henry (1974) first recognized that the appropriately measured opportunity cost for an irreversible investment should include the value of future information. This is because future information has value only if the option to act upon it is preserved. This value is sometimes called the quasi-option value. For environmental problems, the quasi-option value can sometimes go in the opposite direction of what one might expect, leading to lower levels of environmental protection than would be justified without it. This is because investments in abatement equipment—like changes in environmental quality—can themselves be irreversible (see Kolstad 1996 for an example). Alternatively, the value of future information may be so great that aggressive exploitation might be warranted in the short run. The key lesson is that there is a value-of-information margin relevant to management tradeoffs that the standard EU/SEU model ignores.

So far, our discussion of the adverse consequences of inappropriately relying on the EU/SEU model has focused on the claim that it can lead to bad decisions. Two additional criticisms warrant mention. First, because most environmental policy decisions are made by groups of stakeholders—rather than by a single decision maker or by a unified decision-making body—we should ask if the EU/SEU model is useful for guiding decision-making in this context. Consider

the case in which uncertainty is severe, so there are a variety of probability distributions that cannot be ruled out in the face of available evidence. In this case, one might naturally expect stakeholders in high stakes policy decisions to defend the probability distribution that most supports their particular interests or values (Herrick and Sarewicz 2001). But this makes application of the EU/SEU model extremely difficult since it cannot be applied without decision makers agreeing upon a unique distribution. There is a substantial literature that looks at aggregating probabilities across a variety of expert specified distributions, but there is no agreed upon methodology. As such, it may be more appealing to start negotiations from a position that acknowledges that a variety of probability distributions are consistent with the data (see, for example, Lempert et al. 2004 and Iverson 2012).

Finally, one can criticize the machinery of expected utility maximization by taking a behavioral perspective. A behavioral lens asks how realistic agents actually do behave, rather than how an idealized rational agent hypothetically would. Historically, economists have often pushed back on the assertion that public policy decision makers should seek to emulate the common sense logic of the average person (for example, von Neumann and Morgenstern 1944, Savage 1954). After all, they would say, the goal of formal analysis is to facilitate an enlightened perspective that goes beyond heuristic biases. The counter argument is an extension of consumer sovereignty: if people respond to uncertain decisions in a way that conflicts with a particular list of axioms, then policy-makers may want to take these deviations seriously—at the very least, within the democratic process, they may be forced to. Carried further, the goal of maximizing social welfare could be interpreted as saying that the desirability of a particular tradeoff should be evaluated with reference to behavior, not theory.

Behavioral critiques of the EU/SEU model center on two long-standing “paradoxes”—the Ellsberg paradox and the Allais paradox. Ellsberg (Ellsberg 1961) showed that people prefer bets with well-defined odds to bets with unspecified odds even when they get to call the terms of the bet in the latter situation. The finding shows that people are more averse to uncertainty over models than the EU/SEU model would suggest. Allais (Allais 1953) showed that people tend to overweight low-probability high-consequence events relative to what they would under the EU/SEU model. This implies that the EU/SEU model does not accurately describe how people will evaluate risky outcomes when low probability tail events are important. Both paradoxes can be used to justify decision criteria that differ from expected utility maximization.

Some Promising Alternatives

To clarify options for handling difficult information structures, we will focus on a general stochastic dynamic optimization problem written in recursive form using the Bellman equation (Bellman 1957). To keep the discussion concrete, however, we discuss the relevant objects with reference to a specific invasive species problem; namely, the threat of zebra and quagga mussels spreading through Western waterways. As documented in Thomas (2010), these species were introduced to U.S. waters in the 1980’s through transatlantic shipping activities. They spread rapidly through the Great Lakes and the Mississippi River Basin, and they are now widespread in the eastern Midwest and Northeast. More recently, the species have been discovered in some inland lakes in the West. They spread primarily through the transport of recreational watercraft.

We start by defining the standard dynamic programming model as follows:

$$V(\mathbf{s}_t) = \max_u f(\mathbf{u}_t, \mathbf{s}_t; \boldsymbol{\alpha}) + \delta E_\varepsilon [V(\mathbf{s}_{t+1}(\mathbf{u}_t, \mathbf{s}_t, \boldsymbol{\theta}, \boldsymbol{\varepsilon}_{t+1}))]. \quad (1)$$

Here $V(\cdot)$ is the expected net present value of following the optimal control \mathbf{u}_t from a point defined by the state variables \mathbf{s}_t . Instantaneous net benefits of following this control path are given by $f(\mathbf{u}_t, \mathbf{s}_t; \boldsymbol{\alpha})$, where $\boldsymbol{\alpha}$ is a parameter vector. Expected future net benefits are defined as $E_{\varepsilon} [V(\mathbf{s}_{t+1}(\mathbf{u}_t, \mathbf{s}_t, \boldsymbol{\theta}, \boldsymbol{\varepsilon}_{t+1}))]$, which includes a parameter vector $\boldsymbol{\theta}$ and stochastic error vector $\boldsymbol{\varepsilon}_{t+1}$. It is calculated as the probability-weighted sum of the continuation value starting from next period's state \mathbf{s}_{t+1} . The discount factor is $0 < \delta < 1$.

For our maintained example, we assume that (1) represents an interconnected system of reservoirs in the West under threat of mussel invasion. Each reservoir is represented by an element of the state vector \mathbf{s}_t and prevention and control strategies at each reservoir (e.g., boat inspections or physical removal of mussels) comprise elements of the vector \mathbf{u}_t . Spread is stochastic, and depends on the interaction of habitat suitability and factors like boating that increase the opportunity for invasive species to spread.

We define the “standard” stochastic model (near the origin in Figure 1) by an information regime where the instantaneous benefit function and all parameter vectors are known, state variables at time t are observable in contemporaneous time periods, and the distribution (but not the outcomes) of the stochastic shock vector $\boldsymbol{\varepsilon}_{t+1}$ is known and defined by $g(\boldsymbol{\varepsilon}_{t+1})$. The expectation over future outcomes in the Bellman equation is then calculated by

$\int V(\mathbf{s}_{t+1}(\mathbf{u}_t, \mathbf{s}_t, \boldsymbol{\theta}, \boldsymbol{\varepsilon}_{t+1})) g(\boldsymbol{\varepsilon}_{t+1}) d\boldsymbol{\varepsilon}_{t+1}$. We further assume that $g(\boldsymbol{\varepsilon}_{t+1})$ is “standard” in that the probability of tail events are essentially exponentially decreasing as they deviate from the central tendency of the distribution. In the example, these assumptions imply that habitat suitability and spread pressures are known, as are the probabilities of establishment. Furthermore, the state of each reservoir (e.g., the population of mussels in each reservoir) is known at each time t . Ex ante, the state in $t+1$ is unknown—though the distribution over possible states is known.

Next, we examine how movements away from the origin in Figure 1 affect applications of this standard framework.

Severity of Uncertainty

The severity of uncertainty within a standard stochastic EU problem refers to the treatment of current features and future outcomes. With known parameters, the only unknown in the future is the value of $\boldsymbol{\varepsilon}_{t+1}$. Possible values are weighted by the known probability distribution $g(\boldsymbol{\varepsilon}_{t+1})$. For mussels, this implies that the only unknown at time t is the state of the reservoirs in time $t+1$.

This formulation is more general than it might at first appear. In addition to embodying standard stochastic problems, it can also accommodate parametric uncertainty (e.g., a particular forcing parameter in a model of climate change, the level of a particular threshold, the spread of an invasive species) and multiple models of the state transition (e.g., uncertainty over the process generating the state data). Parametric uncertainty could imply that a habitat suitability parameter is not known with certainty, as would be the case in colder reservoirs with low calcium concentrations in high elevation areas. It has long been assumed by scientists that such a water body could not support mussel establishment. Recently, however, this assumption has been questioned due to competing empirical evidence (Thomas, 2010). Multiple models of state

transitions in our example might take the form of competing models of the behavioral response of boaters to various control techniques. For example, competing estimates of the elasticity of substitution between substitute sites may exist.

Given some degree of curvature of the value function, the recognition of parametric uncertainty—which might be some recognition of the fact that the optimizing agent is assumed to “know that s/he doesn’t know”—could affect optimal management through a traditional risk result.⁴ But implementation would still entail a reasonably straightforward application of linear weighting by probabilities as in the EU/SEU case. Letting $g(\varepsilon_{t+1}, \theta, \alpha)$ denote the distribution over unknowns, the relevant expectation becomes

$$\int_{\varepsilon_{t+1}, \theta, \alpha} \delta V(\mathbf{s}_{t+1}(\mathbf{u}_t, \mathbf{s}_t, \boldsymbol{\theta}, \varepsilon_{t+1})) g(\varepsilon_{t+1}, \boldsymbol{\theta}, \boldsymbol{\alpha}) d\varepsilon_{t+1} d\boldsymbol{\theta} d\boldsymbol{\alpha}. \quad (2)$$

The expectation includes uncertainty over the parameters in addition to uncertainty over the stochastic component of the state transitions.⁶

To model behavioral responses, one might also assume that the “objective” probabilities, indicated by $g(\varepsilon_{t+1})$, are transformed through some cognitive process into alternative decision weights, say $\pi(g(\varepsilon_{t+1}))$. Several such weighting schemes have been proposed in the literature. Examples include approaches based on prospect theory and cumulative prospect theory (Khaneman and Tversky, 1979; Tversky and Kahneman, 1992) and the rank-dependent expected utility model (Quiggin, 1982).⁷

For our purposes, the key salient point is that the objective probabilities are transformed by a function $\pi(g(\varepsilon_{t+1}))$. As such, the weights used to form the continuing value of the program on the right-hand side of the Bellman equation are not necessarily linear. Low (high) probability future events may be over (under) weighted, thus altering the calculus in the dynamic program and changing “optimal” management from the perspective of the controlling agent (Wu and Gonzalez, 1996). An excellent example is behavior related to a weather forecast – a 90% chance of rain will likely result in the same action (bringing an umbrella) as a 100% chance (Roberts et al. 2008). Reservoir managers may behave similarly for probability of mussel establishment greater than a certain threshold.

Recently, the notation of non-linear weights has entered the resource valuation literature. This is a particular case of our programming problem where statistical techniques are used to recover relative values of $E[V(\mathbf{s}_{t+1}(\bar{\mathbf{u}}_t, \mathbf{s}_t, \boldsymbol{\theta}, \varepsilon_{t+1}))]$ given a described, and not necessarily optimal, control rule $\bar{\mathbf{u}}$. Examples that test for departures from EU theory or that explicitly estimate weights include Roberts et al. (2008), Glenk and Colombo (2011), Wielgus, et al.

⁴ The degree of curvature is endogenously determined given a specification of instantaneous benefits (preferences) and the state transitions of the system.

⁵ In several papers, Weitzman (1998, 2010) gives an interpretation of the discount rate as a random variable based on stochastic future returns to capital, and Coury and Dave (2010) show how to incorporate non-exponential discounting into dynamic programming problems.

⁶ For ease of exposition, we suppress the dimensionality of the integration process, but note that we integrate over all of the unknowns.

⁷ The reader is referred to Kothiyal, et al. (2011) and Shaw and Woodward (2008) for recent reviews.

(2009), and Burghart, et al. (2007). This literature finds that recovered decision weights associated with money lotteries tend to be “inverted-S” shaped, while weights on environmental outcomes are linear or “S-shaped.” This can have important implications for willingness to pay/willingness to accept environmental policy outcomes when the outcomes are uncertain (see Figure 3).

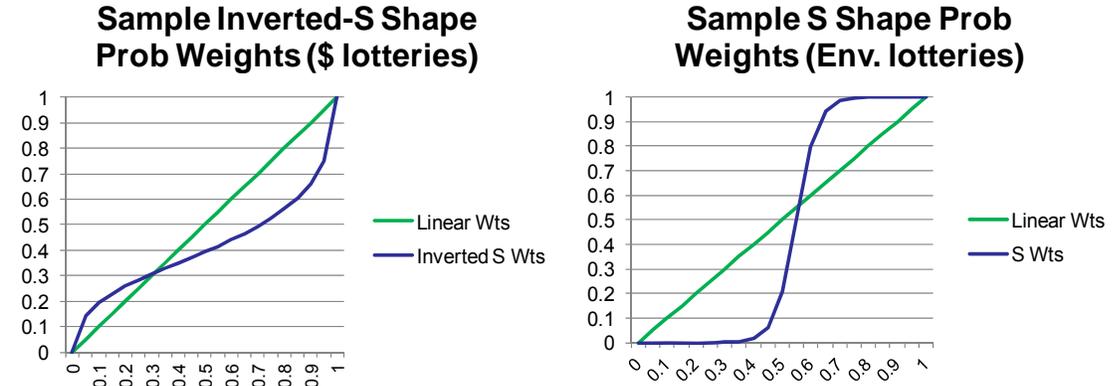


Figure 3: Examples of Probability Weighting Functions: Inverted S-shaped (underweighting high probability events), left, and S-shaped (overweighting high probability events), right

Moving farther along the uncertainty axis in Figure 1, ability to consistently weight potential outcomes breaks down. For example, it may be that the weights $g(\varepsilon_{t+1})$ or $\pi(g(\varepsilon_{t+1}))$ are themselves uncertain. Several terms are used in the economics literature to describe uncertainty about probabilities. These include ambiguity, Knightian uncertainty, and deep uncertainty. Two versions of uncertainty about probabilities can be considered: one in which “second-order probabilities” can be applied across a set of contending probability distributions, the other in which multiple distributions are possible but probabilities cannot be assigned across them. The appropriate formulation depends on the context. In the mussels example, a specification without probabilities may be most appropriate for confronting a novel threat whose characteristics in terms of reproduction, damage, and spread are largely unknown.

The Ellsberg paradox suggests that people display aversion to ambiguity above and beyond their standard aversion to risk. A compelling option for modeling ambiguity aversion is the smooth ambiguity model of Klibanoff et al. (2005) and Klibanoff (2009).⁸ The smooth ambiguity model transforms our dynamic program as follows:

$$V(\mathbf{s}_t) = \max_{u_t} f(\mathbf{u}_t, \mathbf{s}_t; \boldsymbol{\alpha}) + \delta \phi^{-1} \left(E_{\pi} \phi \left(E_{\varepsilon} \left[V(\mathbf{s}_{t+1}(\mathbf{u}_t, \mathbf{s}_t, \boldsymbol{\theta}, \varepsilon_{t+1})) \right] \right) \right), \quad (3)$$

where π are second-order probabilities related to the potential distributions characterizing ε and $\phi(x)$ is a concave function. As in the traditional risk framework, the more concave $\phi(x)$, the more averse the decision maker is to mean preserving spreads in the second-order probabilities. The smooth ambiguity model is applied to climate policy by Millner et al. (2010).

⁸ This specification is attractive here due to the fact that preferences are dynamically consistent and the model has a recursive framework. A non-smooth variant, α – maximin expected utility, is detailed in Ghirardato, et al. (2004) and Melkonyan (2011), and accounts for a range of “optimism” and “pessimism” on behalf of the decision maker. In fact, maximin expected utility is a limiting case with infinite ambiguity aversion (Kilbanoff et al., 2009).

A variety of decision criteria can be considered when probabilities cannot be assigned across a set of probability distributions (i.e., the set of contending forecasting models). In environmental settings, the maximin criterion is most famous because it can be interpreted as implementing a strong version of the precautionary principle. Maximin seeks a policy that is robust to the worst-case distribution. Gilboa and Schmeidler (1989) provide axiomatic foundations for maximin expected utility, a criterion that seeks to maximize expected welfare under the worst-case distribution from a set of possible distributions. Roseta-Palma and Xepapadeas (2004) and Vardas and Xepapadeas (2010) build on recent work in robustness in macroeconomics (Hansen and Sargent 2008) that applies Gilboa and Schmeidler's criterion in a closed loop dynamic control settings—so-called robust control.

Iverson and Perrings (2012) show that maximin can be interpreted as implementing a strictly precautionary response. These authors also show that minimax regret can be interpreted as implementing a strictly "proportional" response. Minimax regret is an alternative decision criterion that Savage (1954) proposed as providing a more reasonable stand in for maximin. Iverson and Perrings (2012) also define a criterion that flexibly varies the relative weight on the competing concerns defined by precaution and proportionality. The suggested criterion nests policies between the extremes of strict precaution and strict proportionality.

In a related direction, Lempert, Popper, and Bankes (2003) employ a regret-based objective function in developing computational methods for identifying policies that perform in a robust way across a wide range of possible models. Lempert and Schlesinger (2000) argue that robust strategies provide a more solid basis for climate policy decision-making in part because they perform reasonably well (if not optimally) "no matter whose view" of the underlying science proves to be correct.

Potential for Learning

We have assumed that if probability distributions for any of the unknown components of the system exist and are known by the decision-maker, then they do not evolve as future information becomes available. But for many environmental and resource management problems, future learning will substantially reduce future uncertainty. Suppose it is believed initially that calcium levels in high elevation reservoirs are insufficient to support mussel establishment, but then a colony of mussels is found at such a location. It seems logical that both the scientific and management communities would take this information into account when designing control strategies.

The ecological paradigm of adaptive management builds on this perspective. Adaptive management of an ecosystem characterized by structural or other uncertainties is recursively structured so that new information is incorporated after either observation or perturbation of the system. Management approaches are changed following the processing of this information. As such, management is "flexible and adaptive" (Holling and Meffe, 1996), but optimality becomes subjective as beliefs about the potential behavior of the system evolve.

Distinctions are made between passive and active adaptive management. Under passive management, potential future learning is not taken into account at the point of decision making. Said differently, the value of information is assumed to be zero when making tradeoffs. Nevertheless, under passive management, beliefs are updated after each observation.

On the other hand, under active management, the value of information is endogenous, and learning is anticipated by the decision maker. This anticipation results in an internal valuation of the additional benefit of future information, which is taken into account when making management decisions.

Active adaptive management has been modeled by augmenting the standard EU formulation to account for the evolution of beliefs regarding uncertain parameters (α and/or θ) and/or states of the system $\mathbf{z}_t \subseteq \mathbf{s}_t$.⁹ Using state-space techniques, implicit or explicit state transition equations for the sufficient statistics characterizing the unknown distributions can be developed on the basis of observations about the system, and incorporated into the state space.

For example, consider the case of what might be termed parametric uncertainty with respect to (an) element(s) of the state transition equations. At time t , let $\varphi \subseteq \theta$ be perceived as random variables characterized by a prior distribution denoted $h(\varphi)$. Perhaps, for example, φ are the elasticities of substitution between various reservoirs, and visitation to each reservoir in the system are observed and recorded each year. Using some sort of information processing rule (e.g., using Bayes' rule), implicit updating equations that define a posterior distribution at time $t+1$ can be written as $h_{t+1}(\varphi) = p(h(\varphi), s_{t+1}(\mathbf{u}_t, \mathbf{s}_t, \theta, \varepsilon_{t+1}))$. Practically, these equations could represent the sufficient statistics of the posterior distribution.

In the passive learning case, the Bellman equation becomes

$$V(\mathbf{s}_t) = \max_{u_t} f(\mathbf{u}_t, \mathbf{s}_t; \alpha) + \delta E_{\varepsilon, \phi} [V(\mathbf{s}_{t+1}(\mathbf{u}_t, \mathbf{s}_t, \theta, \varepsilon_{t+1}))]. \quad (4)$$

Note here that the second term in (4) is the expectation over both the stochastic process and the (random) parameters of interest, but is evaluated at the current, rather than the future, belief. In other words, in forming the optimal management plan, the decision maker does not anticipate the learning (represented by $h_{t+1}(\varphi)$) that may happen.

On the other hand, an active rule would endogenize the updating of the distribution, rendering the Bellman equation as

$$V(\mathbf{s}_t, h_t(\varphi)) = \max_{u_t} f(\mathbf{u}_t, \mathbf{s}_t; \alpha) + \delta E_{\varepsilon, \phi} [V(\mathbf{s}_{t+1}(\mathbf{u}_t, \mathbf{s}_t, \theta, \varepsilon_{t+1}), h_{t+1}(h_t(\varphi), s_{t+1}(\mathbf{u}_t, \mathbf{s}_t, \theta, \varepsilon_{t+1})))] \quad (5)$$

The "states" of the system now include both the physical and belief states. Depending on the circumstances, the agent might find it optimal to deviate from the passive control rule (i.e., to experiment) in order to collect valuable future information about the unknown parameters for use in subsequent management actions. The quantitative effect of such learning is likely problem-specific, but the introduction of the information margin provides a means of augmenting benefit-cost analysis with the potential ex-ante value of information (Bond, 2010). Examples of this type of model in various forms include applications to water and air pollution (Kaplan, et al. 2003; Cunha-e-Sá and Santos, 2008), climate change (Kelly and Kolstad 1999; Lange and Trieck, 2008), shallow lakes (Peterson, et al. 2003; Bond and Loomis, 2009), invasive species

⁹ In a particular probabilistic setting, this latter type of model is termed a partially-observable Markov decision problem.

management (Springborn, 2008; Haight and Polasky, 2010), and more general applications in policy (Brock and Carpenter; 2007).

In the case of ambiguity, the Kilbanoff et al. (2009) model provides the recursive framework that can be applied to learning under ambiguity as well as risk. Updating functions could allow for the evolution of beliefs over the first or second order probabilities. Consistent with the parametric uncertainty example, the recursive formulation in this case becomes

$$V(\mathbf{s}_t, h_t(\boldsymbol{\varphi}), g_t(\boldsymbol{\pi})) = \max_{u_t} f(\mathbf{u}_t, \mathbf{s}_t; \boldsymbol{\alpha}) + \delta \phi^{-1} \left(E_{\pi} \phi \left(E_{\varepsilon, \varphi} \left[V(\mathbf{s}_{t+1}, \mathbf{h}_{t+1}, \mathbf{g}_{t+1}) \right] \right) \right), \quad (6)$$

where $g_t(\boldsymbol{\pi})$ represents the prior/posterior beliefs regarding the second-order probabilities and we have suppressed unnecessary notation. Note that in (6), the value function includes both first- and second-order probabilities as states of the system, resulting in a very complicated treatment of information processing and risk/ambiguity preferences.

At this point, a word of caution is in order for practitioners attempting to model learning structures in this manner. In practice, modeling partial observability/parametric uncertainty/ambiguity under learning suffers greatly from the curse of dimensionality, as each sufficient statistic related to a particular distribution must be included in the value function (Millner, et al. 2010). Such problems may also exhibit all manner of undesirable behavior from a computational standpoint (e.g., non-convexities, non-monotonicities, discontinuities, non-convergence to true parameter values, etc...). Given current solution algorithms, this may restrict analysis to “toy models” with low dimensionality or evaluations of sub-optimal, exogenously defined paths (as in $\bar{\mathbf{u}}$ above). As discussed in the conclusions, however, techniques and computational power are expanding, and certain general principles may become apparent through even simple representations.

Importance of Tail Events

Previously, we assumed the distributions over future (physical) states of the system $g(\varepsilon_{t+1})$ or over parameter values $h(\boldsymbol{\varphi})$ were “standard” in that they declined exponentially with increased distance from the central tendency of the distribution. This is certainly not the case for all distributions. If tail events are far more likely than that described by a normal distribution, then management decisions and policy would be potentially seriously underweighting extreme events.

Consider the case of severe negative events (e.g., a large increase in temperatures as a result of anthropogenic climate change, causing very significant, potentially society-ending effects), where marginal damages tend to infinity yet there is a positive probability of such an event occurring. Weitzman (2009) argues in his “dismal theorem” that standard economic analysis such as benefit-cost analysis cannot be applied or at least is useless, since the expected utility in such a situation is negative infinity (Nordhaus 2011). Others have argued that this is relevant only under fairly restrictive circumstances, but that the “fat tail” problem is still worthy of consideration, especially in the context of large-scale ecosystem change (Weitzman 2011; Nordhaus 2011; Pindyck 2011).

Fat tails and marginal damage are related to the specification of $g(\varepsilon_{t+1})$ (or, in fact, any of the prior distributions assumed in any of the models) and $f(\mathbf{u}_t, \mathbf{s}_t; \boldsymbol{\alpha})$, especially $f_s(\mathbf{u}_t, \mathbf{s}_t; \boldsymbol{\alpha})$ and

$f_{ss}(\mathbf{u}_t, \mathbf{s}_t; \boldsymbol{\alpha})$. Essentially, for the implications of the dismal theorem to hold, infinite negative marginal utility/net benefits must be assumed at some point in the state space (Pindyck 2011; Nordhaus 2011). A thin-tailed $g(\varepsilon_{t+1})$ in this case may result in a more stringent control effort (in the case of climate change) than assuming fat tails (Pindyck 2011). The interaction between $f(\mathbf{u}_t, \mathbf{s}_t; \boldsymbol{\alpha})$ and $g(\varepsilon_{t+1})$ are how the economic implications of extreme tail events are formed. However, the fact that finite observational data provides little to no information about the density within tails of distributions complicates matters considerably for the empiricist or modeler who wishes to take these considerations into account (Nordhaus 2011).

Discussion and Conclusions

The information structure for many environmental and resource management problems does not necessarily match the assumptions of the standard EU/SEU model. Such anomalies can have important policy implications, especially when managing complex nonlinear ecosystems. The severity of uncertainty across environmental outcomes (what precisely is random, and how this randomness is processed and characterized by economic actors), the intertemporal nature of the information structure (whether learning is anticipated or not), and the importance of tail events (including both the preference assumptions and the distributions assumed for the random components of a model) can all interact to explain seemingly paradoxical behavior. This has been repeatedly confirmed in experimental settings and should at least be given consideration when making environmental policy. An understanding of how various information regimes affect benefits/costs and optimal/sub-optimal policies is crucial to the mission of the applied environmental economist, especially given the nature of many of the problems we consider.

Modeling of such issues can shed light on which assumptions are of significant economic importance and how policy can be structured to take these impacts into account. The environmental and resource economics profession seemingly has much to offer in this line of research. Given our relative expertise in modeling revealed and stated preferences of non-market goods, it seems natural that empiricists could contribute to our understanding of information processing, ambiguity aversion, and the slope of marginal utilities in the presence of multiple environmental threats. Key empirical research frontiers include determining “the shape of the [probability weighting function] if we think it might be nonlinear” (Shaw and Woodward 2008, p. 85), evaluating how agents trade-off environmental outcomes in the face of contrary or missing information, (Pindyck 2011) and developing methods that measure the assimilation and processing of new information.

Structural modelers have relevant expertise to analyze the implications of how agents might behave under differing information structures. This also pertains to the types of problems that are most sensitive to the differences. From the impact of fat tails and the degree of uncertainty about the distribution characterizing random processes and parameters, to optimal management under the threat of uncertain processes possibly including thresholds irreversibilities, to the ideal experimental regime that balances future information and “primary” management goals in an adaptive management setting, many questions remain unanswered.

Modeling environmental and resource decisions under alternative information regimes can help identify the key assumptions that drive results. It may also provide a means of exploring the implications of heterogeneous beliefs across both experts and the public at large. Modeling can also contribute to an understanding of the belief conditions under which a proposed

management or policy path may be preferred to others (Bond 2010). These issues and the models representing them are complex. They may require significant investment in methods and techniques (especially numerical) that can account for non-linearities, non-convexities, and large state spaces that are endemic to these applied problems. While each individual problem may be complex and unique, so-called “toy models” could be used to illustrate common principles and results, much like the grossly simplified theoretical models appearing in virtually every economic textbook.

Progress has been made in the engineering literature with advances in real-time approximation of dynamic systems, especially in robotics and artificial intelligence (see, e.g., Atkeson and Stephens 2008 and references therein, and Rust 1997 and Han et al. 2006 for economic applications). These techniques involve approximations of solutions using computational iteration, partial solutions, simple functional forms, and other techniques that exploit the emerging power of computers to perform repetitive tasks. One lesson to learn from this literature is that despite our disciplinary bias towards simple, elegant, and unambiguous *analytical* results, there can be considerable insight gained from *numerical* models and approximations, and that even in economic modeling, “the perfect should not be the enemy of the good” (Voltaire, 1772).

Still, it might be that “there can be no descriptively adequate general theory of risky choice which is rational” (Loomes 2006; Shaw and Woodward 2008). Nevertheless, we would argue that by modeling the various issues raised in this paper, the profession can contribute to a greater understanding of the circumstances under which information regimes in environmental problems are salient features, and thus help resource managers and policy makers make *ex ante* decisions that are ideally pragmatic, yet behaviorally consistent and normatively sound.

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