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Water Management, Risk, and Uncertainty: Things We Wish We Knew in the 21st Century

W. Douglass Shaw and Richard T. Woodward¹

Introduction

A survey is offered of the most difficult and challenging issues to water managers in the 21st Century, focusing on the economics of risks and more so, uncertainty. Risk and uncertainty is addressed a great deal here because so many water management and policy issues involve them, as will be seen below. It is deemed unwise for the water community to model decisions as if there was certainty. For example, traditional decision models that assume certainty often require that the present value of known net benefits be maximized, when in fact it may be that benefits, costs, and the discount are all actually unknown, or at least involve risk.

As is common in decision theory, in this paper risk (with known probabilities) is distinguished from uncertainty, where probabilities cannot be easily, or even never can be known (e.g. Knight, 1921). Economic risk is often synonymous with probability. Other research disciplines often factor the severity of the outcome into the definition of risk, i.e. the “risk” of a disease that has mortality as a possible outcome is worse than one that has morbidity as a possible outcome, even if the probabilities are the same in each case. For psychologists, the definition of risk varies a great deal, and this matters, particularly when risk communication is the focus [see *Fischhoff*, 2009; *Nguyen et al.*, 2010]. Others distinguish between variable quantities, such as the load level of a toxic element in a river, which varies temporally or spatially in a known manner, and quantities which have a single, but unknown “true” value [e.g. *Smith et al.*, 1992].

The riskiness of a situation is fundamentally about the spread of a probability distribution. The distinction between the average and the spread is characterized nicely by considering the “risk” in jumping out of an airplane with a bad parachute. If the parachute is known to fail 99 out of 100 times, then one might actually say there is no “risk” involved with jumping: death is actually nearly certain.² Decision makers are often found to be averse to risk: if the average returns of two gambles are the same, people will prefer the one that has a tighter distribution and, therefore, less risk.

¹ Shaw and Woodward are each Professors, Department of Agricultural Economics, and participants in the Graduate Program in Hydrologic Science and Policy, Texas A&M University. Shaw is also Research Fellow, Hazards Reduction and Recovery Group at A&M. Shaw acknowledges additional funding from the U.S.D.A. Hatch (W-2133) Grant Program. The authors thank Michael Kaplowitz and Frank Lupi for encouraging the paper and for hosting a seminar on this topic at Michigan State University, three anonymous reviewers, and the editor of this journal for comments which ultimately improved the paper. We have benefitted greatly in our discussions about uncertainty over the past years with Bob Berrens, David Bessler, Therese Grijalva, Glenn Harrison, Paul Jakus, Paan Jindapon, Mary Riddel, and Nat Wilcox. They are of course not responsible for anything we get wrong here.

² The authors credit Harris Schlesinger, from whom we took this example.

There is little consensus among economists regarding choice under uncertainty, when the probability distributions are not well understood by subjects, and perhaps even by experts. However, formal analysis and structured decision-making can proceed even in the face of pure uncertainty.

The most common approach to handling uncertainty is to convert the situation from one of uncertainty to one of risk. One way to do this is to create what is called a compound lottery, making a probability distribution itself depend on a second random variable and then averaging over the probabilities. Introducing uncertainty by considering multiple distributions can be implemented through relatively simple Monte Carlo analysis, often done to explore the effects of various risk assumptions. While standard Monte Carlo analysis is fairly standard in much research, simplistic analyses using this process have been criticized on several grounds [see *Smith, Ryan and Evans, 1992*].

For example, simple Monte Carlo exercises often involve multiple draws from the same class or family of probability distributions (continuous/normal), and functional forms are typically assumed to be known with certainty (Pindyck 2010). But real uncertainty may involve not having any idea of the family of distributions to consider. However, there are many other tools that allow analysis of at least some kind when uncertainty rules the day.

Below some of these uncertainty analysis tools are described, in their most recent form. Then, applications of these tools to several issues in the areas of water management are given. The final section offers a short discussion and list of policy recommendations that are for use by researchers, as well as people in the water resources community.

Methods in the Uncertainty Toolkit

Several water resource issues facing society today fit the characterization of pure uncertainty in which probabilities are not known. Such conditions can arise even if the status quo situation is well understood, since pursuing a project can introduce uncertainty. Some believe that nothing should be done about global warming, for example, because even the probabilities of outcomes (the timing and magnitude of impacts) are debated. Developing watersheds or aquatic habitats in manners that have irreversible consequences is another example. Society sometimes chooses to take a precautionary approach, investing in programs to reduce pollution or use of fossil fuels, even when the benefits in the distant future may be largely or completely uncertain.

Most tools of interest to water resource economists fall into categories of empirical-statistical methods, programming approaches, or optimal control techniques. Regardless of the approach taken, the usual decision framework is a variation on ex ante benefit-cost analysis. It is the benefits, not typically the costs, which are hard to estimate, ex ante. The most widely used theoretical framework to frame analysis of the benefits is the expected utility (EU) model, which potentially leads to the measurement of the option price (OP – see Graham 1981), the standard measure of benefits under risk. The EU framework helps greatly to explain why people undertake very risky gambles, or avoid gambles that appear to offer fair payoffs (i.e. turning down the offer to be paid \$1.00 or \$0, each with a fifty-fifty chance, in lieu of being paid \$0.50 with certainty).

The EU-OP framework is one in which probabilities are presumed to be known. There are certainly situations involving such well-known risks in the water-resource arena. For example, flows of rivers are inherently random, but long data histories may allow characterization of

annual or seasonal flows using probability distributions. Perhaps surprisingly however, there are relatively few economic studies in the literature that actually use data collected in a fashion that allows estimation of the OP for individuals in a sample. An exception in the water resources realm is the Monongehela River study by Desvousges et al. (1987), where subjects are told what risks are and the survey elicits their OP. To our knowledge, thus far no researcher has clearly estimated an OP using only a revealed preference valuation approach, i.e. one based on observed behavior.

Thus, stated preference methods are the only ones we have observed in the literature where researchers may have obtained a clear estimate of OP. Problems with getting a clear estimate of an individual's OP using stated preference methods are numerous. First, even if science-based estimates of risk are available, these must be presented to individuals in such a way that the researcher is sure that respondents are understanding them.

Risk communication can be quite difficult, at best, leading to the individual to over or underestimate risks as compared to the science community (see Riddel and Shaw 2006; or see a host of references in Fischhoff 2009; or Nguyen et al. 2010). The problems seem most difficult when the best science suggests that risks are quite small, when the scientists themselves cannot agree, or when the public does not trust the source of the risk estimates. Mortality risk estimates, for example, are often much smaller than 1 in 1,000, prompting the question whether an individual can comprehend the meaning of these small probabilities (Manski 2004, is quite skeptical).

Second, even supposing that risk communication led to an unambiguous subjective probability distribution on the part of the individual which ends up being identical to the scientist's estimates, the next task is to phrase the willingness to pay (or willingness to accept) question in a manner that does not confuse the OP with all of the other valuation concepts (bequest, expected future use, option, and existence value). A thorough review is beyond the scope of this current paper, but many older papers that were scrutinized do not convincingly accomplish this task.

The use of subjective probability or risk estimates is quite important, and especially so when it is apparent that social behavior is being driven by subjective risks that are far different than science-based risks. For example, *Riddel and Shaw* [2006] found, even after trying to communicate science-based risks to their sample of respondents, that the sample's subjective risks of nuclear waste transport and shipping were thousands of times higher than the science-based estimates. In theory and in practice, it is certainly possible to use subjective estimates in empirically modeling behavior: this has been done dozens of times in the literature on cigarette smoking [e.g. *Viscusi*, 1990].

A less-explored problem that arises in subjective estimation of risks or probabilities relates to whether the individual providing the risk estimate is him or herself uncertain about them. A simple case arises when there might be two experts who offer their opinion of the risk of an event, and these widely diverge from one another, and subjects are aware of this divergence. *Savage* [1954] showed that a decision maker's choices could be explained by a model in which it is assumed that the individual takes the expected value of the two risk estimates, maximizing his or her "subjective expected utility." However, many psychologists and economists have demonstrated in laboratory experiments that subjects do not behave in this manner. One thought is that instead, individuals simply use decision heuristics to make complicated

decisions, and that these depart greatly from the assumptions underlying the classic EU framework [see *Tversky and Kahneman, 1974*].

In response to concerns about the validity of the EU framework [e.g. *Smith, 1969*], a host of non-EU models have arisen that allow for a rich set of behaviors when individuals make decisions, and potentially allow for ambiguity [e.g. *Segal, 1987*]. Most of these models incorporate probability weights, including the cumulative prospect theory developed by *Tversky and Kahneman [1992]* and the rank-dependent expected utility model developed by *Quiggin [1993]*. These models account for the fact that compared to those science-based probabilities (p) in the standard EU model, individuals often place more weight on low probability outcomes, and less weight on common outcomes. This can be understood by a model in which probabilities are filtered through a probability weighting function (PWF) such as the inverse S shaped curve in Figure 1. If an individual's PWF lines up on the 45 degree line, then his or her treatment of the risks of a situation will coincide with the science-based estimates. When low probability events are given more weight, the weights, $w(p)$, will take on an S-shape. Non-linearity in the pwf has been found in many studies that obtain them [e.g. *Gonzalez and Wu, 1999*].

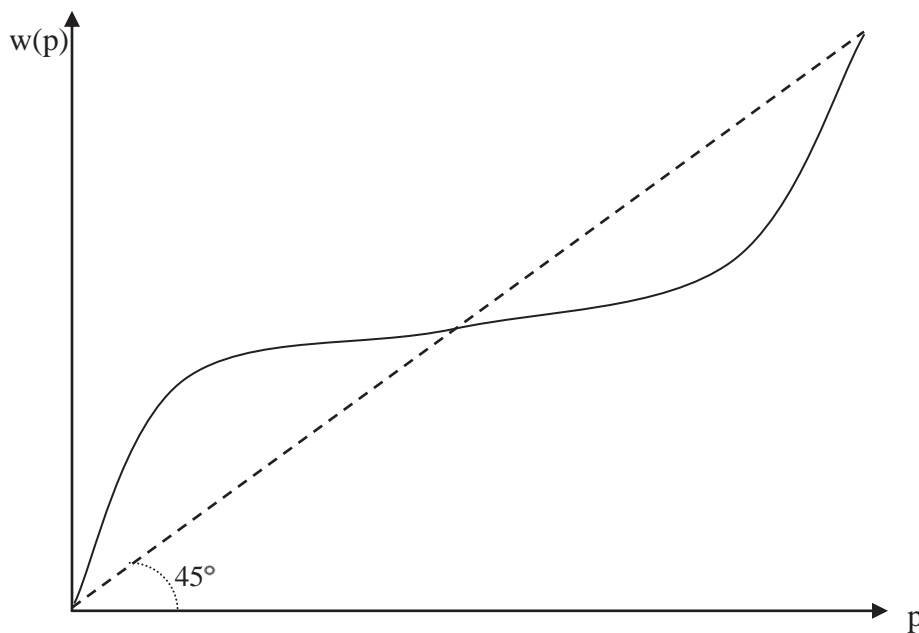


Figure 1: Probability Weighting Function (Inverse S shape)

There is substantial evidence that such non-linear probability weighting often occurs and this can relate to issues in water resource economics (see the focused discussion by *Shaw and Woodward* [2008], relating especially to environmental and resource economics issues). Actually estimating the probability weights is a substantial challenge. Recovering a PWF requires knowledge of weights throughout the spectrum of probabilities, for each individual in a study, and requires identification of each individual's utility function, and risk attitudes. An individual's choices must be observed making a series of similar decisions with gradually changing probabilities. Estimating such PWFs in the "real world," is very difficult, and some are skeptical that PWFs actually provide any improvement over models without weights that focus on reduction in error (see for example, Wilcox 2009). Several economists and decision theorists are leading the way in such methods using laboratory experiments [see *Tanaka, Camerer, and Nguyen*, 2010, for example].

Decision makers may face the problem of *ambiguity*, lacking knowledge about a probability reflecting risks. A simple characterization of at least some degree of ambiguity is the two-expert example above. In the laboratory, or on a survey questionnaire, an individual might be told that there are two "experts" who disagree with one another about their estimate of risks [*Woodward and Bishop*, 1997]. Ambiguity arises when the individual is unable to come to terms with how to treat these opposing views of risk. If an individual is comfortable simply averaging the two estimates of risk, then this is as a compound lottery that reduces the uncertainty to a situation of risk. The individual is thought to be making a decision under something approaching pure uncertainty when averaging does not happen.

The decision maker does not know the probabilities that define the situation with pure uncertainty. In experiments to evaluate choice under uncertainty, a researcher might make no effort at all to communicate the probabilities to individuals, or to elicit them. Subjects in a laboratory or in a survey might simply be informed that outcomes are uncertain, but be asked to proceed with making a choice. Choices in this case might be consistent with a variety of decision heuristics, including minimizing the regret they would experience by making the wrong choice (e.g. in their recent classroom experiment *Grijalva, Berrens, and Shaw* 2011, find that subjects' responses are consistent with this strategy).

In most laboratory experiments that have focused on pure uncertainty, individuals are shown to be averse to ambiguity involving monetary payoffs. Whether they would demonstrate similar traits when confronted with the problem of droughts or flooding has not been tested. Ambiguity, at least in some form, has been also considered now in several empirical models of behavior that do not involve laboratory experiments [see for example the survey-based research by *Viscusi and Magat*, 1992; *Riddell and Shaw*, 2006], and aversion to ambiguity is not always found.

Another potential uncertainty tool is in the area of linear and non-linear programming. One common task is for the programmer to introduce risk. This is often done by simply letting there be two or three states of the world, each with a known probability, and engaging in stochastic optimization. Though this sounds simple, things quickly get complicated with many such states of the world as the computational complexity of the problem can grow geometrically, often leading to intractable problems. It is important that the modelers consider more than one specific probability distribution to add some uncertainty to a programming analysis. *Ritten et al.* (2010) consider a range of projections for precipitation in their analysis of optimal rangeland stocking problems. They recognize that climate change may lead to several possibilities for

randomness in weather patterns, which is consistent with varying predictions from current scientific estimates.

Programmers can further introduce uncertainty using optimal control. Below is the standard expected utility maximization problem for a planner making a policy choice, z :

$$\max_z E_p u(z; \varepsilon), \quad (1)$$

where ε is randomness in the environment that varies according to a known probability distribution P and E_p is the expectation operator for that distribution.

Many mathematicians have considered optimization problems with uncertainty [see *Schmeidler* [1989] and *Gilboa* [1987]]. A relationship between pure uncertainty and probability weighting can be formalized in this context by assuming that individuals make decisions as if they violate well-known properties that probabilities have. For example, consider the state-space corresponding to three outcomes, A, B, and C, with probabilities $p(A)$, $p(B)$, and $p(C)$. It turns out that decision makers often act (i.e. make choices) as though probabilities do not sum up to one. Situations of both “sub-additivity” and “super-additivity” have been found to arise in experimental settings. Such unusual weighting has led to the framework known as Choquet-Expected Utility [*Diecidue et al.*, 2004]. It has been shown that for decision makers who are averse to ambiguity, choices that use nonlinear weighting or in other ways that violate the standard model can be “rational” in a rather rigorous sense of that word.

A particularly relevant extension of conventional optimal control is robust optimal control [see *Hansen and Sargent*, 2001; *Ben-Tal et al.*, 2009], often specified in dynamic economic models. A robust control optimization problem is used when there is a family of possible probability distributions, say \mathbf{P} , and the decision maker is completely uncertain about which distribution is the correct one. The robust-control problem is

$$\max_z \min_{P \in \mathbf{P}} E_p u(z; \varepsilon). \quad (2)$$

That is, the robust optimal policy is the one that is made assuming the worst possible probability from the set of possible distributions, \mathbf{P} , so that the expected outcome will be at least as favorable as the worst case that is identified in (2).

When decision makers are averse to ambiguity, robust control is “rational” in that it is consistent with a set of reasonable axioms (Gilboa and Schmeidler 1989). The approach includes a term that allows for varying degrees of aversion to ambiguity, effectively determining the size of the set \mathbf{P} in (2). At one extreme \mathbf{P} is a single probability distribution and the model maximizes the standard discounted expected value. At the other extreme the model chooses as if only the worst-case scenario is relevant. Increasingly, robust control is used to solve applied problems in engineering though the computational complexity of this specification can be as burdensome as in the standard EU cases discussed above. The following sections offers attempts at using some of the above approaches.

Issues Involving Water Quantity, Risk and Uncertainty

Several pressing and important issues relating primarily to water quantity or scarcity are highlighted. These are limited to topics that are especially difficult to analyze because of risk or uncertainty. On many minds is regional population growth relative to water supply. This problem is typified by struggles in Arizona [see *CBO*, 2006], California [see *Hanemann*, 2002], and in

China [see *Dasgupta*, 2001 and *Gleick*, 2009]. A reviewer of this paper noted that population growth has been high in all three of these regions, but that future water availability and climate impacts are still uncertain in each. This highlights that the relationship between population growth and water allocation is complex. For example, migration can lead to population growth in those areas with the highest income [*Borjas et al.*, 1992]. Predicting population growth and its relationship to water availability is no doubt fraught with uncertainty.

How should water managers proceed to introduce uncertainty here? Consideration of both supply side (availability because of climate uncertainty) and demand side issues is merited. Most risk or uncertainty for natural resource economics of extraction, occurs in relation to extraction costs (e.g. the effect of unknown reserves and discovery), but it may be that future tastes and preferences are unknown as well. In the discussion below two water problems are given that involve risk or uncertainty, the problem of drought and global warming, and the management of instream flows.

Addressing Drought and Global Warming

Precipitation, by its very nature, involves risk, and is regularly characterized using a well-known probability distribution. An emerging issue is whether relatively recent precipitation data is sufficient to be informative regarding large deviations from some mean. Focusing on the use of time trends, *Milly et al.* 2008 recently pronounced the death of the use of such modeling in the area of climate change research. They offer suggestions for a model using nonstationary hydrologic stochastic variables, where these are used to develop probability density functions that do change over time. They note that the challenge in doing this will be daunting. Hundreds of hydrologic studies have focused on using more simple stochastic models of surface and groundwater flow. Economic analysis has built on optimal withdrawals under known risks with allowance for comparison to withdrawals when there is certainty.

Pullen and Colby [2008] illustrate connections between drought indicators and water prices. Their conclusion is that climate variability does affect water price, with some lag and that water markets may work reasonably well to adjust prices in response to scarcity in some contexts. Exacerbating the water allocation and planning problem with potential droughts now is the threat of severe consequences related to global warming. Some are already blaming some increase in droughts in China on climate change [see *Gleick*, 2009]. Augmented precipitation intensity and variability are projected to increase the risks of flooding and drought in many areas [*Bates et al.*, 2008]. Note that the word “risks” is used here by *Bates et al.*, 2008, but many in the global warming science community might argue that impacts are more certain. For example, the head of the White House Council on Environmental Quality stated recently that preparations must be made for the “inevitable” effects of climate change (see *Chipman* 2010).

If risks related to global warming were well known, it would be possible to estimate the OP for water quantity-related changes. The 2008 IPCC report on climate change and water indicates that “climate change challenges the traditional assumption that past hydrological experience provides a good guide to future conditions [*Bates et al.*, 2008, p. 4].” *Schimmelpfennig* [1996] documents failures of climate change researchers to adequately model uncertainty. *Paté-Cornell* [1996] concludes that uncertainty, not risk, characterizes climate change estimates, and states that “Experts, however, tend to underestimate uncertainties...” (p. 148). Still, she and other climate change researchers call for better efforts to handle uncertainty.

Alternatively, one could focus on the agricultural sector and consider the role that climate risks play there in farming, or raising livestock. That is precisely what *Groom et al.* [2008] try to do. They develop a model assuming that farmers use a combination of inputs, and that irrigated water plays the key role in the analysis via an imposed quota during drought. The essential point of their paper is to allow for climate risk to affect crop yield and explore risk attitudes of farmers, demonstrating that allowance for this risk preference yields quite different results than a model that assumes certainty. Using a moment-based approach (i.e. a model that collapses to a simple examination of first (average), second (variance), third (skewness), or higher moments of profit), they are able to uncover risk-attitudes using cross sectional data, which they obtain from a survey of a sample of farmers in Cyprus.

One might criticize the above approach in that it allows for little heterogeneity in risk attitudes across farmers; yet, its attention to risk preferences is certainly a step in the right direction. What is especially relevant is their examination of a water quota or restriction under various sets of information available to water policy managers. *Groom et al.* [2008] illustrate that under a drought-induced water quota, the naive water manager who assumes risk neutrality on the part of farmers will incorrectly predict how inputs will be used. Results vary for different crops, but using vegetables as an example, the naive manager expects fertilizer use to go down as water is restricted, while the sophisticated one does the analysis and expects fertilizer use to go up. Failing to allow for risk aversion, therefore, may well lead to choose the wrong quota.

Two other studies are closely related to the agriculture and water relationship, and they have important ramifications for modeling decisions under risk or uncertainty. In the first, *Lybbert et al.* [2007] consider whether herders in developing countries act as Bayesians when they take in information on rainfall forecasts. Results suggest that they do, but only for below-normal rainfall expectations, not for above-normal rainfall. This study is interesting because it allows for subjective risks of rainfall to affect decisions to manage agriculture (livestock).

Ranjan and Shogren [2006] consider outcomes when farmers put probability weights on the losses of water rights under market transactions. Here again is an effort to introduce non-EU modeling, simulating what happens if farmers have nonlinear probability weighting functions. They show that if farmers overweight the probability of losses, then this results in undervaluing water resources. This is consistent with the fact that many farmers are reluctant to participate in markets such as found in states with drought water banks. Whether markets will work or not to allocate water supplies for growing populations is questionable. Markets likely do better in allocating resources when demand is known with certainty, and thus, water planners would at least wish that long range population projections were accurate.

There is still a great deal of uncertainty about impacts despite tremendous energy put into modeling global warming's impacts on precipitation and temperature. There are several competing global, ocean, and atmospheric models. Each produces results that vary as to the projected impacts and the probabilities associated with them. Most of the models predict that particular regions of the planet will be hotter, while others actually cooler; some will be wetter, and others drier. Consistent features of the models are that climate will be more variable and extreme events will be more violent. However, the probabilities of these outcomes differ considerably across the models.

Competing and differing estimates of the probability of certain outcomes is consistent with the way that several decision theorists and economists characterize pure uncertainty. Water managers and planners might best think of how to cope with uncertainty and not just risk. If they

are continuing to rely on forecasts of demand or supply as if these are certain, they have a long way to go in catching up with climate change issues. The next section features the problem of instream flow and endangered species offering robust optimization as one leading approach to making choices in this uncertain environment.

Application of Robust Control: the Instream Flow Problem

Society may place considerable value on water left in a river or lake, or in the ground. This is in contrast to the notion that only water extracted from a river or lake can have value. Perhaps the latter arose only because it was much easier to assign values for extracted water using conventional economic approaches, than to do so for in-situ water or because residual flows were seen as virtually inexhaustible. But this is changing. Instream flow protection is being considered in a host of states in the U.S. today, in some instances because of the importance of aquatic habitat for endangered or threatened species. Such species and their habitat are protected under the Endangered Species Act (ESA), but there is considerable tension between parties wishing to withdraw water and those who support instream flow, especially when water resources are scarce, as during drought periods.

Several countries adopt the precautionary principle, or something along the lines of the Ciriacy-Wantrup's safe minimum standard [SMS, 1952]. Again here is the notion that under uncertainty, being cautious about protection is prudent. Models of behavior that generate support for the SMS can be found in the literature, and these incorporate uncertainty [e.g. *Ready and Bishop*, 1991; *Woodward and Bishop*, 1997; *Palmmini*, 1999], but general support in economics for the SMS is not a given [see *Margolis and Naevdal*, 2008].

Woodward and Shaw [2008] recently considered the problem of water allocation when features of a species' growth function were uncertain. It turns out that much less is known about species stocks and their growth functions than one might assume. For example, what is the optimal stream flow level to support a certain species of fish? Biologists and hydrologists may not actually know. Even for relatively well-studied fish, oftentimes science still lacks knowledge of some of the most basic properties of the species' growth and reproduction.³ The difference for policy purposes, between risk and uncertainty might be summarized in comparing Figures 2 and 3. In Figure 2, if policy A is pursued, the distribution for the stock is known, and a comparison can be made with policy B. In Figure 3, the distribution related to either policy is not known with certainty, so there is potential overlap in the tails of outcomes, depending on which of the distributions actually pertains.

³ An example of this is found in the Rio Grande silver minnow (*Hybognathus amarus*) as discussed in U.S. Fish and Wildlife Service (2007).



Figure 2: Known Risk Distributions for Policy A and B

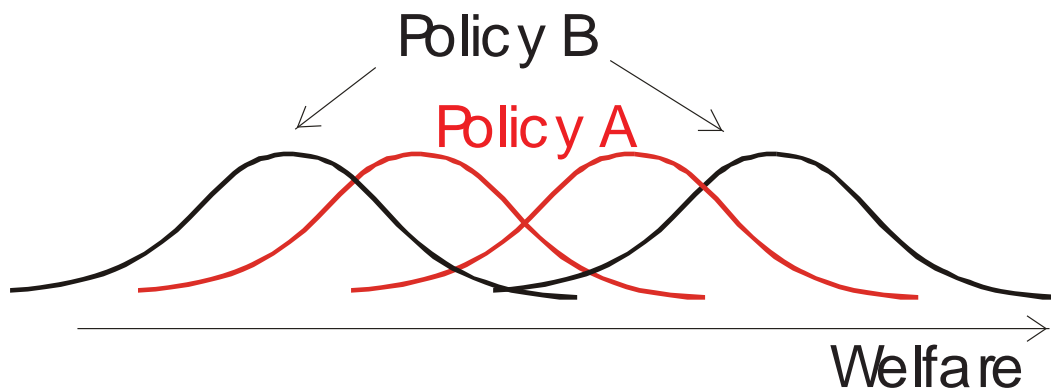


Figure 3: Ambiguity About Distributions for Policy A and B

As mentioned above, robust control is routinely used in engineering applications. For example, structural engineers would not find it acceptable to have a low probability of failure on average; there must be a low probability of failure in all possible scenarios. There are similarly strong intuitive arguments for applications to water management. *Roseta-Palma and Xepapadeas* [2004] apply the approach to the management of groundwater resources, where uncertainty can be substantial, especially in the face of climate change. They conclude that in the face of uncertainty the robust strategy will be to reduce use of groundwater resources. *Woodward and Shaw* [2008] apply the method to the problem of managing instream flows of water in a river in which an endangered species is present. Where there is profound uncertainty about the relationship between the stock's growth and the water level, the authors' show that, at least for a range of stock sizes above some critical minimum stock size, proceeding more slowly with extraction or use makes sense. Hence, the authors show that an SMS approach to management is intuitively attractive and consistent with a formal model of optimal choices under ambiguity.

Conclusions and Policy Recommendations

Water managers have often been characterized as a "risk averse group" [e.g. *Carbone and Dow*, 2005]. This may suggest that most have indeed abandoned the use of certainty models in

preparing for the future, although a paper that tries to assess the average strategy of water managers, nation-wide, remains to be seen.

Hopefully, at the very least planners and managers are strategizing by assuming that risk prevails over certainty. They can then at least adopt an EU framework for decision making (e.g. Graham 1981). What they would probably wish for is more information that at least allows for updating and more precision in estimating risks, or in pinning down probability distributions. Risk models are conducive to updating, as learning happens (e.g. Groom et al. 2008; Lybbert et al. 2007). But such additional information and learning from it may not happen for a long while in some cases, and in others, may not ever happen.

However, for many issues, the incorporation of risk into their decision calculus is not sufficient. Better incorporation of not only risk, but also uncertainty needs to come at the initial planning stage. This may be true when considering investments into new storage or treatment facilities. In cases where pure uncertainty is high, adopting a worst-case scenario, something along the lines of safe minimum standards, may be not only be prudent, but an economically rational approach to a difficult problem.

In a world of uncertainty it is prudent to draw on the growing theoretical and empirical research on choice under true uncertainty as society wrestles with tough issues ahead (e.g. using maxmin EU models or robust optimal control as in Diecidue et al. 2004; Gilboa 1987; Gilboa and Schmeidler 1989; Grijalva et al. 2010; Hansen and Sargent 2001; Palmizi 1999; Roseta-Palma and Xepapadeas 2004; Schmeidler 1989; Woodward and Shaw 2008). These models are not easy to understand, but they are not impossible to implement (see the experiment by Grijalva et al. 2010).

At the very least, even if such models are not tractable, non-expected utility models should be integrated into decision-making. These types of models allow for something to influence decisions that relates to more than just mean risk, and often allow for ambiguity, and possible probability weighting (Gonzalez and Wu 1999; Ranjan and Shogren 2006; Segal 1987; Tanaka et al. 2010; Tversky and Kahneman 1974; 1992; Viscusi and Magat 1992). As a easily implementable first step, water managers that rely on models that only incorporate risk should consider different possible distributions in the way of a sensitivity analysis, as results may vary wildly, depending on the distribution (e.g. Ritten et al. 2010).

Taking such approaches may be costly, but may also tend to diminish the threat of crises. A crisis in the water arena can mean conflicts over water supplies from competing users, morbidity or even mortality for humans and other living organisms from inadequate water supplies at times of drought. By using a decision-making process that explicitly recognizes the inherent uncertainties that are faced, water managers might better be able to reduce the threat of the worst crises.

This all comes at a price, and water managers who adopt a safe strategy will no doubt be criticized for over-reacting, as they already are today when wet years make surplus storage capacity appear wasteful. Ideally, it would be convenient to be able to focus on those problems with known and stable risks where that can be done. However, this seems possible only in geographical regions that can expect very small climate change impacts to arise, if any such places exist.

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