PART 7. MAKING DECISIONS IN THE FACE OF UNCERTAINTY

As we noted in the introduction, there are a number of things that are different about the climate problem (Morgan *et al.*, 1999), but high levels of uncertainty is not one of them. In our private lives, we decide where to go to college, what job to take, whom to marry, what home to buy, when and whether to have children, and countless other important choices, all in the face of large, and often irreducible uncertainty. The same is true of decision made by companies and by governments -- sometimes because decisions must be made, sometimes because scientific uncertainties are not the determining factor (*e.g.*, Wilbanks and Lee, 1985), and sometimes because strategies can be identified that incorporate uncertainties and associated risks into the decision process (NRC, 1986).

Classical decision analysis provides an analytical strategy for choosing among options when possible outcomes, their probability of occurrence, and the value each holds for the decision maker, can be specified, decision analysis identifies an "optimal" choice among actions. Decision analysis is rigorously derived from a set of normatively appealing axioms (Raiffa and Schlaifer, 1968; Howard and Matheson, 1977; Keeney, 1982). In applying decision analysis, one develops and refines a model that relates the decision makers' choices to important outcomes. One must also determine the decision maker's utility function(s)[28] in order to determine which outcomes are most desirable. One then propagates the uncertainty in various input parameters through the model (appropriately accounting for possible correlation structures among uncertain variables) to

[28] Many economists and analysts appear to assume that fully articulated utility functions exist in peoples' heads for all key outcomes, and that determining them is a matter of measurement. Many psychologists, and some decision analysts, suggest that this is often not the case and that for many issues people need help in thinking through and constructing their values (von Winterfeldt and Edwards, 1986; Fischhoff, 1991; Keeney, 1992; Fischhoff, 2005).

generate the expected utility of the various choice options. The best option is typically assumed to be the one with the largest expected utility, although other decision rules are sometimes employed.

When the uncertainty is well characterized and the model structure well known, this type of analysis can suggest the statistically optimal strategy to decision makers. Because there are excellent texts that outline these methods in detail (e.*g.*, Hammond *et al.*, 1999), we do not elaborate the ideas further here.

In complex, and highly uncertain contexts, such as those involved in many climate-related decisions, the conditions needed for the application of conventional decision analysis sometime do not arise (Morgan *et al.*, 1999). Where uncertainty is large, efforts can be made to reduce the uncertainties - in effect, reducing the width of probability distributions through research to understand underlying processes better. Alternatively, efforts can be made to improve understanding of the uncertainties themselves so that they can be more confidently incorporated in decision-making strategies.

In most cases more research reduces uncertainty. Classic decision analysis implicitly assumes that research always reduces uncertainty. While eventually it usually does, in complex problems, such as some of the details of climate science, many years, or even many decades may go by, during which one's understanding of the problem grows richer, but the amount of uncertainty, as measured by our ability to make specific predictions, remain unchanged, or even grows larger because research reveals processes or complications that had not previously been understood or anticipated. That climate experts understand this is clearly demonstrated in the results from Morgan and Keith (1995) shown in Table 7.1. Unfortunately, many others do not recognize this fact, or choose to ignore it in policy discussions. This is not to argue that research in understanding climate science, climate impacts, and the likely effectiveness of various climate management policies and technologies is not valuable. Clearly it is. But when it does not immediately reduce uncertainty we should remember that there is also great value in learning that we knew less than we thought we did. In some cases, all the research in the world may not eliminate key uncertainties on the timescales of decision we must make.

This raises the question of what considerations should drive research. Not all knowledge is likely to be equally important in the climate-related decisions that individuals, organizations and nations will face over the coming decades. Thus, while it is often hard to do (Morgan *et al.*, 2006), when possible, impact assessors, policy analysts and research planners should consider working backward from the decisions they face to design research programs which are most likely to yield useful insights and understanding.

There are two related decision-making/management strategies that may be especially appealing in the face of high uncertainty. These are:

Resilient Strategies: In this case, the idea is to try to identify the range of future circumstances that one might face, and then seek to identify approaches that will work reasonably well across that range.

*Adaptive Strategies***:** In this case, the idea is to choose strategies that can be modified to achieve better performance as one learns more about the issues at hand and how the future is unfolding.

Both of these approaches stand in rather stark contrast to the idea of developing optimal strategies that has characterized some of the work in the integrated assessment community, in which it is assumed that a single model accurately reflects the nature of the world, and the task is to choose an optimal strategy in that well specified world.

The ideas of resilience and adaptation have been strongly informed by the literature in ecology. Particularly good discussions can be found in Clark (1980) and Lee (1993). A key feature of adaptive strategies is that decision makers learn whatever they can about the problem they face and then make choices based on their best assessment and that of people whose advice they value. They seek strategies that will let them, or those who come after them, modify choices in accordance with insights gained from more experience and research. That is, rather than adopt a decision strategy of the sort shown in Figure 7.1A in which nothing is done until research resolves all key uncertainties, they adopt an iterative and adaptive strategy that looks more like that shown in Figure 7.1B. Adaptive strategies work best in situations in which there are not large non-linearities and in which the decision time scales are well matched to the changes being observed in the world.

A familiar example of a robust strategy is portfolio theory as applied in financial investment, which suggests that greater uncertainty (or a lesser capacity to absorb risks) calls for greater portfolio diversification. Another example arose during the first regional workshop conducted by the National Assessment Synthesis Team in Fort Collins, CO, in preparation for developing the U.S. National Climate Change Assessment (NAST, 2000). Farmers and ranchers participating in the discussion suggested that, if possible climate change introduces new uncertainties into future climate forecasts, it might be prudent for them to reverse a trend toward highly-specialized precision farming and ranching, moving back toward a greater variety of crops and range grasses.

Deep uncertainty

Decision makers face deep uncertainty when those involved in a decision do not know or cannot agree upon the system model that relates actions to consequences or the prior probability distributions on the input parameters to any system model[29]. Under such conditions multiple representations can provide a useful description of the uncertainty.

Most simply, one can represent deep uncertainty about the values of empirical quantities and about model function form by considering multiple cases. This is the approach taken by traditional scenario analyses. Such traditional scenarios present a number of challenges, as documented by Parson *et al.* (2007). Others have adopted multi-scenario simulation approaches (IPCC WGIII, 2001) where a simulation model is run many times to create a large number of fundamentally different futures and used directly to make policy arguments based on comparisons of these alternative cases.

[29] A number of different terms are used for what we call here 'deep uncertainty.' Knight (1921) distinguished risk from uncertainty, using the later to denote factors poorly described by quantified probabilities. Ben-Haim (2001) refers to severe uncertainty and Vercelli (1994) to hard as opposed to the more traditional soft uncertainty. The literature on imprecise probabilities refers to probabilities that can lie within a range.

In the view of the authors of this report, considering a set of different, plausible joint probability distributions over the input parameters to one of more models provides the most useful means to describe deep uncertainty. As described below, this approach is often implemented by comparing the ranking or desirability of alternative policy decisions as a function of alternative probability weightings over different states of the world. This is similar to conventional sensitivity analysis where one might vary parameter values or the distribution over the parameters to examine the effects on the conclusions of an analysis. However, the key difference is one of degree. Under deep uncertainty the set of plausible distributions contains members that in fact would imply very different conclusions for the analysis. In addition to providing a useful description of deep uncertainty, multiple representations can also play an important role in the acceptance of the analysis when stakeholders to a decision have differing interests and hold differing non-falsifiable, perceptions. In such cases, an analysis may prove more acceptable to all sides in a debate if it encompasses all the varying perspectives rather than adopting one view as privileged or superior (Rosenhead and Mingers, 2001).

There exists no single definition of robustness. Some authors have defined robust strategy as one that performs well, compared to the alternatives, over a very wide range of alternative futures (Lempert *et al.* 2003). This definition represents a "satisficing" criterion (Simon, 1959), and is similar to domain criteria (Schneller and Sphicas, 1983) where decision makers seek to reduce the interval over which a strategy performs poorly. Another formulation defines a robust strategy as one that sacrifices a small amount of optimal performance in order to obtain less sensitivity to broken assumptions. This robustness definition underlies Ben-Haim’s (2001) "Info-Gap" approach, the concept of robustness across competing models used in monetary policy applications (Levin and Williams, 2003), and to treatments of low probability, high-consequence events (Lempert *et al.*, 2002). This definition draws on the observation that an optimum strategy may often be brittle, that is, its performance may degrade rapidly under misspecification of the assumptions and that decision makers may want to take steps to reduce that brittleness[30], For instance, if one has a best-estimate joint probability distribution describing the future, one might choose a strategy with slightly less than optimal performance in order to improve the performance if the tails of the best-estimate distribution describing certain extreme cases turn out to larger than expected[31]. Other authors have defined robustness as keeping options open. Rosenhead (2001) views planning under deep uncertainty as a series of sequential decisions. Each decision represents a commitment of resources that transform some aspect of the decision-maker's environment. A plan foreshadows a series of decisions that it is anticipated will be taken over time. A robust step is one that maximizes the number of desirable future end states still reachable, and, in some applications, the number of undesirable states not reachable, once the initial decision has been taken.

These definitions often suggest similar strategies as robust, but to our knowledge, there has been no thorough study that describes the conditions where these differing robustness criteria lead to

[30] United States Federal Reserve Chairman Alan Greenspan described an approach to robust strategies when he wrote "…For example policy A might be judged as best advancing the policymakers' objectives, conditional on a particular model of the economy, but might also be seen as having relatively severe adverse consequences if the structure of the economy turns out to be other than the one assumed. On the other hand, policy B might be somewhat less effective under the assumed baseline model … but might be relatively benign in the event that the structure of the economy turns out to differ from the baseline. These considerations have inclined the Federal Reserve policymakers toward policies that limit the risk of deflation even though the baseline forecasts from most conventional models would not project such an event."

[31] Given a specific distribution one can find a strategy that is optimal. But this is not the same as finding a strategy that performs well (satisfices) over a wide range of distributions and unknown system specifications.

similar or different rankings of alternative policy options. Overall, a robustness criterion often yields no single best answer but rather helps decision makers to use available scientific and socio-economic information to distinguish a set of reasonable from unreasonable choices and to understand the tradeoffs implied by choosing among the reasonable options. Robustness can be usefully thought of as suggesting decision options that lie between an optimality and a minimax solution. In contrast to optimal strategies that, by definition, focus on the middle range of uncertainty most heavily weighted by the best estimate probability density function, robustness focuses more on, presumably unlikely but not impossible, extreme events and states of the world, without letting them completely dominate the decision.

One common means of achieving robustness is via an adaptive strategy, that is, one that can evolve over time in response to new information. Two early applications of robust decision making to greenhouse gas mitigation policies focused on making the case for such robust adaptive strategies. These studies also provide an example of a robust strategy as one that performs well over a wide range of futures. Morgan and Dowlatabadi (1996) used variants of their ICAM-2 model in an attempt to determine the probability that specific carbon tax policy would yield net positive benefits. Their sensitivity analysis over different model structures suggested a range that is so wide, 0.15 to 0.95, as to prove virtually useless for policy purposes. Similarly, Table 7.2 illustrates the wide range of effects due to alternative ICAM model structures one finds on the costs of CO_2 stabilization at 500 ppm (Dowlatabadi, 1998). To make sense of such deep uncertainty Casman *et al.* (1999) considered adaptive decision strategies (implemented in the model as decision agents) that would take initial actions based on the current best forecasts, observe the results, revise their forecasts, and adjust their actions accordingly. This study highlights the importance of how we can build in robust strategies by building policies around different state variables. For example, the most common state variable in climate policy is annual emissions of GHGs. This variable suffers from high variability induced by: stochastic economic activity, energy market speculations, and inter-annual variability in climate. All of these factors can drive emissions up or down, outside the influence of the decision-variable itself or how it influences the system (i.e., a shadow price for GHGs). A policy that uses atmospheric concentration of CO_2 and its rate of change, is much less volatile and much better at offering a robust signal for adjusting the decision-variable through time. The study reports that atmospheric forcing, or GHG concentrations are far more robust that alternative state variables such as emission rates or global average temperature over a wide range of model structures and parameter distributions. This finding has important implications for the types of scientific information that may prove most useful to decision makers.

Similarly, Lempert *et al.* (1996) used a simple integrated assessment model to examine the expectations about the future that would favor alternative emissions-reduction strategies. The study examined the expected net present value of alternative strategies as a function of the likelihood of large climate sensitivity, large climate impacts, and significant abatement-cost-reducing new technology. Using a policy region analysis (Watson and Buede, 1987), the study found that both a business as usual and a steep emissions-reduction strategy that do not adjust over time presented risky choices because they could prove far from optimal if the future turned out differently than expected. The study then compared an adaptive strategy that began with moderate initial emissions reductions and sets specific thresholds for large future climate impacts and low future abatement costs. If the observed trends in impacts or costs trigger either threshold, then emissions reductions accelerate. As shown in Figure 7.2, this adaptive strategy performed better than the other two strategies over a very wide range of expectations about the future. It also proved to be close to optimal otherwise. For those expectations where one of the other two strategies performed best, the adaptive strategy performed nearly as well. The study thus concluded the adaptive decision strategy was robust compared to the two non-adaptive alternatives.

These robust decision making approaches have been applied more recently using more sophisticated methods. For instance, Groves (2006) has examined robust strategies for California water policy in the face of climate and other uncertainties and Dessai and Hulme (2007) has applied similar approaches to water resource management in the UK. Similarly, Hall (Hine and Hall, 2007) has used Haim's Info-Gap approach to examine robust designs for the Thames flood control system in the face of future scientific uncertainty about sea level rise.

Surprise

Recent attention to the potential for abrupt climate change has raised the issue of "surprise" as one type of uncertainty that may be of interest to decision-makers. An abrupt or discontinuous change represents a property of a physical or socio-economic system. For instance, similarly to many such definitions in the literature, the United States National Academy of Sciences has defined an abrupt climate change as a change that occurs faster than the underlying driving forces (NRC, 2002). In contrast, surprise represents a property of the observer. An event becomes a surprise when it opens a significant gap between perceived reality and one's expectations (van Notten *et al.*, 2005; Glantz *et al.*, 1998; Hollings, 1986; Schneider *et al.*, 1998).

A number of psychological and organizational factors make it more likely that a discontinuity will cause surprise. For instance, individuals will tend to anchor their expectations of the future based on their memories of past patterns and observations of current trends and thus be surprised if those trends change. Scientists studying future climate change will often find a scarcity of data to support forecasts of systems in states far different than the ones they can observe today. Thus, using the taxonomy of Figure 1.1, the most well established scientific knowledge may not include discontinuities. For example, the sea level rise estimates of the most recent IPCC Fourth Assessment Report (IPCC, 2007) do not include the more speculative estimates of the consequences of a collapse of the Greenland ice sheet because scientists' understanding of such a discontinuous change is less well-developed than for other processes of sea level rise. Planners who rely only on the currently well-established estimates may come to be (or leave their successors) surprised.

The concepts of robustness and reliance provide a useful framework for incorporating and communicating scientific information about potential surprise[32]. First, these concepts provide a potential response to surprise in addition to and potentially more successful than trying to predict them. A robust strategy is designed to perform reasonably well in the face of a wide range of contingencies and thus a well-designed strategy will be less vulnerable to a wide range of

[32] Robustness and resilience are related concepts. The former generally refers to strategies chosen by decision makers while the later is a property of systems. However, the concepts overlap because decision makers can take actions that make a system more resilient.

potential surprises whether predicted or not. Second, the robustness framework aims to provide a context that facilitates constructive consideration of otherwise unexpected events (Lempert *et al.*, 2003). In general, there is no difficulty imagining a vast range of potential outcomes that might be regarded as surprising. It is in fact rare to experience a major surprise that had not been previously imagined by someone (*e.g.*, fall of the Soviet Union, Katrina, Pearl Harbor, 9/11). The difficulty arises in a decision making context if in the absence of reliable predictions there is no systematic way to prioritize, characterize, and incorporate the plethora of potential surprises that might be imagined. A robust decision framework can address this problem by focusing on the identification of those future states of the world in which a proposed robust strategy would fail, and then identify the probability threshold such a future would have to exceed in order to justify a decision maker taking near-term steps to prevent or reduce the impacts of such a future.

For example, Figure 7.3 shows the results of an analysis (Lempert *et al.*, 2000) that attempted to lay out the surprises to which a candidate emissions-reduction strategy might prove vulnerable. The underlying study considered the effects of uncertainty about natural climate variability on the design of robust, near-term emissions mitigation strategies. This uncertainty about the level of natural variability makes it more difficult to determine the extent to which any observed climate trend is due to human-caused effects and thus makes it more difficult to set the signposts that would suggest emissions mitigation policies ought to be adjusted. The study first identified a strategy robust over the commonly discussed range of uncertainty about the potential impacts of climate change and the costs of emissions mitigation. It then examined a wider range of poorly characterized uncertainties in order to find those uncertainties to which the candidate robust strategy remains most vulnerable. The study finds two such uncertainties most important to the strategies' performance: the probability of unexpected large damages due to climate change and the probability of unexpectedly low damages due to changes in climate variability. Figure 5.6 traces the range of probabilities for these two uncertainties that would justify abandoning the proposed robust strategy described in the shaded region in favor of one of the other strategies shown on the figure. Rather than asking scientists or decision makers to quantify the probability of surprisingly large climate impacts, the analysis suggests that such a surprise would need to have a probability larger than roughly 10 to 15 percent in order to significantly influence the type of policy response the analysis would recommend. Initial findings suggest that this may provide a useful framework for facilitating the discovery, characterization, and communication of potential surprises.

Behavioral decision theory

The preceding discussion has focused on decision making by "rational actors." In the case of most important real-world decision problems, there may not be a single decision maker, decisions get worked out and implemented through organizations, in most cases formal analysis plays a subsidiary role to other factors, and in some cases, emotion and feelings (what psychologists term "affect") may play an important role.

These factors are extensively discussed in a set of literatures typically described as "behavioral decision theory" or risk-related decision making. In contrast to decision analysis that outlines how people should make decisions in the face of uncertainty is they subscribe to a number of axioms of rational decision making, these literatures are descriptive, describing how people actually make decisions when not supported by analytical procedures such a decision analysis.

Good summaries can be found in Kahneman *et al.* (1982), Jaeger *et al.* (1998), and Hastie and Dawes (2001). Recently investigators have explored how rational and emotional parts of human psyche interact in decision making (Slovic, *et al.,* 2004; Peters *et al.,* 2006; Loewenstein *et al.,* 2001; Lerner *et al.,* 2003; Lerner and Tiedens, 2006). Far from diminishing the role of affect-based decision making, several of these authors argue that in many decision settings it can play an important role along with more analytical styles of thought.

There are also very large literatures on organizational behavior. One of the more important subsets of that literature for decision making under uncertainty concerns the processes by which organizational structure can play a central role in shaping the success of an organization in coping with uncertainty and strategies they can adopt to make themselves less susceptible to failure (see for example: LaPorte and Consolini, 1991; Vaughan, 1996; La Porte, 1996; Paté-Cornell *et al.,* 1997; Pool, 1997; Weick and Sutcliffe, 2001).

The "precautionary principle" is a decision strategy often proposed for use in the face of high uncertainty. There are many different notions of what this approach does and does not entail. In some forms it incorporates ideas of resilience or adaptation. In some forms, it can also be shown to be entirely consistent with a decision analytic problem framing (DeKay *et al.,* 2002).

However, among some proponents, precaution has often taken the form of completely avoiding new activities or technologies that might hold the potential to cause adverse impacts, regardless of how remote their probability of occurrence. In this form, the precautionary principle has drawn vigorous criticism from a number of commentators. For example Sunstein (2005) argues:

> …a wide variety of adverse effects may come from inaction, regulation and everything in between. [A better approach]…would attempt to consider all of these adverse effects, not simply a subset. Such an approach would pursue distributional goals directly by, for example, requiring wealthy countries – the major contributors to the problem of global warming – to pay poor countries to reduce greenhouse gases or to prepare themselves for the relevant risks. When societies face risks of catastrophe, even risks whose likelihood can not be calculated, it is appropriate to act, not to stand by and merely hope.

Writing in a similar vein before "precaution" became widely discussed; Wildavsky (1979) argued that some risk taking is essential to social progress. Thompson (1980) has made very similar arguments in comparing societies and cultures.

Precaution is often in the eye of the beholder. Thus, for example, some have argued that while the European Union has been more precautionary with respect to climate change and CO_2 emissions in promoting the wide adoption of fuel efficient diesel automobiles, the Unites States has been more precautionary with respect to health effects of fine particulate air pollution, stalling the adoption of diesel automobiles until it was possible to substantially reduce their particulate emissions (Wiener and Rogers, 2002).

Table 7.1 In the expert elicitations of climate scientists conducted by Morgan and Keith (1995), experts were asked to design a 15-year long research program funded at a billion dollars per year that was designed to reduce the uncertainty in our knowledge of climate sensitivity and related issues. Having done this, the experts were asked how much they thought their uncertainty might have changed if they were asked the same question in 15 years. The results below show that like all good scientists the experts understand that research does not always reduce uncertainty. Note: Expert 3 used a different response mode for this question. He gave a 30% increase by a factor of ≥2.5.

Expert Number	Chance that the experts believe that their uncertainty about the value of climate sensitivity would *grow* by >25% after a 15yr. $\$10^9$/yr. research program
1	10
2	18
3	30 (Note 1)
4	22
5	30
6	14
7	20
8	25
9	12
10	20
11	40
12	16
13	12
14	18
15	14
16	8

Table 7.2 - Illustration from Casman *et al.* (1999) of the wide range of results that can be obtained with ICAM depending upon different structural assumptions, in this case, about the structure of the energy module and assumptions about carbon emission control. In this illustration, produced with a 1997 version of ICAM, all nations assume an equal burden of abatement by having a global carbon tax. Discounting is by a method proposed by Schelling (1994). Other versions of ICAM yield qualitatively similar results

		Model Variants								
Model Components		**M1**	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**	**M8**	**M9**
Are new fossil oil & gas deposits discovered?		no	**yes**	no	no	**yes**	**yes**	no	**yes**	**yes**
Is technical progress that uses energy affected by fuel prices and carbon taxes?		no	no	**yes**	no	**yes**	**yes**	**yes**	**yes**	**yes**
Do the costs of abatement and non-fossil energy technologies fall as users gain experience?		no	no	no	**yes**	no	no	**yes**	**yes**	**yes**
Is there a policy to transfer carbon saving technologies to non Annex 1 countries?		no	no	no	no	no	**yes**	**yes**	no	**yes**
TPE BAU in 2100 (EJ)	Mean	1975	2475	2250	2000	3425	2700	1450	3550	2850
TPE control in 2100 (EJ)	Mean	650	650	500	750	500	500	675	750	725
CO_2 BAU 2100 (10^9TC)	Mean	40	50	50	40	75	55	25	73	55
	Std. Deviation	*28*	*18*	*36*	*29*	*29*	*23*	*22*	*27*	*21*
Mitig. Cost (%Welfare)	Mean	0.23	0.44	0.14	0.12	0.48	0.33	0.05	0.23	0.17
	Std. Deviation	*0.45*	*0.23*	*0.23*	*0.22*	*0.28*	*0.12*	*0.07*	*0.12*	*0.11*
Impact of delay (%Welfare)	Mean	-0.1	0.2	-0.6	0.0	-1	-0.5	-0.1	-0.6	-0.4
	Std. Deviation	*1*	*0.3*	*1*	*0.7*	*1.2*	*0.9*	*0.5*	*0.8*	*0.6*

Notes: TPE = Total Primary Energy.
BAU = Business as Usual (no control and no intervention).
Sample size in ICAM simulation = 400.

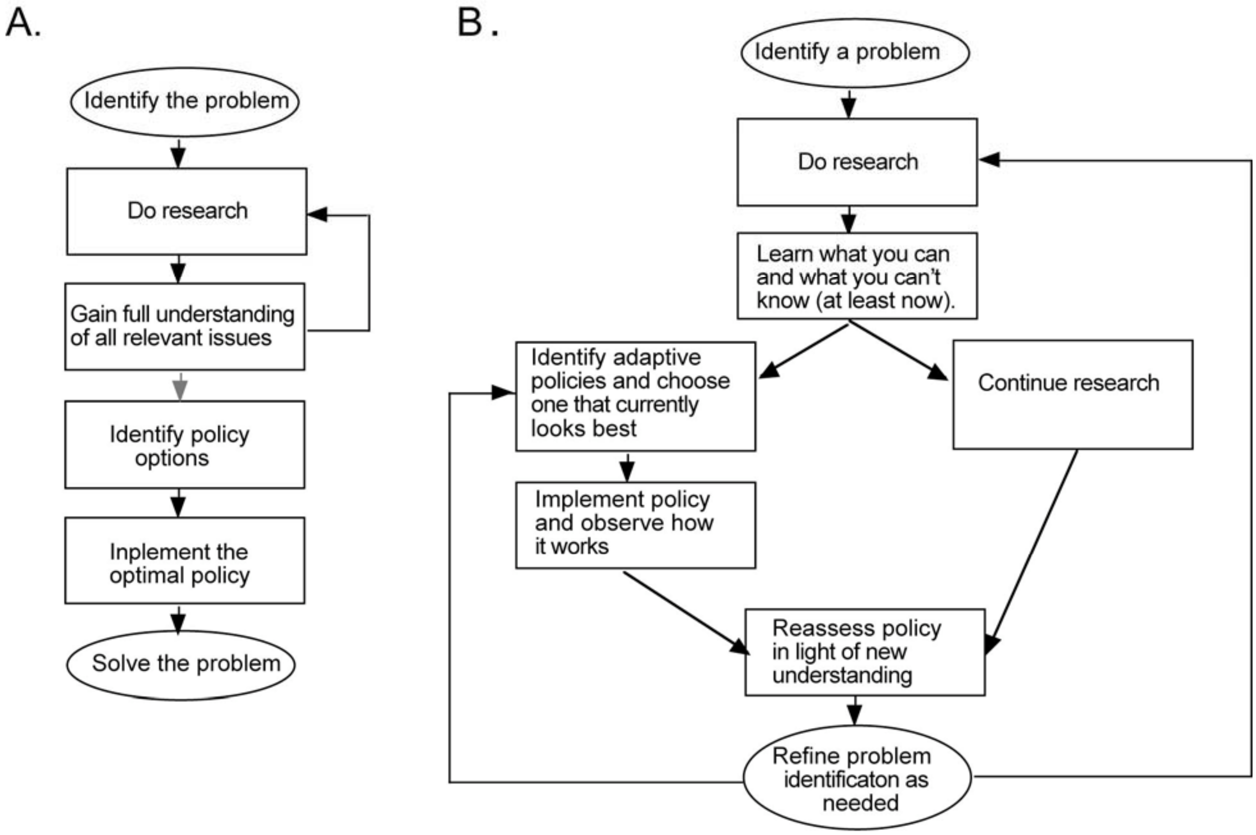

Figure 7.1 In the face of high levels of uncertainty, which may not be readily resolved through research, decision makers are best advised to not adopt a decision strategy in which nothing is done until research resolves all key uncertainties (A), but rather to adopt an iterative and adaptive strategy (B).

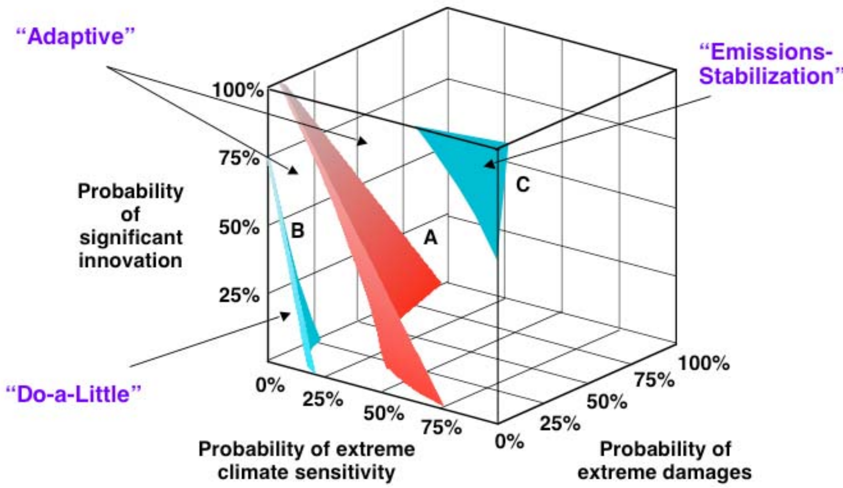

Figure 7.2 Surfaces separating the regions in probability space where the expected value of the "Do-a-Little" policy is preferred over the "Emissions-Stabilization" policy, the adaptive strategy is preferred over the "Do-A-Little" policy, and the adaptive strategy is preferred over the "Emissions-Stabilization" policy, as a function of the probability of extreme damages, significant innovation, and extreme climate sensitivity (Lempert *et al.*, 1996).

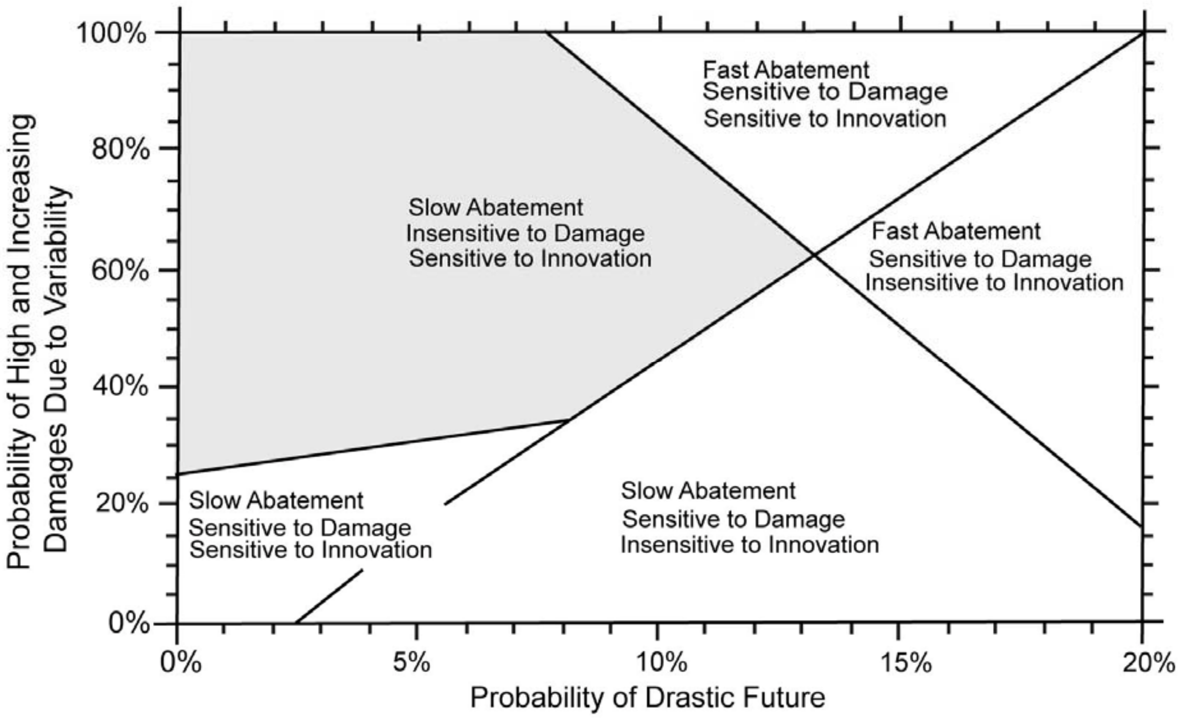

Figure 7.3 Estimates of the most robust emissions abatement strategy as a function of expectations about two key uncertainties -- the probability of large future climate impacts and large future climate variability (Lempert and Schlesinger, 2006). Strategies are described by near-term abatement rate and the near-term indicators used to signal the need for any change in abatement rate. The shaded region characterizes range of uncertainty over which one strategy of interest is robust.

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