Available online at www.sciencedirect.com
ScienceDirect
Global Environmental Change 17 (2007) 73–85
Global Environmental Change
www.elsevier.com/locate/gloenvcha

A new analytic method for finding policy-relevant scenarios

David G. Groves*, Robert J. Lempert

RAND, 1776 Main Street, Santa Monica, CA 90407, USA

Received 19 May 2006; received in revised form 20 November 2006; accepted 20 November 2006

Abstract

Scenarios play a prominent role in policy debates over climate change, but questions continue about how best to use them. We describe a new analytic method, based on robust decision making, for suggesting narrative scenarios that emerge naturally from a decision analytic framework. We identify key scenarios as those most important to the choices facing decision makers and find such cases with statistical analysis of datasets created by multiple runs of computer simulation models. The resulting scenarios can communicate quantitative judgments about uncertainty as well as support a well-defined decision process without many drawbacks of current approaches. We describe an application to long-term water planning in California.

Keywords: Scenarios; Climate change; Uncertainty; Water management

1. Introduction

Scenarios increasingly make important contributions to policy debates over climate change. They help commutate the potential seriousness and uncertainty surrounding climate impacts, provide reference cases for future analyses, and can support risk assessments and policy choices. For instance, the Special Report on Emissions Scenarios (SRES) (Nakicenovic et al., 2000) created four families of 21st century emissions scenarios for the Intergovernmental Panel on Climate Change's (IPCC) Third Assessment Report (Houghton et al., 2001). Widely used to convey the uncertainty over future levels of anthropogenic greenhouse gases, these scenarios illuminate key trends driving these emissions (such as economic growth rates, the extent of globalization, and the direction of technological change), and have provided inputs to numerous studies of potential climate change impacts and policies.

Despite the usefulness of the SRES and other such climate scenarios, there remains a significant gap between current scenario practice and its potential contributions (Parson et al., 2006). Two of the most important, unresolved methodological challenges involve the best means to choose three or four scenarios to summarize what is often a very wide range of uncertainties and how best to include probabilistic information with such scenarios. This paper will describe a new analytic method for identifying scenarios that may help resolve both these questions.

In principle, well-developed methods exist for choosing a small set of scenarios. As described by Schwartz (1996), a scenario exercise should begin by describing the decision challenge facing the scenario users. The exercise next identifies the most significant driving forces affecting future trends relevant to this decision based on their level of uncertainty and their potential impact. The exercise then proposes three or four scenarios that explore different combinations of these driving forces and finally fleshes each scenario out into a self-consistent and compelling story about the future.

This approach to scenario development is often called the scenario-axes method, because the scenarios can be graphically displayed along axes defined by the driving forces. For instance, the SRES team developed both qualitative storylines and quantitative runs of simulation models. They arrayed the storylines along axes representing two key forces underlying future emissions—the extent to which: (1) future development balances environmental concern as well as economic growth and (2) nations align

*Corresponding author. Tel.: +1 510 868 1819; fax: +1 310 260 8151.
E-mail address: groves@rand.org (D.G. Groves).

0959-3780/$ - see front matter
doi:10.1016/j.gloenvcha.2006.11.006

themselves within regional or global groupings and institutions. Fig. 1 reproduces a diagram used often in SRES publications. A typical output of the scenario-axes approach, it shows how the four combinations of these two driving forces define the main SRES storylines—labeled A1, B1, A2, and B2—about the key influences on future greenhouse gas emissions.

The scenario-axes method derives from the view that scenarios should change the way decision makers see their environment, challenge and reorganize their mental models, and give them new intuition about the way the world can work (Wack, 1985). A simple range of plausible values for some important parameter, such as future greenhouse gas emissions, is seen as insufficient to accomplish this goal. Rather, the scenarios must present a small number of diverse futures that fundamentally engage and confront the decision makers' view of the future. Accordingly, the scenarios aim to describe futures that differ in ways intensely important to the decision-making audience, and to relate these differences to the alternative paths that might be followed by a small number of fundamental trends affecting the decision makers' world.

While widely used in one form or another, this scenario-axes approach often fails to achieve its goals with the diverse audiences commonly found in public policy debates. In many such cases, the multiplicity of combinations of a large number of uncertainties suggests hundreds to millions of potentially interesting scenarios. The choice of a handful of the most interesting scenarios often rests on the particular concerns and values of those crafting them. These choices may not fully reflect the diverse views of the relevant policy community, who may see the chosen scenarios as arbitrary or biased towards some particular

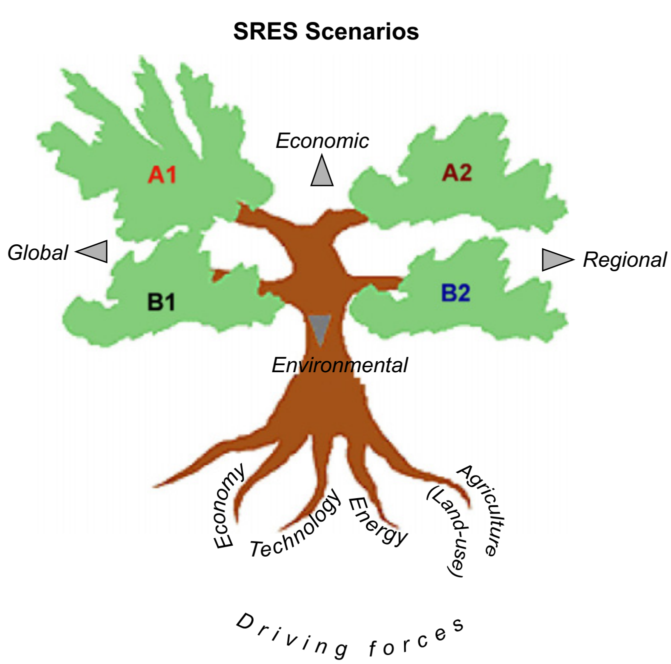

Fig. 1. Scenario axes used for SRES scenarios (Nakicenovic et al., 2000).

policy outcome. Parson et al. (2006) note that the unavoidable role developers' judgments play in constructing scenarios provides ample opportunity for partisan challenges to their relevance and accuracy. Even within a scenario-developer group, the scenario-axes method may prove insufficient to capture the diversity of views. For instance, van 't Klooster and van Asselt (2006) conducted ethnographic research to describe how futurists in Dutch planning agencies create scenarios. They found that the standard scenario-axes technique failed to serve as a unifying structure for diverse participants. Rather, the process devolved into several fundamentally different interpretations of the role the driving forces played in supporting the scenarios.

These shortcomings of the scenario-axes method strongly influenced the SRES process. The SRES team produced storylines prior to their quantitative model runs and featured the former prominently in their publications. However, compared to the use made of SRES's range of quantified emissions paths, the climate community largely ignores the storylines' analysis of key driving forces. The quantified paths provide a foundation for virtually all serious assessments of future climate change and policies, while the story lines exist primarily as four short paragraphs perfunctorily quoted, if mentioned at all. There is arguably little integration, and occasional inconsistency, between the SRES storylines and model runs (Parson et al., 2006). Substantive divergence also existed among the SRES team over the meaning of some storylines. In the end, the team failed to agree on descriptive names, relying instead on the unevocative final choice of the storyline labels A1, A2, B1, and B2.

Current scenario practice also leaves unresolved the question of whether and how to best incorporate probabilistic information. Following recommendations in the scenario literature (Schwartz, 1996), the SRES developers chose not to include any likelihood estimates with their scenarios. Rather the SRES team labeled all the scenarios as "equally sound," language intended to suggest that policy makers should seriously consider each scenario. This decision, however, has generated considerable debate, and Parson et al. (2006) argue that the probability issue remains central to concepts of how scenarios ought to be developed, interpreted, and used to support decision makers.

Many commentators, such as Schneider (2001), Reilly et al. (2001), Giles (2002), and Webster et al. (2003), note that probabilities are the standard language of risk assessment and decision analysis and that decision makers will ultimately require information about the likelihood of various scenarios in order to make sound judgments about the resources they should allocate to address them. If the scenario-developers do not suggest which scenarios are most and least likely, decision makers will use probabilistic information obtained from other, likely less expert, sources.

Others, such as Wack (1985), Grubler and Nakicenovic (2001), Allen et al. (2001), and Lempert et al. (2004), argue that any such probabilities would be misleading and detrimental to the credibility of the scenarios among diverse audiences. They note the difficulty of making meaningful probability estimates of many key driving forces such as future technological and political developments. They also note the challenge of defining the boundaries of a particular scenario in a large, multivariate space of possibilities and thus the technical difficulty of unambiguously assigning a probability weighting. Most importantly, those opposed to placing probabilities on scenarios contend that such quantification will impede the scenarios' ability to encourage a diverse group of participants, who may often hold different expectations about the likelihood of alternative futures, to engage with and agree on the range of uncertainties they face.

The traditional scenario literature also leaves unresolved how the scenarios ought to support decision making. Some scenario-planning literature does suggest using scenarios to assess the robustness of alternative policies (van der Heijden, 1996), but offers no systematic means of doing so that would stand scrutiny in the policy debates surrounding an issue such as climate change.

The new analytic method described in this study aims to address both the challenge of choosing a small number of relevant scenarios and incorporating probabilistic information with those scenarios. The central idea is to use multiple runs of computer simulation models to identify those scenarios most important to the choices facing decision makers. This scenario-identification process emerges naturally from robust decision making (RDM) (Lempert et al., 2003), a decision analytic framework based on the concept of identifying strategies robust over a wide range of often poorly-characterized uncertainties.

In brief, RDM starts with one or more proposed policy actions, which may be suggested by policy analysis or drawn from the policy debate. Integrated assessment computer simulations report the strategies' performance over a very wide range of plausible future states of the world. As described in more detail below, statistical cluster-finding algorithms then identify one or more easily-interpretable, low-dimensional regions in the often large, multivariate space of plausible futures where the proposed policy actions of interest perform particularly well or poorly compared to the alternatives (Lempert et al., 2006). The resulting clusters of futures suggest scenarios that are particularly relevant to the decision makers' choices. This process not only yields scenarios with a clear justification for their choice, but also quantitative measures of merit for their ability to summarize the most policy-relevant uncertainties.

This process also suggests likelihood thresholds for the scenarios that might cause decision makers to prefer one strategy over another. For instance, the analysis might suggest to policy makers debating the choice between Strategies A and B that they should favor the latter only if they believed the odds of some extreme scenario were greater than 10:1. Scenario developers can then compare such thresholds to a wide range of views about the likelihood of this scenario. This approach can reduce the risk of overestimating the certainty of such estimates or of provoking rejection of the scenarios by those who disagree about their likelihood.

The next section of this paper will review the RDM approach from which the proposed scenario-identification process derives. The paper then presents an example application to the challenge of water resource management in California (Groves, 2005) to introduce the proposed process and to suggest how policy makers can best use the resulting scenarios. The paper will close with observations about the strengths and weaknesses of this new approach, and how it might be applied more broadly to other climate change policy questions.

2. Robust decision making

The traditional optimum expected utility approach to decision making under uncertainty has proved extraordinarily useful for a wide range of decision challenges (see Morgan and Henrion, 1990 for an excellent review). In brief, the process begins with a system model that describes outcomes of interest contingent on the choice of strategy. Uncertainties are characterized with probability distributions over input parameters to the system model. The analysis then recommends the strategy with the optimal expected utility contingent on these distributions. In sophisticated applications, sensitivity analysis (Saltelli et al., 2000) can then suggest how this ranking of policies might be affected by different assumptions about parameter values or probability distributions. But at its heart, this optimum expected utility framework addresses decisions under uncertainty with two distinct and sequential steps. First, risks are characterized by a single set of probability distribution over future states of the world. Second, this risk characterization is used to rank the desirability of alternative policy choices.

There is widespread agreement that this traditional optimum expected utility approach, at least in its most basic form, is insufficient to address decision challenges with the characteristics of climate change (see for instance Arrow, 1995; Dessai et al., 2004; Jaeger et al., 1998; Lempert et al., 2004; Morgan et al., 1999; Sarewitz and Pielke, 2000). In particular, climate change affects a large number of diverse interests and presents uncertainty so large that it is not possible to confidently define a system model or prior probability distributions on all the inputs. We use the term deep uncertainty to describe such conditions, defined as the situation where decision makers do not know nor cannot agree upon the system model that relates action to consequences, the prior probabilities on the inputs to the system model(s), or the value function that ranks the desirability of the consequences. If applied under conditions of deep uncertainty, traditional optimum expected utility methods can encourage analysts and decision makers to be overconfident in their estimates of uncertainty in order to make predictions more tractable (see, for example, Metlay, 2000); can make agreement on actions more difficult as parties gravitate towards the differing expert pronouncements of probability distributions most compatible with their own individual values, policy priorities, or decision contexts (Herrick and Sarewitz, 2000); and can lead to strategies vulnerable to surprises which might have been countered had the available information been used differently (Lempert et al., 2002; Rayner, 2000).

RDM provides a quantitative decision-analytic approach to decision making under conditions of deep uncertainty that attempts to address some of these problems and, in so doing, may also provide a rigorous, quantitative approach for choosing a small number of representative scenarios and incorporating probabilistic information with these scenarios. RDM is one of a variety of approaches that recognize the importance of robustness as a decision criteria appropriate under conditions of deep uncertainty (Ben Haim, 2001; Metz et al., 2001; Rosenhead, 1989; Rosenhead et al., 1972; Yohe et al., 2004). It has been described extensively in the scholarly (Lempert et al., 2003, 2006; Lempert and Popper, 2005) and popular literature (Light, 2005; Popper et al., 2005).

RDM proceeds from the observations that decision makers often manage deep uncertainty by choosing strategies whose good performance is relatively insensitive to poorly characterized uncertainties. RDM formalizes this notion with the concept of robust strategies, that is, ones that perform relatively well, compared to the alternatives, across a wide range of plausible future states of the world. RDM uses computer simulation models, not to predict the future, but to create large ensembles of hundreds to millions of plausible future states that are used to identify candidate robust strategies and systematically assess their performance. Search algorithms, interactive visualization, and statistical analyses then help users: (1) identify robust strategies whose satisfactory performance is largely independent of the eventually revealed true values of most unknowns, and (2) characterize the few deep uncertainties most important to the choice among strategies.

RDM is consistent with traditional optimum expected utility analysis, but inverts its order. While expected utility decision analysis first characterizes the uncertainty as a prelude to ranking decision, RDM is an iterative process that begins with decision options and then runs the expected utility machinery many times in order to identify potential vulnerabilities of these candidate strategies, that is, combinations of model formulations and input parameters where the strategy performs relatively poorly compared to the alternatives. The analysis then suggests new or modified strategies that might perform better in these vulnerable futures and characterizes the tradeoffs involved in choosing among these decision alternatives. In contrast to traditional sensitivity analysis, which often suggests how the ranking of strategies may change with differing assumptions, RDM seeks to identify strategies whose satisfactory performance compared to the other strategies is relatively insensitive to all or most of the most significant uncertainties. As part of this process, RDM uses statistical cluster-finding algorithms to identify regions of parameter or probability space where alternative decisions have significantly different performance (Lempert et al., 2006), similar to the policy-region analysis of Watson and Buede (1987). These regions can usefully be interpreted as policy-relevant scenarios.

Traditional scenarios represent another popular approach to informing decision under deep uncertainty that also inverts the order of traditional expected utility analysis. Like RDM, the scenario-axes method also begins by identifying strategies of interest to decision makers and then seeking key driving forces most relevant to those decisions.[1] Given the multiplicity of plausible futures, the scenario literature emphasizes this focus as important to the communicative power of a small set of scenarios. No small set of scenarios can adequately summarize all plausible futures, and only by focusing on those most relevant to their concerns can several scenarios capture decision makers' attention. Many of the practical struggles groups have reaching consensus on a small number of representative scenarios appear to derive from difficulty retaining this decision-focus throughout a qualitative scenario-creation process. Similarly, the desire to use scenarios within the traditional optimum expected utility decision analytic framework clearly underlies many attempts to include probabilistic information with scenarios. Much of the opposition seems fueled by a sense that such a decision framework is not the best context in which to use scenarios.

RDM provides a quantitative decision analytic framework consistent with the process and motivation of traditional, qualitative scenario methods. The approach thus offers the possibility of blending some of the best features of analytic decision analysis and narrative scenario-based planning. In particular, RDM may provide a systematic means for identifying a small number of representative scenarios and using them with probabilistic information as part of a structured decision analytic process. At the same time, the approach, designed to avoid some of the difficulties inherent in applying optimum expected utility methods under deep uncertainty, may also help maintain and enhance scenarios' ability to communicate this deep uncertainty to diverse audiences.

3. Using scenarios to inform California water planning

The challenge of water resource management in California provides an excellent application of the RDM-approach to

[1]This similarly is of course no coincidence. RDM is an example of the school of computational, multi-scenario simulation approaches (see Metz et al., 2001, (Section 10.14.4)) that aim to incorporate ideas from scenario-based planning into a quantitative framework.

identifying scenarios. The California Department of Water Resources (DWR) has recently completed the latest of its 25-year, long-term, water planning documents—the California Water Plan (DWR, 2005). For the past 50 years, DWR has generally used single best-estimate forecasting in its long-term planning documents. The most recent water plan for the first time addresses uncertainty about the future using a traditional scenario approach.[2] Our group both participated in DWR's scenario process as well as contributed to the agency's efforts to identify improved methods for addressing uncertainty in future California water plans.

Table 1
Resource management strategies considered in the California Water Plan Update 2005 (DWR, 2005)

Agricultural lands stewardship	Recharge area protection
Agricultural water use efficiency	Recycled municipal water
Conjunctive management and groundwater storage	Surface storage—CALFED
Conveyance	Surface storage—regional/local
Desalination	System reoperation
Drinking water treatment and distribution	Urban land use management
Economic incentives	Urban runoff management
Ecosystem restoration	Urban water use efficiency
Floodplain management	Water transfers
Groundwater remediation	Water-dependent recreation
Matching water quality to use	Watershed management
Pollution prevention	Other resource management strategies
Precipitation enhancement	

3.1. The 2005 California Water Plan scenario process

The 2005 update of the California Water Plan (hereafter 2005 CWP) presents a broad overview of the short- and long-term issues facing water resources management in California. The document lays out a new framework for meeting various objectives including state-wide water reliability and environmental preservation and restoration, and it includes descriptions of more than 25 different resource management strategies that ought to be considered as future management and investment decisions are made (Table 1). Notably, the 2005 CWP was developed with the substantial participation of a diverse 65-member advisory committee comprised of stakeholders drawn from agencies and organizations across the state.

In contrast to prior plans, the 2005 CWP strongly emphasizes uncertainty about future water management conditions. It discusses challenges in estimating future urban, agricultural, and environmental water needs. It describes numerous institutional challenges affecting future water supplies including water rights and environmental and water quality legal requirements. It also details many uncertain risks to the aging existing infrastructure—particularly those facing the levee system within the San Francisco Bay-Delta. Finally, it highlights ways in which climate change may affect the state's water system. These discussions recognize that many of these factors are poorly understood and thus pose a formidable challenge to planning (DWR, 2005).

The DWR planning staff and CWP advisory committee struggled to agree upon the appropriate analytic framework for evaluating future water needs, available resources, and appropriate management strategies, given the substantial uncertainty about future conditions. Many participants believed that the existing simulation models of the water management system were ill-suited for planning purposes because they were too complex to be adequately understood by interested parties, imbedded too many important and contentious assumptions about how the system functioned, or were too cumbersome to evaluate the many proposed management options under a wide range of possible future conditions. Furthermore, the participants argued that a deterministic approach to water supply and demand forecasting, as had been applied in past water plans, would not be appropriate given the growing appreciation for the uncertainties about future water management conditions.

The 2005 CWP staff and advisory committee ultimately chose to initiate a traditional scenario planning approach to help select among the many possible management strategies. As is often the case with large, pluralistic organizations, the 2005 CWP staff was unable to involve a small, core group of participants throughout the entire scenario-building exercise. Instead, DWR held several meetings, each attended by a different group of between 15 and 21 people, to shape the development of a set of initial scenarios that only considered variations in factors affecting water demand. A smaller group of DWR staff and meeting facilitators then used this input to develop the ultimate scenario narratives. The official 2005 CWP presented three scenarios of water demand, named "Current Trends", "More Resource Intensive", and "Less Resource Intensive." DWR deferred analysis of management strategies and water supply conditions to future editions of the Water Plan.

Throughout the scenario process, the advisory committee members and other stakeholders expressed apprehension.[3] There was concern that three scenarios could not encompass all the relevant uncertainties affecting future

[2]In prior Water Plans separate forecasts of future water supply and demand under different hydrologic conditions were sometimes developed (see for example the 1998 California Water Plan (DWR, 1998)). We argue that these do not represent distinct "scenarios" of water demand and supply, as they arise from the same assumptions for all underlying factors. The differences between the forecasts only arise from different expectations for precipitation drawn from the same assumed distribution of hydrology. Such projections could be likened to engineering reports that describe the performance of a road or bridge under summer and winter conditions.

[3]See California Water Plan Update 2005 Public Advisory Committee (2005) for a discussion of areas in which committee members agreed and disagreed (available at http://www.waterplan.water.ca.gov/docs/cwpu2005/vol4/vol4-background-acview.pdf).

water demand. Observers also rightly observed that considering water demand in isolation of supply and active management diminishes the role that feedbacks among them could play. For example, as each baseline water demand scenario specifies a single trend in water price, the relevance of such a scenario could be dramatically diminished under supply conditions that would never support such a price trend.

The small number of scenarios developed for the 2005 CWP also proved problematic. There was considerable ambiguity about the descriptions of the scenarios and connotations of the various scenario names. For example, there was no consensus on what "Current Trends" meant and what a "Current Trends" scenario should look like. Many stakeholders also tried unsuccessfully to identify scenarios that matched their views of the future. Without such scenarios, some stakeholders feared that future analyses based on these scenarios would not lead to a serious consideration of their preferred management approach. For example, at least one group participating in the 2005 CWP chose to develop and publish an analysis of its own scenario (Gleick et al., 2005). Finally, many participants expressed confusion and concern about how the scenarios would inform the significant choices facing California water managers.

3.2. Quantifying the California Water Plan scenarios

DWR invited our group to participate in the Water Plan scenario process, in particular by developing a model that could quantify their three narrative scenarios. To support this request and our subsequent RDM work, we developed a simple low-resolution model in the Analytica software package[4] that could estimate urban and agricultural water demand for each of California's 10 hydrologic regions (Fig. 2) under alternative demographic, economic, agricultural, and water management conditions.[5]

The model, described in detail in Groves (2005), estimates urban water demand by quantifying plausible trends of households, employees, persons (as a proxy for institutional water use), and per unit demand for each from the year 2000 (an average year climatically for most of California) to 2030.[6] Future urban water demand is then computed by multiplying the future demand units and their average water use. Agricultural water demand is estimated by specifying future state-wide changes in irrigated land area and multi-cropping, and trends in parameters that define how much water is needed per area of crop. Changes in crop-mix are estimated through a set of rules that apportion the statewide changes to the hydrologic regions.

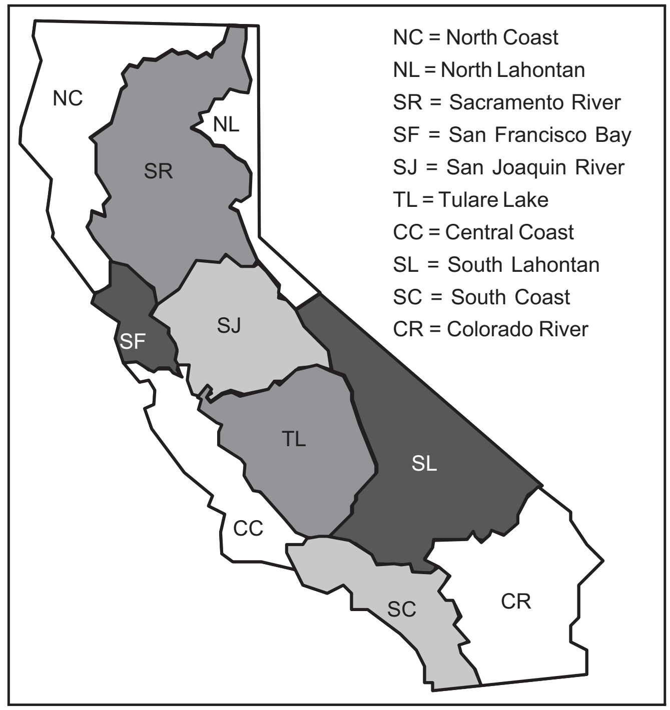

Fig. 2. California's 10 hydrologic regions (Groves, 2005). The RDM-scenario analysis focuses on the South Coast (SC) region.

This low-resolution model considers the effects of about 30 key uncertainties, including population and economic growth rates, water price and conservation trends, and a variety of parameters related to agricultural water use. The model is designed to be calibrated to the results of California's high-resolution water demand models. That is, the low-resolution model can reproduce the results of cases run by the more detailed models and can thus be used to interpolate among and extrapolate beyond this small number of examples.[7]

Each model run is based upon average current conditions that evolve over time (from 2000 to 2030) according to parameters representing the major factors that are believed to influence future water demand. Scenarios are distinguished from one another by the specification of a unique set of factors representing various trends and parameters in the model.

We used the model to provide quantified time series for future California water demand by sector and region for each of DWR's three narrative scenarios (Groves et al., 2005), and the results are featured prominently in state publications presenting the 2005 California Water Plan (e.g. DWR, 2005).

[4]Analytica is available from Lumina Decision Systems, Inc. (www.lumina.com).

[5]The model also included a rough estimate of additional water needs for environmental purposes.

[6]This basic method of forecasting urban water demand is similar to the approach taken by other urban water demand models such as IWR-MAIN (PMCL, 1999).

[7]For the Water Plan analysis, detailed modeling results of state-wide water demand were not available for comparison with the scenario estimates. Instead, we used recent demographic and agricultural land use estimates to inform the "Current Trends" scenario to assure that the scenarios were consistent with the best available forecasts of future water use factors.

Table 2
Parameter list and ranges used in the RDM analysis and values for 2005 CWP current trends scenario

Parameter	Parameter range[a]		Current trends scenario
	Low	High	
Population growth (% of DOF estimate)	0.75	1.25	1.0
Share of multi-family houses (% change from Current Trends)	−5%	+10%	+0%
Single family household size (% change from Current Trends)	+0%	+20%	+0%
Multi-family household size (% change from Current Trends)	+0%	+20%	+0%
Single family use price elasticity	−0.35	−0.05	−0.16
Multi-family use price elasticity	−0.07	−0.03	−0.05
Single family use income elasticity	0.20	0.60	0.40
Multi-family use income elasticity	0.25	0.65	0.45
Single-family use household size elasticity	0.20	0.60	0.40
Multi-family use household size elasticity	0.30	0.70	0.50
Employed fraction (% change from Current Trends)	+0%	+2.5%	+0%
Commercial use price elasticity	−0.25[b]	−0.07	−0.085
Industrial use price elasticity	−0.25[b]	−0.07	−0.085
Public use price elasticity	−0.25[b]	0.0	0.0
Urban naturally occurring conservation (includes 5% efficiency)	5%	25%	15%
Marginal cost increase of policy-induced efficiency	0.5	2	n/a

[a]The parameter ranges are drawn from the consultation with DWR staff. See Groves (2005) for more details.
[b]Lower bound of price elasticity factors suggested by Pacific Institute (Gleick et al., 2005).

3.3. Identifying policy relevant scenarios using RDM

We also used this model to support DWR's consideration of improved methodologies for handling uncertainty in future water plans. This stylized analysis focuses on the urban sector of Southern California to demonstrate how RDM can identify policy-relevant scenarios for the California water planning community (Groves, 2005).

We first modified the demand model described above to consider only the South Coast hydrologic region and to include a simple representation of future average-year water supplies. The model has 16 key uncertain parameters shown in Table 2. The scenario model was also expanded to evaluate the performance of hypothetical water management strategies consisting of new supply projects and improved urban water use efficiency for Southern California across a wide range of future water management conditions.[8] The analysis considers 24 strategies reflecting each combination of zero to three new supply projects (each yielding 300,000 acre-feet per year—about 3.7 million m^3 per year—of new supply) and efficiency improvements between 0% and 25% (in 5% intervals).

The performance of a particular strategy is evaluated by an aggregate cost measure (net cost) which includes the costs of (1) developing new supply, (2) increasing urban water use efficiency, and (3) acquiring expensive spot-supply in years in which average annual demand exceeds average annual supply.[9]

We use RDM methods to identify policy-relevant scenarios, which in turn can be used to identify robust policies and represent the remaining tradeoffs facing decision makers. The analysis begins by identifying a single base case strategy that leads to the best (or optimal) outcome (lowest net cost) for the future conditions described by DWR's "Current Trends" water demand scenario, contingent on assumptions about future water demand, the performance and cost characteristics of the notional new supply, and urban water use efficiency programs. This base case strategy builds one new 300,000 acre-feet per year water supply project and improves water use efficiency by 10% over 30 years.

The analysis then identifies the future states of the world in which this base case strategy performs poorly compared to the alternative strategies described above, independent of any assessment of the likelihood of these states of the world. The low-resolution model compares the performance of a large set of alternative strategies over many plausible states. For each strategy, we use a 500-point Latin hypercube experimental design[10] to efficiently sample the space of plausible future states described by the 16 model uncertainties. The study identifies poorly performing states of the world as those with high regret where, following Savage (1954), we define regret as the difference between the base case strategy's net cost in a particular state of the world and the net cost of the optimal strategy in that state of the world. In this example, the regret for the

[8]For this analysis, we do not consider the existing management planning occurring in Southern California. See Wilkinson and Groves (2006) for a more specific examination of Southern California water management options using a variant of the model described here.

[9]The cost for meeting unanticipated demand can also be interpreted as a damage function for shortages.

[10]A Latin hypercube sample is created by dividing each exogenous factor into segments with sizes inversely proportional to the number of samples desired for each segment. The actual sample is then randomly sampled from within each of the segments. This provides an efficient space-filling experimental design for any given number of points in the sample.

base case strategy exceeds a hypothetical threshold value of interest to water managers in 86 of the 500 scenarios generated in the experimental design.[11]

To quantitatively identify scenarios, Lempert et al. (2006) introduced the use of Friedman and Fisher's (1999) "Patient" Rule Induction Method (PRIM) to find and characterize clusters in the database of model runs that represent states of the world where the strategies have significantly different performance. PRIM is a data-mining algorithm designed to generate a set of low-dimensional "boxes" in high-dimensional data containing regions where the value of a particular function is large (or small) compared to its value outside these boxes. PRIM seems particularly useful for suggesting scenarios because it aims to optimize both the classification accuracy of the boxes (the percentage of large or small function values they contain) and the interpretability of the boxes (the simplicity of the rules needed to define them).

We implement PRIM using publicly available software[12] that inputs a dataset (which can be the output of a model run over many combinations of input values) and a criterion for interesting cases defined, as in Lempert et al. (2006), as those where the regret of the proposed strategy exceeds some threshold value. The algorithm outputs descriptions of several alternative low-dimensional regions, or "boxes," that contain a high density of and span a high proportion of the interesting cases.

PRIM generally suggests several alternative scenarios along with two quantitative measures of merit—the coverage (or cluster size) and density of total states of interest captured by each region—that can help users choose among them. The coverage and density measures are generally inversely correlated since a larger cluster likely includes a lower density of high-value data. The PRIM software thus presents the user with tradeoff curves (such as the one shown in Fig. 3) that display clusters with different combinations of coverage and density. These clusters often differ in the number and identity of the driving forces that define them. Users then choose the cluster with the desired density/coverage tradeoff and interpretability, that is, the one whose particular set of defining driving forces makes it meaningful to the user as a scenario. After choosing a cluster, the records within it are removed from the database and PRIM can be run again on the remaining records to produce additional clusters.

We use PRIM to find low-dimensional clusters of high regret states of the world for the base case water management strategy in the 16-dimensional uncertainty space defined by the input parameters (Table 2) to our water management model. The resulting two clusters are shown in Fig. 4. The first cluster is defined by two of the model's 16 uncertainty input parameters. Irrespective of the value of the other uncertain parameters, any state of the world

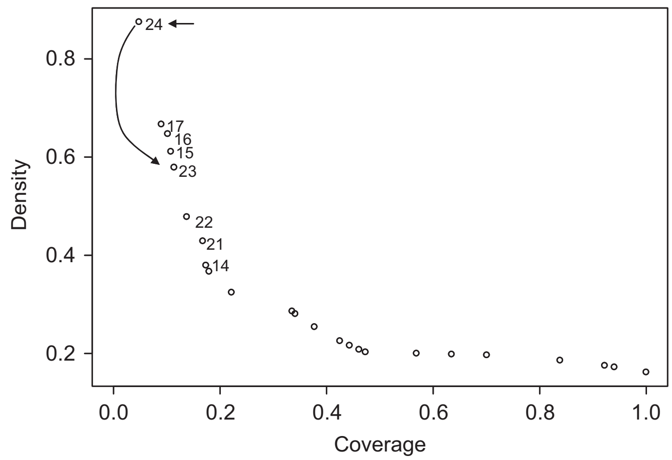

Fig. 3. Tradeoff curve for various PRIM-identified clusters. The *x*-axis (Coverage) is the cluster size relative to the space containing all cases and the *y*-axis (Density) indicates the fraction of cases of interest in each cluster. This study evaluated each clusters indicated by numbers in the figure and chose Cluster 24 (indicated by an arrow), which initially constrained 6 parameters. We dropped the four least significant parameters which decreased the box mean and increase the support to levels equivalent to those for Cluster 23. This cluster defines the Rapid Growth scenario described below.

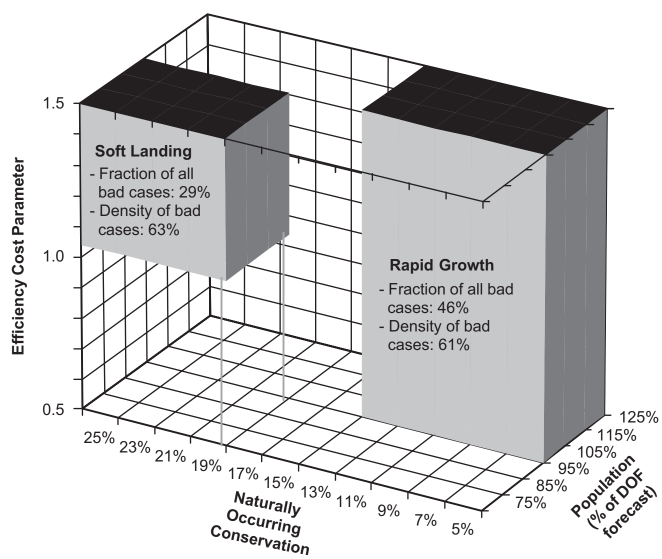

Fig. 4. Two clusters, defined by 3 of 16 uncertain model inputs, which capture 75% of the states of the world where the base case water management strategy performs poorly. The population axis represents the population growth rate expressed as a percentage of the California Department of Finance population forecast growth from 2000 to 2030 (DOF, 2004).

where population grows more than 95% of the California Department of Finance forecast (DOF, 2004) and where exogenous efficiency gains (or naturally occurring conservation) are less than 15% over 30 years is a member of this first cluster. We label this scenario the *Rapid Growth* scenario, as it reflects conditions in which demand growth is greater than anticipated due to higher population growth

[11]In this analysis, costs for new supply, efficiency, and spot supply as well as the regret threshold are notional.

[12]PRIM is available at http://stat.stanford.edu/~jhf/SuperGEM.html.

and lower naturally occurring conservation. In this scenario, costs are incurred to increase supply through the spot-market.

The second cluster is defined by three parameters. Any state in which population grows at a rate less than 97% of the Department of Finance forecast, in which exogenous efficiency gains are greater than about 19% over 30 years, and in which the slope of the marginal cost curve for efficiency is greater than 1.04 is a member of this second cluster.[13] We label this scenario the *Soft Landing* scenario, as it reflects conditions in which demand growth is lower than anticipated due to lower population growth rates and higher naturally occurring conservation and the cost of policy-induced efficiency is more expensive than anticipated. This scenario is undesirable not because of water shortages (as with the *Rapid Growth* scenario) but because of over-development of the region's supply. In this scenario the level of new supply and efficiency improvements are higher than needed, leading to unnecessary expenditures.

The RDM-scenario process thus identifies a small number of key driving forces particularly important to the decision makers' choice. Of the 16 uncertainties in the model, Fig. 4 identifies three—the population growth rate, the rate of exogenous conservation, and cost (or effectiveness) of new efficiency programs—as most policy-relevant. The process also suggests a small number of scenarios for consideration. In a traditional scenario exercise, the three uncertain driving forces along the axes of Fig. 4 would suggest eight different scenarios (one in each corner). The current analysis, however, identifies the two most important as a focus for policy-makers' attention.

The RDM-scenario process also provides measures of merit to help users assess the quality of a particular set of scenarios. In the current example, the two scenarios contain 75% of all the states of the world in the sample where the base case water management strategy has significantly higher costs than the best alternatives. The *Rapid Growth* scenario contains 40 (46%) and the *Soft Landing* scenario contains 25 (29%) of these 86 states where the base strategy performs poorly. The density of poor-performance states for the base case strategy inside these clusters is 61% and 63%, respectively—about 15 times the density of such states outside the clusters (~4%).

This example suggests that RDM provides a quantitative method that can identify a small number of policy-relevant scenarios consistent with the goals of traditional scenario methods but without some its chief shortcomings. The two scenarios in Fig. 4 are policy-relevant because they characterize the key vulnerabilities of the base case water management strategy. A decision maker who believes that one or both of these scenarios is likely may want to consider alternative strategies that perform adequately in such scenarios or devise new strategies that are less sensitive to the future states of the world represented by these scenarios.

It is also interesting to recall that traditional scenario practice often focuses on an external world with driving forces separate from and unaffected by the decisions of the scenario users. But often the most policy-relevant uncertainties include those that affect the performance of the decision makers' choices. The scenario process described here identified one such uncertainty—the cost of new efficiency programs in the *Soft Landing* scenario—as being more important to the success of the leading policy than all other factors except for population growth and naturally occurring efficiency. As traditional scenario analyses typically consider only exogenous factors in scenario construction, they would not have considered such an uncertainty.

3.4. Incorporating probabilistic information with scenarios

RDM and its associated scenario-identification process also provide a natural means to incorporate probabilistic information with scenarios. The current debate divides into two camps. On the one side, some argue that users require guidance on likelihoods to use the scenarios for decision making and that assigning probabilities to the scenarios helps incorporate the best available expert information. On the other side, some argue that scenario probability estimates suggest a misleading degree of certainty about the future and will inhibit the scenarios' ability to gain acceptance among users holding a wide range of expectations about the future. Furthermore, when disparate assessments of probabilities exist, there is no universally accepted way to adjudicate such disagreements.

Our proposed approach aims to address both sides' concerns by reporting the threshold likelihood decision makers would have to ascribe to a scenario in order to change their proposed policy strategy. That is, the approach asks "How likely would this scenario have to be in order to justify a change of strategy?"

As an example of this approach, Fig. 5 shows the optimum water management strategy estimated by our model for the South Coast region as a function of the probability of the *Soft Landing* (horizontal axis) and *Rapid Growth* (vertical axis) scenarios. If the *Rapid Growth* scenario is considered highly likely (upper left hand corner) policy makers ought to choose two new supply projects and seek 10% efficiency improvements (labeled a 2–10% strategy). If the *Soft Landing* scenario is considered highly likely (lower right-hand corner) policy makers ought to choose no new supply and 5% efficiency improvements (labeled 0–5%). Finally, if neither scenario is considered likely (lower left-hand corner), policy makers ought to choose their base case strategy of one new supply project and 10% efficiency improvements (labeled 1–10%).

[13]The marginal cost of reducing water demand through efficiency is specified to increase as a function of the percentage reduction. In other words, the first percentage of reduction in water demand due to efficiency is less expensive than subsequent reductions. This marginal cost schedule is simply represented by the following formula: $Mc_{\text{eff}} = a + b$ (Efficiency%). The model can reflect uncertainty in both parameters a and b. For this study, $a = 10$ and b ranges between 0.5 and 2.

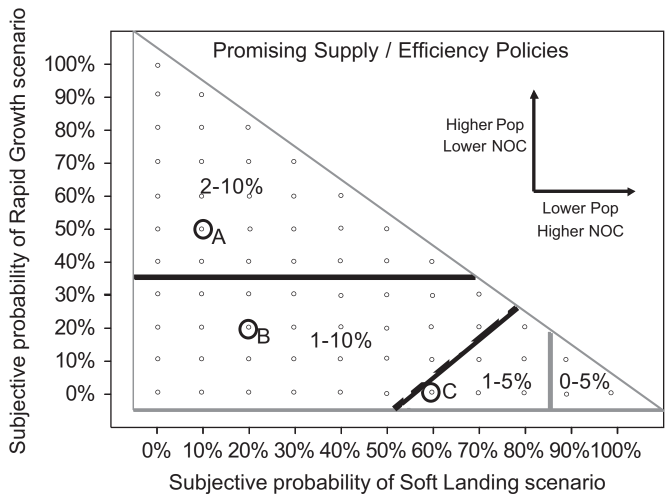

Fig. 5. Optimal water management strategies (labeled *n*-*x*%, where *n* is the number of new supply projects and *x* the policy-induced efficiency improvement) as a function of the probability of the *Rapid Growth* and *Soft Landing* scenarios (Groves, 2005). Dark lines indicate probability thresholds where 1–10% strategy is no longer optimal. Labels A, B, C indicate expectations of three notional groups using the analysis, as discussed in the text.

For decision makers considering the base case strategy, this figure thus defines critical likelihood thresholds for the *Rapid Growth* and *Soft Landing* scenarios. If decision makers believe *Rapid Growth* has a probability of 35% or greater they ought to consider choosing additional supply projects. Similarly, if they believe *Soft Landing* has a probability greater than 50 to 80% they ought to consider reducing their efficiency improvement goals. The lower, 50% threshold is more relevant if the decision makers believe that the *Rapid Growth* scenario is highly unlikely while the higher, 80% threshold is more relevant if decision makers believe *Rapid Growth* has a likelihood approaching 20%.

Incorporating probabilistic information as thresholds provides several benefits. First, the approach rests within a clear analytic framework for using these scenarios to support decisions. Second, the approach avoids a false sense of certainty associated with a specific probability estimate and preserves the scenarios' ability to gain acceptance and facilitate communication among users with diverse expectations about the future. For instance, imagine this analysis provides information to a group of decision makers from three distinct factions. Group A believes that the *Rapid Growth* scenario is very likely (50% chance) and the *Soft Landing* scenario is very unlikely (10% chance). Group B believes that neither scenario is likely (20% chance each). Group C believes that the *Soft Landing* scenario is most likely (a 60% chance) and the *Rapid Growth* scenario is not likely at all. Fig. 5 can demonstrate to each Group the policy implications of their expectations about the future, reassure them that the model fairly represents their point of view, and help each group understand the thinking of the others.

Finally, this threshold approach provides a framework for communicating any available information about the likelihood of the alternative scenarios. For example, probabilistic population forecasts for Southern California and expert elicitations could suggest likelihoods for the *Rapid Growth* and *Soft Landing* scenarios. The results of both analyses could be displayed on Fig. 5 and enable decision makers to consider the policy tradeoffs.

This approach of incorporating probabilities could also be applied to scenarios generated by the traditional scenario-axes method. For instance, an analysis conducted for California officials concerned about the impacts of climate change on their long-term water management plans might determine whether a plan was particularly sensitive to one or more of the four SRES emissions scenarios and, if so, how likely these scenarios would have to be in order to suggest a modification of that plan. However, this probability threshold approach is likely to be more successful for RDM-identified scenarios than those developed by traditional means. First, the RDM-approach will identify scenarios that most strongly influence the choice of strategy, guaranteeing that plots such as Fig. 5 will show a range of strategies. Second, traditional scenarios actually represent points, rather than regions, in a high-dimensional uncertainty space. Formally all such points have zero-probability, which complicates the interpretation of any probabilistic information associated with them (Parson et al., 2006). In contrast, the RDM approach identifies regions of uncertainty space with clear boundaries, which eases the identification of well-defined probabilities with such scenarios.

3.5. Supporting the development of adaptive strategies

If the expectations of Groups A, B, and C accurately reflect the true range of uncertainty about the probabilities of the *Rapid Growth* and *Soft Landing* scenarios, then none of the strategies shown in Fig. 5 may be sufficiently robust. A solution to this dilemma may be to expand the menu of decision options and, in particular, identify adaptive strategies that can perform well over wider range of potential futures. The RDM approach is designed to help identify and assess such robust, adaptive strategies (Lempert et al., 2003).

Groves (2005) conducts an additional iteration of the analysis described in this study in order to identify such robust adaptive water management strategies. This analysis considers additional uncertainty about future supply due to climate change and then identifies hedging actions to reduce the sensitivity of policy choice to the different likelihood assessments of the two scenarios. As the candidate strategies were found to be sensitive to uncertainties about future demand growth (driven primarily by population growth and efficiency trends), the study added a new set of strategies that are adaptive, in that they change in response to future observations of emerging trends in population and conservation. Specifically, the adaptive strategies allow the "purchase" of options to develop new supply projects if they are deemed needed at sometime in the future. The model specifies that the new supply projects would be initiated if the anticipated margin between average supply and demand fell below a predefined threshold. This addition of policy characteristics, which in this case made the strategy better able to adapt over time to new information, exemplifies the iterative process by which RDM can help expand the set of policy levers under consideration. These new adaptive policies succeeded in generating an improved set of options that reduced the performance difference of the best strategies as assessed by the three decision makers. More robust policies, such as these, can make it easier for these decision makers to agree on a single policy despite their different expectations about the future.

4. Discussion

Scenarios have proved useful for communicating and organizing uncertain information about future climate change. But key methodological challenges remain. In particular, previous scenario exercises have had difficulty summarizing all the relevant uncertainty with a small number of scenarios that prove meaningful and acceptable to diverse policy audiences. Current scenario practice also leaves unresolved the best means to incorporate probabilistic information with scenarios. This has prompted intense debate among those who want to assign likelihoods in order to use scenarios as part of an expected utility decision analysis and those who object on the grounds that such likelihoods will inhibit the scenarios' ability to gain acceptance among an audience with diverse views about the future. These unresolved methodological issues have bedeviled many scenario exercises, notably that which produced the SRES emissions scenarios.

This study proposes a new quantitative method for identifying scenarios, based on RDM methods that may address both these methodological questions. This new method, however, poses a number of challenges. First, it requires computer simulation models that can satisfactorily compare the performance of alternative decision options of interest to the decision makers. Not all scenario exercises have appropriate models readily available. In addition, the RDM approach can require significantly more computer resources than would be needed to flesh out a small number of storylines with quantitative runs. Faster computer speeds and the availability of cluster computing will increasingly relax this constraint, but there will certainly be applications for which RDM's computational requirements will prove prohibitive.

There is also no guarantee that the cluster-finding algorithms will identify a small set of easily interpretable scenarios that contain most of the future states of the world where a strategy of interest performs poorly relative to the alternatives. In part, this depends on the robustness of the proposed strategies. An insufficiently robust strategy may have too many different types of vulnerabilities. In such cases, the analysts and perhaps decision makers must first use RDM to identify more robust strategies before they can attempt to identify a small set of scenarios. In addition, the particular cluster-finding algorithm demonstrated in this study (PRIM) may not prove effective with all shapes and configurations of clusters within the multi-dimensional space of futures. In ongoing work,[14] we are comparing the ability of PRIM and alternative algorithms to properly characterize test-clusters with a variety of shapes and dimensions. Initial results suggest that it may be necessary to use several algorithms in parallel to ensure that good scenarios are identified.

Finally, the proposed method tightly couples the choice of scenario to a particular decision, which may limit the relevant audience. This feature might count as both a drawback and a benefit to our proposed approach. Given the effort required to conduct a scenario exercise, the more widely they can be used the better. Yet commentators such as Parson et al. (2006) fault current scenario methods for insufficient focus on the needs a particular audience. Much of the effort involved with the RDM approach involves creating the analytic machinery needed to generate the large ensembles of cases and to identify the scenario clusters. Once this machinery is in place the marginal cost of creating additional sets of scenarios is relatively small. Thus the RDM approach may facilitate the ability to generate different sets of scenarios appropriate for different audiences.

This new RDM scenario-identification approach also promises a number of benefits. It offers a systematic, quantitative method for identifying a small number of scenarios that well summarize a multiplicity of plausible futures important to the decisions facing the users. While these users may have widely differing expectations and values, as long as they face common decisions they may nonetheless agree on the relevance of the scenarios. Importantly, the cluster-finding algorithm also provides measures of merit to assess the clusters' ability to concisely summarize all the vulnerable cases and suggests a variety of different clusters to users, who can then choose the combination that simultaneously provides the best coverage of the vulnerable futures and the most meaningful scenarios. These metrics of scenario quality can also help resolve debates over which driving forces are truly most important. The resulting scenarios can engage the mental models of decision makers because they directly address a question that individuals with very different worldviews and policy preferences may all find compelling: What are the most important vulnerabilities of the strategy under consideration?

The approach also provides a decision analytic framework that naturally incorporates deeply uncertain probabilistic information with scenarios. Rather than highlight

[14]For a description of our current research, see http://www.rand.org/ise/projects/improvingdecisions/.

the expert consensus on the likelihood of alternative scenarios, the approach emphasizes how likely the scenarios would need to be in order to affect the users' choice of strategy. Such threshold likelihoods can then be compared to various expert estimates. This reframing of the debate allows the scenarios to contribute to a structured decision-analytic process and to include expert judgments about likelihood. But it also retains scenarios' ability to provide common ground among users with differing expectations about the future and acknowledges the deep uncertainty underlying the expert probability estimates. After all, if users had high confidence in the probabilities, they would not turn to scenarios.

The RDM scenario-identification approach has shown promise in addressing California water resource management and might similarly inform other climate policy applications. For instance, future updates of the SRES emissions scenarios might use such methods to address the needs of a variety of audiences. Some users, such as natural resource managers and those charged with flood and storm defenses may be affected by greenhouse gas emissions but cannot affect them. RDM scenarios might help such users understand the key drivers that might force emissions above of below key thresholds of concern and the early warning signs that a threshold might be crossed. Other users, such as national government officials, can implement policies aimed at reducing emissions. RDM scenarios might help such users determine the key factors that would make one mitigation approach more effective than another. As the RDM scenario-identification approach would quickly make clear, there is little reason to believe that the key driving forces for these two audiences need be the same.

Traditional scenario development methods rest on a crucial insight—that a small number of diverse stories about an unpredictable future can help individuals and groups seriously grapple with and better prepare for inconvenient or unexpected futures. But traditional approaches for creating such scenarios, such as the scenario-axes method, have not always proved successful in public policy debates such as climate change. This study proposes a new, quantitative approach to identifying scenarios. Like traditional scenario-axes methods, it seeks scenarios most important to the decision facing the scenario users while acknowledging the deep uncertainty they face. Like traditional optimum expected utility approaches, it provides a quantitative decision analytic framework in which to use these scenarios. The proposed RDM scenario-identification approach thus combines some of the best features of both traditional methods and may prove very useful in supporting scenario exercises for climate change and other important policy questions.

Acknowledgments

The authors gratefully acknowledge the helpful comments of two anonymous reviewers and the generous support of the National Science Foundation (Grant no. SES-0345925) and the Pardee RAND Graduate School. We also would like to thank Evolving Logic for the use of its CARs^{TM} software and Kamyar Guivetchi and Scott Matyac of the California Department of Water Resources for their assistance and collaboration.

References

Allen, M., Raper, S., Mitchell, J., 2001. Uncertainty in the IPCC's Third Assessment Report. Science 293, 430–433.

Arrow, K.J., 1995. Economic and social dimensions of climate change. In: J.J.H. et al. (Ed.), Climate Change 1995. Cambridge University Press, New York.

Ben Haim, Y., 2001. Information-Gap Decision Theory: Decisions Under Severe Uncertainty. Academic Press.

California Water Plan Update 2005 Public Advisory Committee, 2005. The Advisory Committee View. California Water Plan Update 2005, Sacramento, CA.

Dessai, S., Adger, W.N., Hulme, M., Turnpenny, J., Koler, J., Warren, R. (Eds.), 2004. Defining and experiencing dangerous climate change—an editorial essay, Climatic Change 64, 11–15.

DOF, 2004. Population Projections by Race/Ethnicity, Gender and Age for California and Its Counties 2000–2050. Available at: http://www.dof.ca.gov/HTML/DEMOGRAP/DRU_Publications/Projections/P3/CALIFORNIA_.XLS.

DWR, 1998. Bulletin 160-98: California Water Plan Update. California Department of Water Resources, Sacramento, CA.

DWR, 2005. California Water Plan Update 2005. *B-160-05*, California Department of Water Resources, Sacramento, CA.

Friedman, J.H., Fisher, N.I., 1999. Bump hunting in high-dimensional data. Statistics and Computing 9, 123–143.

Giles, J., 2002. When doubt is a sure thing. Nature 418, 476–478.

Gleick, P.H., Cooley, H., Groves, D., 2005. California Water 2030: An Efficient Future. The Pacific Institute, Oakland, CA.

Groves, D.G., 2005. New Methods for Identifying Robust Long-term Water Resources Management Strategies for California. Pardee RAND Graduate School, Santa Monica, CA.

Groves, D.G., Matyac, S., Hawkins, T., 2005. Quantified Scenarios of 2030 California Water Demand. California Water Plan Update 2005, California Department of Water Resources, Sacramento, CA.

Grubler, A.N., Nakicenovic, N., 2001. Identifying dangers in an uncertain climate. Nature 412, 15.

Herrick, C., Sarewitz, D., 2000. Ex Post Evaluation: A More Effective Role for Scientific Assessments in Environmental Policy. Science, Technology, and Human Values 25 (3), 309–331.

Houghton, J.T., Ding, Y., Griggs, D.J., Noguer, M., Linden, P.J.V.d., Dai, X., Maskell, K., Johnson, C.A., 2001. Climate Change 2001: The Scientific Basis. Cambridge University Press, Cambridge.

Jaeger, C., Renn, O., Rosa, E., Webler, T., 1998. Decision analysis and rational action. In: Rayner, S., Malone, E.L. (Eds.), Human Choice and Climate Change. Battelle Press, Columbus, OH, pp. 141–216.

Lempert, R., Nakicenovic, N., Sarewitz, D., Schlesinger, M., 2004. Characterizing climate-change uncertainties for decision-makers. Climatic Change 65, 1–9.

Lempert, R.J., Popper, S.W., 2005. High-performance government in an uncertain world. In: Klitgaard, R., Light, P. (Eds.), High Performance Government: Structure, Leadership, and Incentives. RAND, Santa Monica, CA.

Lempert, R.J., Popper, S.W., Bankes, S.C., 2002. Confronting surprise. Social Science Computing Review 20 (4), 420–440.

Lempert, R.J., Popper, S.W., Bankes, S.C., 2003. Shaping the Next One Hundred Years: New Methods for Quantitative, Long-term Policy Analysis. RAND, Santa Monica, CA.

Lempert, R.J., Groves, D.G., Popper, S.W., Bankes, S.C., 2006. A general, analytic method for generating Robust strategies and narrative scenarios. Management Sciences 52 (4), 514–528.

Light, P.C., 2005. The Four Pillars of High Performance: How Robust Organizations Achieve Extraordinary Results. McGraw-Hill, New York.

Metlay, D., 2000. From tim roof to torn wet blanket: predicting and observing groundwater movement at a proposed nuclear waste site. In: Sarewitz, D., Pielke, Jr., R., Beverly, Jr., R. (Eds.), Prediction: Science, Decision Making, and the Future of Nature. Island Press, Covelo, CA, pp. 199–228.

Metz, B., Davidson, O., Swart, R., Pan, J., 2001. Climate Change 2001: Mitigation. Contribution of Working Group III to the Third Assessment[TAR] Report of the Intergovernmental Panel on Climate Change (IPCC). Cambridge University Press, Cambridge, UK.

Morgan, M.G., Henrion, M., 1990. Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis. Cambridge University Press, Cambridge, UK.

Morgan, M.G., Kandilikar, M., Risbey, J., Dowlatabadi, H., 1999. Why conventional tools for policy analysis are often inadequate for problems of global change. Climatic Change 41, 271–281.

Nakicenovic, N., Alcamo, J., Davis, G., de Vries, B., Fenhann, J., Gaffin, S., Gregory, K., Grubler, A., Jung, T.Y., Kram, T., La Rovere, E.L., Michaelis, L., Mori, S., Morita, T., Pepper, W., Pitcher, H.M., Price, L., Riahi, K., Roehrl, A., Rogner, H.-H., Sankovski, A., Schlesinger, M., Shukla, P., Smith, S.J., Swart, R., van Rooijen, S., Victor, N., Dadi, Z., 2000. Special Report on Emissions Scenarios: a special report of Working Group III of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge.

Parson, E.A., Burkett, V., Fischer-Vanden, K., Keith, D., Mearns, L., Pitcher, H., Rosenweig, C., Webster, M., 2006. Global-Change Scenarios: Their Development and Use, Synthesis and Assessment Product 2.1b. US Climate Change Science Program.

PMCL, 1999. IWR-MAIN Water Demand Management Suite, User's Manual and System Description. Planning and Management Consultants, Ltd., Carbondale, IL.

Popper, S.W., Lempert, R.J., Bankes, S.C., 2005. Shaping the future. Scientific American 292 (4), 66–71.

Rayner, S., 2000. Prediction and other approaches to climate change policy. In: Sarewitz, D. (Ed.), Prediction: Science, Decision Making, and the Future of Nature. Island Press, Washington, DC, pp. 269–296.

Reilly, J., Stone, P.H., Forest, C.E., Webster, M.D., Jacoby, H.D., Prinn, R.G., 2001. Uncertainty and Climate Change Assessments. Science 293, 430–433.

Rosenhead, J., 1989. Robustness analysis: keeping your options open. In: Rosenhead, J. (Ed.), Rational Analysis for a Problematic World. Wiley, Chichester.

Rosenhead, M.J., Elton, M., Gupta, S.K., 1972. Robustness and optimality as criteria for strategic decisions. Operational Research Quarterly 23 (4), 413–430.

Saltelli, A., Chan, K., Scott, M., 2000. Sensitivity Analysis. Wiley, New York, NY.

Sarewitz, D.R.A., Pielke, J., 2000. Science, Prediction: Decisionmaking, and the Future of Nature. Island Press, Washington, DC.

Savage, L.J., 1954. The Foundation of Statistics. Dover Publications.

Schneider, S.H., 2001. What is 'dangerous' climate change? Nature 411, 17–19.

Schwartz, P., 1996. The Art of the Long View—Planning for the Future in an Uncertain World. Currency-Doubleday, New York, NY.

van 't Klooster, S.A., van Asselt, M.B.A., 2006. Practising the scenario-axes technique. Futures 38 (1), 15–30.

van der Heijden, K., 1996. Scenarios: The Art of Strategic Conversation. Wiley and Sons, Chichester, UK.

Wack, P., 1985. The Gentle Art of Reperceiving—Scenarios: Shooting the Rapids (part 2 of a two-part article). Harvard Business Review (November–December), pp. 2–14.

Watson, S.R., Buede, D.M., 1987. Decision Synthesis: The Principles and Practice of Decision Analysis. Cambridge University Press, Cambridge.

Webster, M., Forest, C., Reilly, J., Babiker, M., Kicklighter, D., Mayer, M., Prinn, R., Sarofim, M., Sokolov, A., Stone, P., Wang, C., 2003. Uncertainty analysis of climate change and policy response. Climatic Change 61 (3), 295–320.

Wilkinson, R., Groves, D.G., 2006. Rethinking Water Policy Opportunities in Southern California—An Evaluation of Current Plans, Future Uncertainty, and Local Resource Potential. UC Santa Barbara, Water Policy Program, Santa Barbara.

Yohe, G., Andronova, N., Schlesinger, M., 2004. To Hedge or not against an uncertain climate future. Science 306, 416–417.