Methods for Long-Term Environmental Policy Challenges

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How do we study long-term policy challenges where the outcomes are difficult to anticipate far into the future? After a brief overview of the broad classes of methods used to inform long-term policy decisions, this article will review in more depth three analytic methods—statistical methods, robust decision-making, and adaptive agent-based models—that provide innovative examples. The article considers the application of each method to climate change, the quintessential example of a difficult, long-term policy challenge.

Statistical methods, which find past patterns in data and project them into the future, are an example of the broader class of quantitative forecasting methods. Applied to climate change, statistical methods have been employed in the debate on the Environmental Kuznets Curve (EKC) which envisions a model of the various stages of pollution intensity as economies become substantially richer. Robust decision-making (RDM) draws from both the broad classes of formal decision analysis and scenario planning. RDM relates short-term policy interventions to different clusters of long-term environmental futures. Adaptive control, along with multi-agent modeling, provides a novel ability to analyze cooperation and conflict among multiple agents in their choice of strategies. The comparison of all three methods focuses on the challenge of global climate change and a potential transition to a low-carbon future. In the final section, we will offer guidance on choosing among methods.

Overview of Methods Used to Study Long-Term Policy Challenges[1]

People have long speculated about the future, both as a means to satisfy their curiosity and in order to influence the course of events. They have used means ranging from narratives of the future, to academic techniques such as Delphi and Foresight (explained below), to quantitative modeling, formal decision analysis, and scenarios. This breadth of methods suggests that a rich trove of ex-

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[1] This section draws on Lempert, Popper, and Bankes 2003.

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perience and insights exists to guide future efforts but that no existing method satisfactorily addresses perhaps the key challenge of long-term policy analysis—how to come to grips with the many alternative plausible futures?

From the earliest times, storytelling has been an important vehicle for developing and communicating explanations of the future. Written accounts of utopias—ideal societies whose citizens live in a condition of harmony and well being—date back at least as far as Plato's Republic (c. 360s BC). In more recent times, science fiction has used the dynamics of social and scientific-technical change as a springboard to explore the currents propelling people away from their familiar worlds. Such narratives of the future provide an extraordinarily powerful means of engaging the imagination. The obvious problem with using narratives about the long term to inform present-day actions is that, while these stories may offer compelling, insightful commentary about current options, they are usually wrong in many important details about the future.

Narratives generally flow from the imagination of a single individual. In attempts to improve their accuracy, futurists have developed various processes to assemble the wisdom of groups. Delphi methods,[2] first developed at the RAND Corporation in the 1950s, seek consensus on future trends from a wide range of experts. In successive rounds, experts respond to a list of questions, view each other's answers, and then revise their views in light of what others believe. The answers are presented anonymously to eliminate any undue weight on the response from high status members of the group. In contrast to Delphi, Foresight exercises[3] are open group processes that aim to create venues where leaders from governments, business, science, technology, and other sectors can come together to share normative and positive views on future developments. Both Foresight and Delphi can successfully amalgamate prevailing expert opinion, but the scale of these enterprises and their focus on consensus often makes it difficult for them to articulate a wide range of futures, particularly those with discontinuities, wild cards, or surprises.

Futurists employ a wide range of quantitative methods, from statistical forecasting to simulation models, to trace out paths into the future. Simulation models[4] in particular play an important role because of their ability to methodically track how different components of a system interact with each other and how over time these interactions can cause significant deviations from current trends. This ability is crucial, since shifts or discontinuities in today's trends often prove most salient in creating future dangers and opportunities and therefore in determining the challenges policy-makers face in shaping the long-term future. Simulations can also create a virtually unlimited set of future paths. The difficulty is that any simulation model of the future is sure to be wrong. In particular fields of inquiry, simulations can incorporate known facts into a single

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[2] E.g. Gordon and Helmer 1964.

[3] Georghiou et al. 2008.

[4] E.g. Hughes 1999; and Meadows, Meadows, and Randers 1993.

package and serve as a surrogate for the actual system. Thus aerospace engineers can confidently simulate the performance of a yet-unbuilt aircraft. Futurists, however, aim to simulate novel, uncertain conditions. Their models are unverifiable and virtually certain to miss some important trend or interaction.

Formal decision-analytic methods[5] aim to address such uncertainty about the future. The most common approaches characterize uncertainty by placing probability distributions over future states of the world and then using this information to rank the efficacy of alternative policy options. For instance, an analysis of long-term climate policies might characterize uncertainty about the climate's sensitivity (a key scientific estimate of how much the climate may warm due to a given amount of human emissions) with a probability distribution that suggests a high likelihood of a moderate value but some small chance of a devastatingly large value, generating significant risks of catastrophic events.[6] These probabilistic approaches can prove immensely valuable for many decision problems where the risks are relatively well characterized. But many long-term policy problems present deep uncertainties where the probabilities themselves are uncertain and the models that incorporate these probabilities are unverifiable. In such situations, these probabilistic approaches can lead policymakers astray because they will tend to underestimate the uncertainties and may contribute to political gridlock because they rest policy choices on unverifiable assumptions and models.

Scenario planning[7] explicitly embraces the concept of multiple views of the future. Scenarios are descriptions of possible paths into the future and are often produced by group exercises that generate three or four such possible paths, intended as a set to stimulate a group's thinking and to help them evaluate strategies that might perform well across multiple futures. Scenarios are often presented in narrative form to capture decision-makers' imaginations, and usually combine a familiar future with challenging ones to help decision-makers overcome psychological barriers to confronting an appropriately wide range of potential outcomes. However, current scenario practice often falls short of the method's potential promise. In particular, it is often hard to capture a full range of the relevant futures in three or four scenarios, so that the choice of any small set may seem arbitrary or biased. In addition, it is not clear how to relate scenarios to a formal process that compares the efficacy of alternative policy choices.

Three Methods to Study Long-Term Climate Policy

While the broad classes of potential approaches to analyze long-term environmental policy have been sketched above, considerations of space suggest con-

[5] Morgan and Henrion 1990.

[6] Weitzman 2007.

[7] Bradfield et al. 2005.

centrating on three prominent examples in more detail, namely statistical methods, robust decision-making, and a range of adaptive and agent-based models. We use the example of climate change throughout to illustrate major aspects of these respective methods. The methods can be applied to a much broader set of global environmental issues, however, such as nuclear waste, biodiversity, or desertification.

Statistical Methods

What is statistics about? A crisp answer has been provided by Braumoeller and Sartori:

> [Statistics] permits the researcher to draw inferences about reality based on the data at hand and the laws of probability. The ability to draw inferences is immensely helpful in assessing the extent to which the empirical expectations generated by theories are consistent with reality.[8]

Training in statistics is now common in many fields of social science and an extensive textbook literature exists.[9] Statistical analyses of environmental policy are becoming more common;[10] they have also been applied to the effect of international environmental institutions.[11] Of particular importance in the context of long-term environmental policy is the use of statistical models as one of the available quantitative methods for forecasting the key drivers of future pollution trajectories in view of the increases in wealth that we observe over the past half century around the globe. One example of statistical analyses is the Environmental Kuznets Curve (EKC), a hypothesis that captures the nexus between increasing wealth and pollution, the latter either conceptualized as exposure to pollution or as per capita emissions. In the following, we will first characterize the basic argument behind the EKC and second introduce the readers to the central debate about the validity and shortcomings of the state of research. In a third step, we will suggest under which conditions statistical methods might be best employed to assess environmental transitions.

Environmental Kuznets Curve

Much of the modern debate on the EKC can be attributed to Grossman and Krueger[12] who suggest that for urban sulfur dioxide concentrations and smoke we can observe a trajectory of pollution continually rising with increasing levels of per capita income. Once a turning point is reached, pollution decreases as per capita income increases further, amounting to a stylized bell-shaped or inverted

[8] Braumoeller and Sartori 2004, 129.

[9] E.g. Wooldridge 2002; and Wooldridge 2009.

[10] E.g. Underdal 2002; McLean and Stone 2006; Ringquist and Kostadinova 2005; and Sprinz 2004.

[11] Breitmeier, Young, and Zürn 2006; Mitchell 2002; and Sprinz 2007.

[12] Grossman and Krueger 1991.

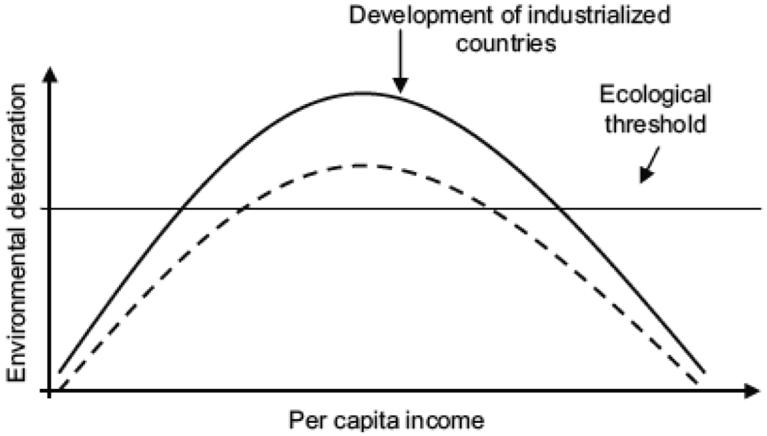

Figure 1
Stylized Environmental Kuznets Curve

Source: Huang, Lee, and Wu 2008, 240.

U-shaped curve. This turning may occur close to or at a substantial distance from some critical ecological threshold or normatively preferred state of the environment (see Figure 1). The bell-shaped trajectory is related to a similarly shaped trajectory which Simon Kuznets originally hypothesized for the degree of inequality as societies increase per capita income over time. This pattern for urban sulfur dioxide concentrations and smoke is supposed to hold across 42 countries included in the study. By contrast, a close to monotonically declining pattern was found for suspended particles. Dasgupta et al. augment the expectations underlying the EKC:

> In the first stage of industrialization, pollution in the environmental Kuznets curve world grows rapidly because people are more interested in jobs and income than clean air and water, communities are too poor to pay for abatement, and environmental regulation is correspondingly weak. The balance shifts as income rises. Leading industrial sectors become cleaner, people value the environment more highly, and regulatory institutions become more effective. Along the curve, pollution levels off in the middle-income range and then falls toward pre-industrial levels in wealthy societies.[13]

The EKC Debate

While Seldon and Song[14] provide early support for the findings by Grossman and Krueger 1991, albeit with different turning points (peaks), we nevertheless

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[13] Dasgupta et al. 2002,147.
[14] Seldon and Song 1994.

witness a lively debate over the past two decades on the EKC, in particular over whether the findings are induced by the choice of datasets, the specification of the statistical models, and the statistical methods chosen. In combination, these points illustrate the advantages and disadvantages of employing statistical methods to analyze long-term pollution trajectories. We will turn to each of these issues further below.

First, data on sulfur emissions provides the most consistent support for the inverted U-shaped relationship between per capita wealth and per capita pollution emissions (or concentrations). The record is generally more mixed for other pollutants. Some of the discussion relates directly to the questions to which degree the findings depend on the particular dataset chosen. In an extensive re-analysis of the original study of Grossman and Krueger 1991, Harbaugh, Levinson, and Wilson[15] probe the original dataset for comprehensiveness, duplication, and errors and conclude that some of the revision of data may lead to substantively different shapes of the functional relationship, such as different peaks or more S-shaped relationships. Countries with more monitoring sites may be relatively overrepresented in cross-sectional comparisons, if appropriate corrections are omitted. Furthermore, the functional trajectory may vary widely, depending on how the dependent variable is conceptualized and how the overall model is specified. As a consequence, they find U-shaped rather than inverted U-shaped relationships between per capita wealth and pollution.[16] Finally, there seem to be different pollution trajectories for wealthy as compared to less wealthy countries.

Second, the specification of the econometric models may influence the findings. Most regression models explain pollution (e.g. per capita emissions or pollution concentrations) as a function of per capita gross domestic product (GDP), raised to the first, second, and third powers. Some studies also include a range of control variables. In general, there is very little theoretical guidance regarding which control variables to include, thereby reducing the potential of statistical methods to test specific theories or hypotheses. Various summary reviews of the EKC controversy conclude that trade openness either does not matter[17] or that no clear picture emerges.[18] Political variables seem to play an important role, perhaps even a dominant role. For example, Dasgupta et al.[19] suggest that if the damage from pollution is recognized as wealth increases, more resources can subsequently be dedicated for pollution reduction, and the prospects for law enforcement improve as wealth rises. Furthermore, as we witness a rise in environmental NGOs over the past few decades, it is plausible that their activities have begun to influence pollution patterns.[20] As a consequence,

[15] Harbaugh, Levinson, and Wilson 2002, 544.
[16] Harbaugh, Levinson, and Wilson 2002, 546.
[17] Yandle, Bhattarai, and Vijayaraghavan 2004, 15.
[18] Stern 2003.
[19] Dasgupta et al. 2002, 152–153.
[20] Panayotou 1997.

pollution policies may actually dampen the EKC and allow latecomers to avoid the historical peaks generated by the early industrializers (see also dashed trajectory in Figure 1).

A third aspect of the EKC debate relates to the statistical methods chosen for analysis. Early studies focused on cross-national analyses, although the conceptual point of the EKC is a longitudinal country-level trajectory *over time* which can be properly captured by cross-level analysis only under very fortunate conditions.[21] Later analyses used time series cross-sectional analyses, especially random effects and fixed effects models which make substantially different assumptions about the components of the error term. Since there is growing agreement on the appropriateness of the use of fixed effects models (time-invariant effects which may vary considerably across countries), it is important to note that broad generalizations beyond the sample analyzed cannot be made as country-specific effects need to be taken into account.[22] Finally, it has been questioned whether persistent trends have been adequately modeled in various analyses of the relationship of pollution with per capita wealth. If both components of the analysis are trends, co-integration must be explicitly modeled to avoid inappropriate inferences.[23]

The hypothesis of an inverted U-shaped relationship between environmental dangers and per capita wealth has been applied to a variety of domains outside classical air pollution, including biodiversity, conservation issues, water pollution, and carbon dioxide emissions. Given the importance of a changing climate, we briefly review the state of research regarding a possible EKC for carbon emissions.

The empirical support for an EKC in the case of carbon dioxide is mixed[24] (see also Figure 2). A recent review of studies found that slightly more studies displayed an inverted U-shaped trajectory as opposed to other functional relationships between per capita wealth and per capita CO_2 emissions.[25] Differences in data sources do not lead to substantively different analyses.[26] In particular, the bell-shaped trajectory is more pronounced for OECD countries, whereas the trajectory for non-OECD countries clearly levels off and displays a minor decline of carbon dioxide emissions as per capita wealth increases.[27] Such a finding, however, should not be surprising as only countries which made the complete transition from poverty to wealth should provide diachronic support or lack of support for the EKC, whereas low- and mid-income level countries have not yet traversed the full range of the values for economic wealth.

Many of the analyses of an EKC for carbon dioxides restrict themselves to the core question of the effect of wealth on pollution emissions[28] whereas com-

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[21] Deacon and Norma 2004.

[22] Stern 2003.

[23] Stern 2003.

[24] Galeotti, Lanza, and Pauli 2006.

[25] Martinez-Zarzoso, Bengochea-Morancho, and Morales-Lage 2007, Table A1.

[26] Galeotti, Lanza, and Pauli 2006.

[27] Galeotti, Lanza, and Pauli 2006.

[28] E.g. Galeotti, Lanza, and Pauli 2006; Huang, Lee, and Wu 2008; and Roberts and Grimes 1997.

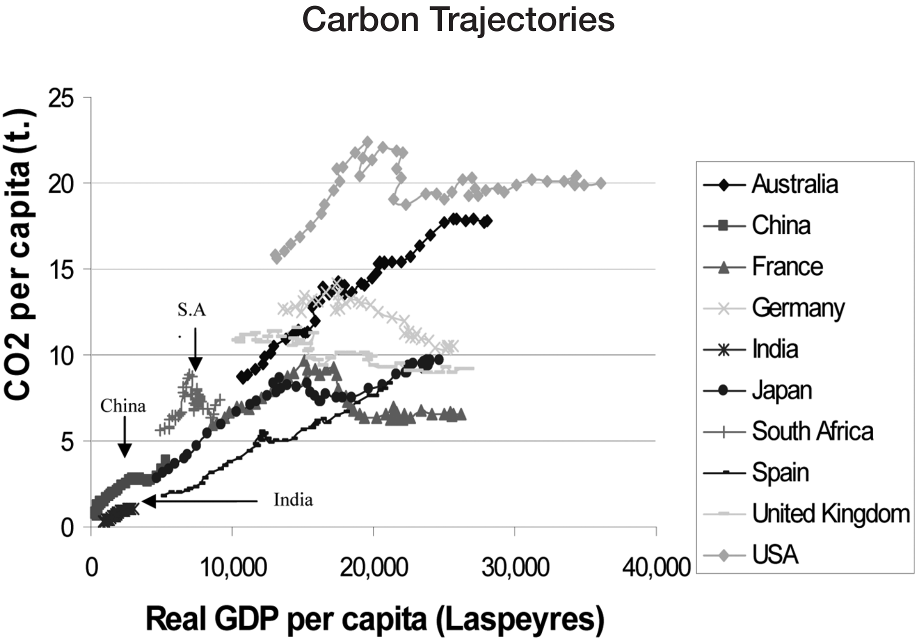

Figure 2
The Carbon Kuznets Curve (1960–2004)

Sources: World Resources Institute 2009; and Heston, Summers, and Aten 2006.

paratively few studies also include time as well as country effects. Schmalensee, Stoker, and Judson[29] find support for the EKC trajectory, yet also highlight that country effects may be particularly pronounced even over four decades, whereas remaining within-country variation is accounted for in roughly equal proportions by time and income effects. Others call into question whether an EKC pattern can be found for non-OECD countries as these countries may not follow a uniform model of economic/environmental stages.[30] The latter study suggests that we should not expect a homogenous pattern across countries.

The data in Figure 2 illustrate that different countries have been following different trajectories since the second half of the 20th century. Some mature developed countries, such as the US, Australia, and Spain are still trending upwards in terms of per capita emissions as their per capita wealth increases. China and India, as rapidly developing countries, are increasing their per capita levels substantially, although China is clearly more carbon-intensive than India is at comparable levels of economic development. Three industrialized countries, namely Germany, France, and the UK, have managed to reach a turning

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29. Schmalensee, Stoker, and Judson 1998, 19.
30. Roberts and Grimes 1997, 196.

point and are reducing per capita carbon emissions as their wealth increases. Our data suggest that different clusters of industrialized countries follow different trajectories.

As in the case of the general discussion of the EKC, many authors suggest that factors other than economic wealth should be included in better specified models. Policies and institutional variables, international trade exposure, as well as the diffusion of technologies, should be considered for inclusion. If we can corroborate the existence of distinct clusters of pollution trajectories, we will have to account for political, locational, and other explanatory factors which set such groups of countries apart. If differences between clusters remain persistent, we may also have to conjecture different sets of policy advice for coping with the various trajectories. Applied to rapidly developing countries such as India, Brazil, and China, this would pose the vexing question of whether they are more likely to follow the upward sloped cluster of developed countries or whether they follow the bell-shaped cluster. The "choice" among trajectories may be consequential for the amount of global greenhouse gas emissions generated as well as the climate impacts to be expected.[31]

The Usefulness of Statistical Methods

The discussion surrounding the proposition of an EKC has spurred a vivid debate, but remains inconclusive. Differences in assessments may spring from data problems, different specifications of statistical models, or the choice of econometric estimation techniques. Thus, statistical methods leave the reader in an uncomfortable situation with respect to assessing the EKC hypothesis. How could we do better? And how useful are statistical methods for making long-term forecasts?

There has been considerable experience in using statistical models to make forecasts of GDP over long periods of growth. Once the oil price crises of the 1970s and early 1980s shattered the structural relations among the input factors for production, long-term economic predictions of GDP looked highly inadequate compared to reality. Making forecasts over the next 50 to 100 years for climate trajectories would engender wide uncertainty bands. We should expect structural uncertainties to originate from future economic performance, political variables (ability to induce low-carbon transitions?) and technological advances. While statistical models are well suited to analyze the past and very useful for short-term forecasts, we only recommend conditional forecasts based on specific assumptions about important clusters of variables.

More generally *ex post* analyses should be conducted over long time spans, e.g. 50 to 100 years, to capture economic as well as environmental transitions rather than focus on shorter time spans of 15 to 20 years. Such long trajectories

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[31] See the special issue of the *Journal of Environment & Development* 14 (1) for the relevance of the EKC on assessing emission projections.

would also better probe the (thin) theoretical proposition of the EKC as long-term patterns. In addition, more complete specification of the explanatory side of the statistical analyses would reduce undue reliance on overly simple models. For example, it is likely that institutional variables and wealth interact, thereby leading to more nuanced theoretical propositions. In some respect, this would be a welcome return to the beginning of the EKC discussion on the decomposition of the factors which account for environmental transitions.[32] And while statistical models are not well suited for forecasts over half a century or longer, they may help inform the development of multiple scenarios, which can then be used in a decision-analytic framework such as robust decision-making to systematically examine how near-term policy interventions relate to sets of potential long-term futures.

Robust Decision-Making

Any long-term environmental policy analysis must confront the fundamental challenge that the long-term future remains fundamentally unpredictable. Long-term forecasts—whether generated by statistical extrapolations, causal models, or future narratives—can certainly provide valuable insights, but savvy policy-makers cannot confidently rely on a prediction of events decades into the future to inform their decisions. The failures of long-term forecasts are legend. Any future projections based on statistical analysis of observed trends are valid only insofar as the future exhibits no significant and novel deviations from past patterns of behavior. Policy analysts may respond to the unpredictability of the long-term future by offering predictive models as a means to generate insights, constructing scenarios from model outputs, or ignoring the long-term all together.

This unpredictability of the long-term future is one instance of "deep uncertainty," a condition where the parties to a decision do not know or do not agree upon the system model relating potential actions to outcomes, the prior probabilities for the value of key uncertain input parameters to the system model(s), and/or the value function that should be used to rank alternative outcomes. A number of different terms have been used for concepts similar to what we define as deep uncertainty. Knight[33] contrasted risk and uncertainty, using the latter to denote unknown factors poorly described by quantifiable probabilities. Ellsberg's paradox[34] addresses conditions of ambiguity where the axioms of standard probabilistic decision theory need not hold. There is an increasing literature on ambiguous and imprecise probabilities.[35] The Info-Gap Decision Theory addresses conditions described as severe uncertainty.[36]

[32] Dasgupta et al. 2002; and Grossman and Krueger 1991.
[33] Knight 1921.
[34] Ellsberg 1961.
[35] de Cooman 2001; and Ben-Haim 2001.
[36] Ben-Haim 2001.

Robust decision-making is a decision theoretic framework that aims to support decisions under such conditions of deep uncertainty. As such, RDM provides a natural and useful method for conducting long-term policy analysis. In contrast to more traditional decision-analytic approaches, RDM treats uncertainty with multiple representations of the future, as opposed to a single (probabilistic) forecast, and uses robustness, as opposed to an optimality condition, to evaluate alternative strategies that might be pursued by policy-makers.[37] Thus, in contrast to other quantitative decision-analytic methods, RDM also adopts key concepts from scenario planning.[38]

In brief, RDM uses computers to support an iterative, quantitative process in which policy analysts use the computer to a) lay out a wide range of plausible paths into the long-term future and b) look for near-term policy options that are robust—i.e. that, compared to the alternatives, perform reasonably well across a wide range of those futures using many different values to assess performance.[39] The process begins by proposing one or more near-term strategies that may be robust across a wide range of futures. Computer simulation models and/or extrapolations from data then suggest a wide range of potential future states of the world and test the performance of proposed strategies in each future state. Statistical algorithms then summarize the key characteristics of those states where each strategy performs poorly compared to the alternatives.[40] The strategies can then be revised to hedge against these stressing futures, and the process is repeated for the new strategies.[41]

This process thus helps policy-makers to identify strategies whose good performance is relatively insensitive to the key uncertainties and to characterize the key tradeoffs among such robust strategies. Rather than requiring reliable predictions of the future, this process allows policy-makers to gain a systematic understanding of their best near-term options for shaping a long-term future while fully considering not all, but at least a vast multiplicity of plausible futures. It is important to note that RDM aims not to support science by generating theory-based predictions that can be empirically tested as true or false, but is intended to use natural and social science information to support and improve policy decisions. Because a robust strategy meets multiple objectives reasonably well over a wide range of plausible futures, RDM is particularly useful when many parties to the decision have different expectations and interests. The approach can help groups reach consensus on near-term actions without requiring agreement either on the particular future that is likely to come to pass or the objectives that the policy shall achieve.

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[37] Lempert and Collins 2007.

[38] Groves and Lempert 2007.

[39] In addition to this definition, one can usefully define robustness as trading some optimal performance for less sensitivity to assumptions and as keeping options open (see Lempert and Collins 2007).

[40] Lempert et al. 2006.

[41] Lempert, Popper, and Bankes 2003.

It is useful to contrast RDM with the more traditional optimum expected utility approach to decision analysis.[42] These "predict-then-act" approaches begin with a system model that describes how the choice of strategy may affect outcomes of interest. Uncertainties are characterized with a single set of joint probability distributions over input parameters to the system model. The analysis recommends the strategy with the optimal expected utility contingent on these distributions. This process, which provides the basis for most existing methods of risk and decision analysis,[43] requires sufficient information so that one can calculate the probability distributions of future outcomes of interest. This is why this approach has been labeled "predict-then-act." For instance, an insurance company might predict the likelihood a particular driver would suffer an accident in the coming year before deciding what premium to charge.

Predict-then-act approaches have proven extraordinarily useful for a wide range of decision problems, but can run into problems under the conditions of deep uncertainty almost universally characteristic of long-term policy problems. Predict-then-act can encourage analysts and decision-makers to be overconfident in their estimates of uncertainty in order to make predictions more tractable and can make it more difficult for parties with different expectations and values to come to agreement on actions, since the method asks them first to agree on predictions. It can also lead to strategies that are vulnerable to surprises which might have been countered had the available information been used differently.[44] Lempert and Collins[45] compare RDM, optimum expected utility, and precautionary approaches to an environmental decision problem similar to that posed by abrupt climate change, that is, one involving a physical system with a potentially sudden, adverse response if pollution concentrations exceed some deeply uncertain threshold level. This study suggests that the RDM approach is preferable to the optimum utility approach when two conditions both hold. First, the uncertainty must be sufficiently deep. Second, the set of alternative policy options must be sufficiently rich to allow of the potential for robust strategies. Many long-term environmental problems fit these two criteria.

RDM has been used in a variety of studies of long-term climate change policy. For instance, RAND recently used the approach to help Southern California's Inland Empire Utilities Agency (IEUA) assess vulnerabilities related to climate change in its long-range water resource management plans and to evaluate its most effective options for responding to those vulnerabilities.[46] IEUA serves a semi-arid area of roughly 800,000 people with an expected 30 percent population growth over the next twenty years. Like all California water utilities, IEUA is required by law to look several decades into the future and demonstrate how they will meet projected water demand in their service area. Such planning pro-

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[42] Morgan 2008; and Lempert, Nakicenovic, Sarewitz, and Schlesinger 2004.

[43] Morgan and Henrion 1990.

[44] Lempert et al. 2002.

[45] Lempert and Collins 2007.

[46] Groves and Lempert 2007.

cesses have traditionally assumed that the statistics of future regional climate, for instance precipitation patterns, will be similar to historic patterns in each region. Under climate change, this assumption of statistically stationary climate is likely to fail. In particular, IEUA anticipated that their current long-range plans might adversely be affected by future changes in precipitation, storm intensity, and declines in California snow pack. RAND used RDM to help IEUA lay out several hundred long-term scenarios that explored a range of future climate conditions, as well, as a range of other key uncertain planning assumptions such as the timing of achieving resource-development milestones, local hydrology, water use intensity in future development, the future costs of various responses options, and the impacts of climate change on imported water supplies. The analysis identified the key vulnerabilities to IEUA's current plan, and suggested that these vulnerabilities could largely be eliminated by a) more aggressive near-term efforts to promote water conservation and b) careful monitoring of climate trends and responding with additional measures if adverse trends are detected in the future.

These results were presented in a series of workshops to IEUA's leadership, technical staff, local elected officials, and representatives of the local business and environmental communities.[47] Survey methods were used in an attempt to measure the impacts of this analysis on these constituencies with diverse interests and expectations about the future. In particular, the surveys inquired about improvement in participants' understanding of the climate challenge and any change in views regarding the agency's best near-term actions as a result of participation in the RDM analysis. Improvements on both measures were detected. Respondents reported that they thought RDM would be difficult to explain to their colleagues, but that the approach was the most useful among those offered for planning purposes.[48] At the time of this writing, IEUA appears to have modified its long-range plans in accord with this analysis.[49]

In addition to such work on adaptation to climate impacts, RDM has also informed studies on mitigation of greenhouse gas emissions.[50] An early example provides perhaps one of the clearest expositions of the method. Lempert, Schlesinger, and Bankes[51] used a simple integrated assessment model to compare three alternative approaches to greenhouse gas emissions: relatively modest 100-year emission reduction goals; aggressive 100-year emissions reduction goals; and an adaptive strategy that began with relatively modest reductions, that set specific thresholds for observed trends in climate impacts and costs of abatement, and that would significantly increase emission reduction rates if either threshold were observed in the future.

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[47] Groves and Lempert 2007.

[48] The workshops also presented analyses using identical models and data organized into traditional scenario planning and into a probabilistic forecasting decision framework.

[49] See Congressional testimony by IEUA General manager Rich Atwater (29 January 2008).

[50] See, for instance, Lempert 2007.

[51] Lempert, Schlesinger, and Bankes 1996.

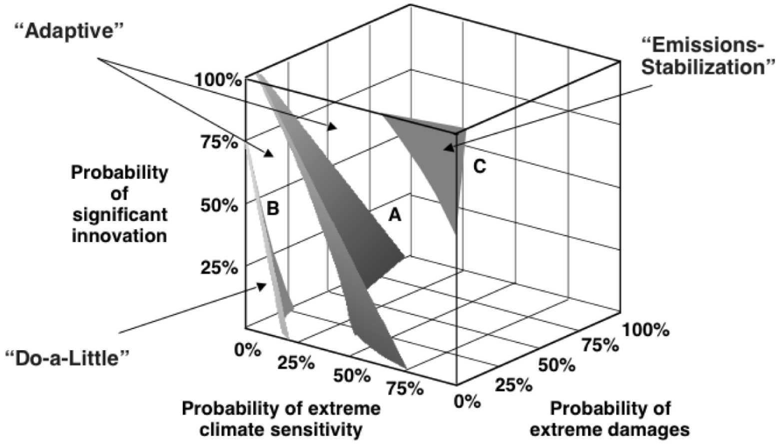

Figure 3
Comparison of Adaptive Strategy and Two Less Robust Policy Options

Source: Lempert et al. 1996.

As shown in Figure 3, the analysis found that the first two strategies both present risky choices because they could prove far from optimal if the future turned out differently than expected. The surface (A) in the figure separates regions of assumptions where the expected value of the modest long-term emission reductions goals are preferred over the aggressive long-term emission reduction goals as a function of three key uncertainties affecting the choice among alternative greenhouse gas mitigation policies. These are the likelihood of a large climate sensitivity, the likelihood of very costly damages due to climate change, and the likelihood that technological innovation will significantly reduce the costs of reducing greenhouse gas emissions.[52] Thus the modest reduction goals are preferred over the aggressive ones when the probability of extreme sensitivity, damages, and significant innovation are all relatively small. The aggressive goals are preferred when these probabilities are all large. The study also finds that the expected value of both the modest and aggressive reduction goals are far from optimal when the assumptions underlying them do not hold, that is, if the aggressive goals are chosen when the probabilities are small or the modest goals are chosen when the probabilities are large.

In contrast, the two surfaces labeled (B) and (C) in Figure 3 separate the regions of assumptions where the adaptive strategy is preferred over modest

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[52] The quantitative definitions for large climate sensitivity, large damages, and significant innovation are described in detail in Lempert, Schlesinger, and Bankes (1996). In brief summary, the study defines a large climate sensitivity as greater than 4.5 °C, large damages as greater than 3.5 percent of GDP with a temperature increase of 2.5 °C, and significant innovation as abatement costs dropping at more than 2 percent per year.

goals (B) and aggressive goals (C). The adaptive strategy proves optimal over a very wide range of expectations about the future. The study also finds that the expected value of the adaptive strategy is close to that of the modest and aggressive goals in the regions where those two strategies are optimal. The study thus concluded the adaptive decision strategy was more robust than the other two options.

As suggested by these climate change examples, RDM advocates a particular and well-structured approach to long-term policy analysis. This approach emphasizes the comparison of the long-term implications of near-term choices, rather than the long-term forecasts themselves. Within an RDM framing, a long-term decision occurs when reflecting on possible events decades or more in the future causes policy-makers to consider and perhaps chose near-term actions different than they would otherwise pursue. Long-term policy analysis thus aims to help policy-makers identify, assess, and choose those near-term actions which most reliably will led to more favorable long-term outcomes over a very wide range of future contingencies. RDM transforms the age-old question of "what will the future bring?" into the more answerable one—"what can we do today to better shape the future to our liking?"

Adaptive Approaches in Long-Term Climate Decision-Making

Simulation models, along with statistical models, are one of the primary means of understanding the long-term behavior of environmental and other systems. In recent years, adaptive control and multi-agent modeling have gained increasing interest as new approaches to simulation modeling because they offer a novel ability to analyze cooperation and conflict among multiple agents in their choice of strategies.

Adaptive Control and Decision-Making

Adaptive control implements actions based on updated information and decision rules that respond to the changing state of a system. Agents decide and act on the basis of incomplete knowledge, restrained to a spatial and temporal window of information. Adaptive targeting observes the result of the changing system environment, partly caused by the actions of all agents, and over time adjusts the control variables towards reaching targets or staying within viability domains.[53]

Adaptive control is an extension of established optimal control methods, often used to maximize time-discounted utility functions, which include expected benefits, potential climate damages, and the costs invested. In globally aggregated optimal growth models a production function represents the flow of economic output, depending on capital, labor and technology. Utility functions

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[53] Scheffran 2008a.

are based on the assumption of a global decision-maker who has complete knowledge and selects an optimal time-discounted control path. Such functions are hard to establish for long-term climate change because there are too many factors and interactions which are highly uncertain and beyond control. Furthermore, the complex socio-economic interaction among multiple agents undermines predictability.

Viability theory, an alternative decision framework also used with optimal control methods, defines objective limits or implements value-based judgments to stay within viable constraints of a system.[54] Viable control is a useful instrument to manage the complex interaction between the economic, environmental, and political spheres in natural resource management,[55] adjusting the set of admissible actions to the viability domain that can represent sustainability criteria. Many policy proposals, such as the European Union call to limit climate change to no more than a 2 °C increase in global mean temperature, follow a viable control decision framework.

One viability approach used in climate decision-making is the Tolerable Windows Approach (TWA) that restrains and adjusts the path of greenhouse gas (GHG) emissions to keep global average temperature change within viable limits of natural and social systems and to avoid critical levels of danger.[56] The admissible corridor defined by guardrails can be perceived as the space within which future climate policy can maneuver, taking into consideration the vulnerabilities and adaptive capacities, as well as critical thresholds for disasters and extreme events.[57]

Figure 4 shows the basic modeling framework for an adaptive control approach, which uses a viability framework and a single agent who acts by applying the available resources to change the system environment, given by variables that measure the state of the system and the positions of other agents. This process is a generalization of the adaptive decision strategy shown in Figure 3. The observed impacts and associated uncertainties are evaluated based on the agent's values and goals which are a function of the benefits, risks and costs of the actions. In a repeated feedback and adaptation cycle the actions are adjusted according to rules in response to environmental changes and their evaluation (both for the natural and the social environment).

In climate policy, adaptive control constrains and adjusts GHG emissions towards a target or viability domain of the climate system (e.g. a specific range of carbon concentration or global-average temperature change). A possible decision rule is to increase investment in emission reductions when future projected emissions exceed a critical temperature threshold. This requires updated information about the distance from the current position to critical temperature

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[54] Aubin 1991.

[55] See, for instance, Aubin and Saint-Pierre 2007.

[56] Bruckner et al. 1999; and Petschel-Held et al. 1999.

[57] Schneider 2004.

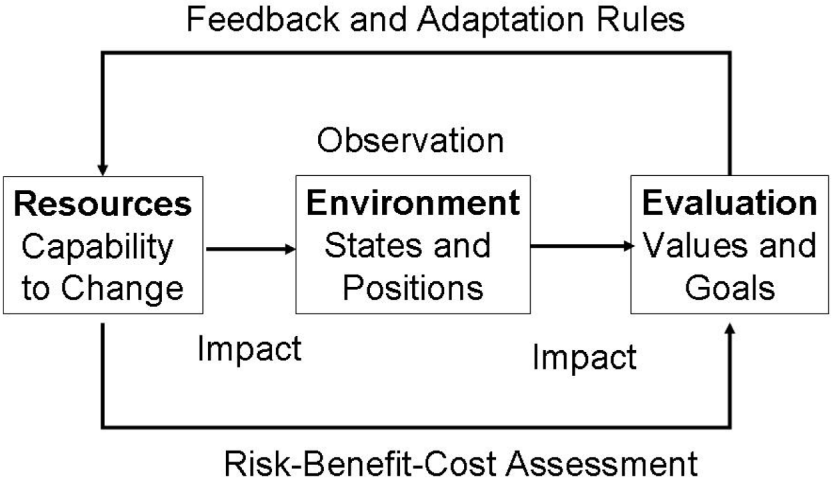

Figure 4
The Adaptation Cycle for a Single Agent

thresholds and the rate of temperature change, based on climate models and observations.

The problem of stabilizing CO_2 concentration at a limit which is supposed to be tolerable can be analyzed within the adaptive control framework. For large climate uncertainties, short-term actions may focus on low-hanging fruit—that is actions with high-benefit-cost ratios such as minimizing and managing waste—until scientific knowledge has reduced uncertainties to the degree that more costly options become attractive or long-term infrastructure measures are seen to be making a difference. Continuously updated scientific information is essential to estimate whether future trends can be perceived as tolerable or require changing the course of action.

An exemplary case demonstrates the difference between optimal and adaptive control (Figure 5).[58] Showing the fraction of total investment allocated to the low emission energy path over time, the upper two bars represent the transition from the fossil high-emission energy path to an energy path with half the CO_2 emissions at twice the cost per energy unit. The left bar shows the optimal control path for a time-discounted utility function which delays the energy transition until about 2040 due to the higher initial costs and the discounting of climate damage. The right bar represents adaptive control towards a 2°C temperature limit by end of the century which requires much earlier investment in

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[58] Figure 5 is based on the model framework and data described in Scheffran 2008a to generate new results.

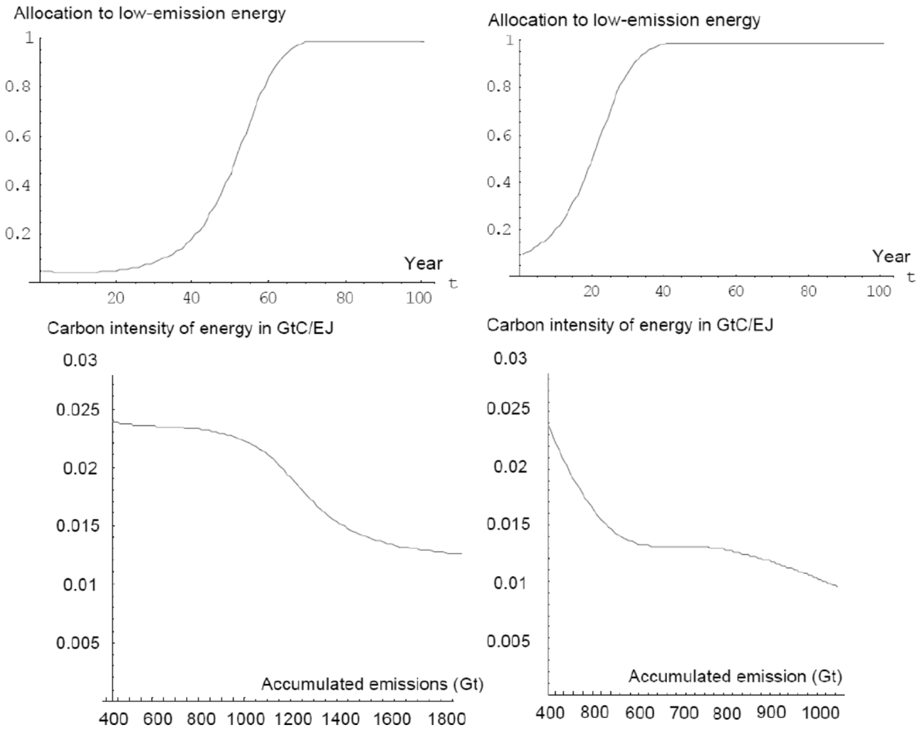

Figure 5
Transition Of Investment Allocation To Low-Emission Technology (Upper Bars) For Optimal Control (Left) And Adaptive Control (right). The lower bars represent the resulting change in carbon intensity (Gigaton carbon/Exajoule) over accumulated emissions (Gigaton) for these cases.

low-emission technology. As a result the lower bars depict the carbon intensity of the energy system over the accumulated emissions, where the adaptive strategy (right bar) shows a much more rapid decline in carbon intensity than the optimal control strategy (lower left).

Time plays a crucial role here. There can be a considerable time lag between emission reductions and their impact on the climate system. Temperature effects may be expected decades after peak emissions of CO_2 whereas sea level changes may occur hundreds of years after concentrations have stabilized. This problem is aggravated by the fact that due to the inertia of the socio-economic system the effect of policies will be delayed, too. This is true of, in particular, the replacement of infrastructure and technology, such as buildings, power stations or transport systems, which can take several decades or more.

Adaptive decision-making is also able to address the problems of time dis-

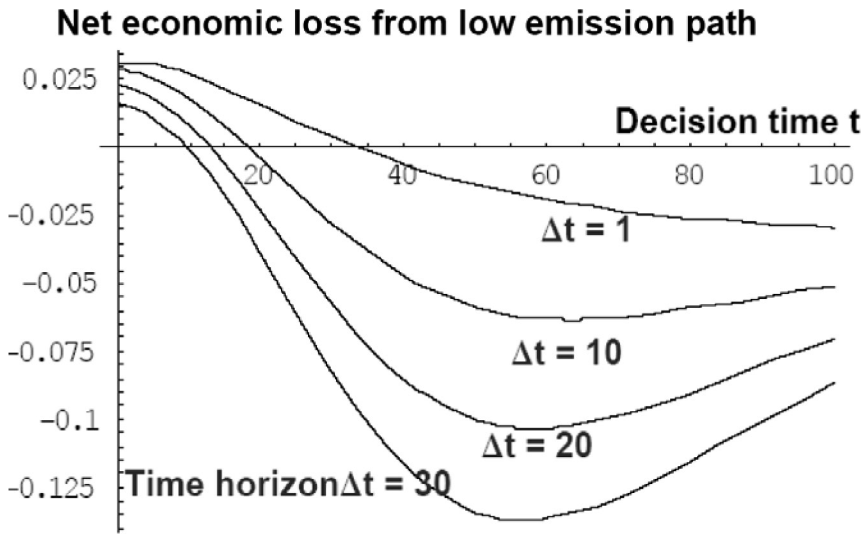

Figure 6
Net economic loss of switching from high-emission energy path to low-emission path, as a function of the decision time and future decision period (time horizon) in years. For more information see text.

Source: Scheffran 2008a.

counting, that is the degree to which decision-makers take the future time horizon into consideration and compare decisions with consequences occurring at different times. Because of the uncertainties of the distant future, choosing an appropriate discount rate for impacts spread out over decades or even centuries is a controversial issue.[59] While optimal control theory usually assumes exponential discounting of utility over an indefinite future period, in bounded rationality the future horizon is adjusted to the knowledge and perception of agents, depending on ethical criteria and precautionary principles that can shape control strategies.

Figure 6 shows that the conditions of switching to low-carbon solutions critically depend on the length of the decision period and the time at which the decision is taken.[60] The graph presents the relative economic loss (including expected damage from climate change) of switching from the high-emission energy path to the low emission path which in the beginning (time $t = 0$) acts as a barrier against technical progress. For later decision times however that barrier vanishes and becomes negative which implies a net gain from technology switching. While for a future time horizon of only one year, relative economic

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[59] Weisbach and Sunstein 2008.
[60] Scheffran 2008a.

losses disappear after about 35 years, this time shrinks to 10 years for a time horizon of 30 years—an indicator that climate mitigation actions are more favored for longer time horizons with larger climate damage.

Agent-Based Modeling and Multi-Agent Interaction

The interaction between the climate and the economic system is shaped by multiple agents who choose targets as well as actions following decision rules to influence a common system environment and interact with each other.[61] At global levels of decision-making the main agents are governments of nation states or groupings among them, often clustered along regional boundaries. At local levels, individual citizens and consumers are key players who affect or are affected by global warming. The multi-level process between local and global decision-making passes through several layers of aggregation (from billions of citizens to a few diplomats representing their countries), with each layer having its own decision procedures for setting targets and implementing them into real actions. The outcomes for each agent are highly dependent on the actions of other agents. Given these complexities, a crucial issue is how the world can act together and cooperate on climate change, managing the transition from individual competition to cooperative action.

Global governance involves multi-agent and multi-level decision-making that may follow two different approaches. In a top-down approach global decision-making bodies define global targets for emission reductions which are to be implemented at lower levels, in particular by nations. In a bottom-up approach local agents such as citizens, consumers, and companies pursue their individual interests, which affect higher levels, e.g. by electing municipal and national governments or by selecting products with higher or lower environmental impacts. In reality both approaches interfere with each other at each level and can potentially lead to conflict but also help to bridge the micro-macro interaction in a self-organized or hierarchical manner.

The collective action problem is to agree on emission paths that avoid dangerous climate change and make sure that the cumulative emissions by all human beings will not exceed this limit. Assuming that there is an agreed cap on aggregate emissions, it is a challenge to find institutional mechanisms to ensure that individual limits are assigned to each agent and that their compliance is ensured, avoiding the tragedy of the commons.

Various tools have been developed to understand the interaction among multiple stakeholders and to help identify possible solutions.[62] An established approach is game theory which provides an optimizing framework for analyzing interdependent decision-making and negotiations among players on climate change.[63] In a dynamic (repeated) game situation the players mutually

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[61] Macal and North 2007.

[62] Scheffran 2006b.

[63] For instance, see Carraro and Filar 1995; Svirezhev et al. 1999; Finus 2001; Carbone et al. 2003; Kemfert 2004; Kilgour and Wolinsky-Nahmias 2004; and Haurie and Viguier 2005.

adapt their targets, values, and actions to those of other players to change the outcome to their own favor.[64] For multiple criteria, a conflict may occur if some criteria lead to a positive evaluation while others lead to a negative evaluation. This conflict can be diminished by pursuing actions that improve on all criteria (win-win).

The limits of game theory are well known, because of problems with the assumption of the rational actor paradigm and the difficulty in finding optimal strategies in multi-option and multi-player environments. Agent-based modeling (ABM) appears more appropriate to analyze complex interaction among multiple agents who follow given action rules and stimulus-response mechanisms to form complex social macro-patterns in virtual landscapes of artificial societies.[65] Agent-based models are a powerful tool for simulating social and political systems[66] but have provided only limited support for policy-making because they are often most useful in situations where the future is unpredictable and traditional analytic methods for decision-making are least effective.[67] The attention has been shifted from games to ABM in collective action problems.[68] Unlike game theory, where the selection of options is determined by the rule of optimizing utility, ABM faces the difficulty of selecting among an infinite number of possible rules to adequately describe real-world decisions. To avoid the problems of both approaches, we suggest an approach between dynamic games and ABM, with utility functions and decision rules co-evolving.

For a large number of homogenous agents, methods and concepts from statistical physics, non-linear dynamics, and complexity science have been used to describe phenomena of complex adaptive systems such as self-organization or micro-macro phase transitions.[69] Observed macroscopic properties emerge from the behavior of the component agents, interacting in a collective way. Applications range from moving crowds and traffic systems to urban, demographic, and environmental planning. Increasingly ABM is applied in environmental management and climate policy.[70] ABM permits the coupling and embedding of social interaction into environmental models, taking into account the adaptive, disaggregated nature of human decision-making as well as collective responses to changing environments and management policies.[71]

Cooperative approaches include the international transfer of investments and technologies to shift the composition and learning rates of the energy system towards emission reductions. In negotiations, agents adapt and restrain their freedom of action with an eye towards achieving mutual benefits, reducing

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[64] Scheffran 2002.

[65] See Epstein and Axtell 1997; and Gaylord and D'Andria 1998.

[66] Janssen and Ostrom 2006; and Cedermann 2001.

[67] Lempert 2002.

[68] See Axelrod 1984 and Axelrod 1997, as well as Ostrom 2000; and Janssen and Ostrom 2006.

[69] Helbing 1995; Weidlich 2000; and Schweitzer 1997.

[70] Weber, Barth, and Hasselmann 2003; Weber 2004; Patt and Siebenhüner 2005; and Billari et al. 2006.

[71] Scheffran 2006a.

costs or diminishing risks. To avoid the prisoners' dilemma which blocks cooperation between two players because of short-sighted individual behavior, states need binding and verifiable agreements. Coalition formation describes the transition from individual to collective action as a bargaining process where the probability of joining a coalition increases with the value agents expect from it.[72] In the future, the whole decision-making cycle needs to be analyzed in a way that combines multiple phases and levels of aggregation between local and global layers, with each layer having its own decision procedures for setting targets and implementing them.[73]

Conclusions

Long-term climate change poses challenges for the decision-making process and for the decision methods and tools applied in the process. Decisions under deep uncertainty and complexity fail to satisfy the requirements for established rational choice methods such as optimal control and game theory, because we lack perfect foresight and complete information. New decision-making and management approaches are required to adjust actions and targets to the limited knowledge about the state of the climate system and to the capabilities available to decision-makers.

This article explored a range of methods to study long-term environmental policy challenges. Which are the comparative advantages and areas of overlap among the three methods introduced above? Let us offer some tentative answers:

First, statistical methods are best geared to testing theories, and they employ the power of probability theory to postdict (and sometimes predict) outcomes. The prerequisites are extant and well specified theories—which are rare in the context of long-term environmental problems. Using propositions from robust decision-making may help us in statistically diagnosing the appropriateness of past behavior in terms of the adequacy or inadequacy of robust strategies that had been employed.

Second, robust decision-making actually needs one or more quasi causal model(s) for generating its broad range of trajectories under varying assumptions before near-term strategies can be clustered with respect to their long-term implications. Given the need to explore broad parameter spaces, computational efficiency and model completeness necessitate some balancing. RDM is most useful when a) the uncertainty is deep, as opposed to well-characterized by reliable joint probability distributions, b) the decision space is sufficiently rich to allow for potentially robust strategies, and c) the behavior of the system is sufficiently complex so that a human needs a formal model to track the consequences of various decisions. If c) does not hold, then a qualitative scenario

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[72] Göbeler and Scheffran 2003; Scheffran 2006b; and Eisenack et al. 2006.

[73] Scheffran 2006a; and Scheffran 2008b.

analysis may be sufficient. If b) or a) do not hold, then traditional subjective expected utility analysis may be the most appropriate decision framework.

Third, adaptive control and agent-based modeling may prove particularly useful in exploring the behavior of actors and their collective implications in situations when perfect foresight and complete information are not possible. Such simulations describe the interaction of agent behavior and decision rules within a complex system with dynamics to manage outcomes across multiple decisions levels. These approaches replicate typical patterns of social interaction and study conditions for conflict and cooperation that shape long-term policies.

Overall, the three methods described here may be most useful in combination rather than seen as alternatives. Statistical methods forecast future behavior with fidelity to past trends, but provide less information about how such trends may change in the decades ahead. Adaptive control and agent-based modeling explore how our understanding of agents' decision criteria and of social interactions may play out in novel situations. However, for applications such as climate change, these approaches are often used in a viability decision framework, which addresses uncertainty about socio-economic systems but may assume away uncertainty about the level of the dangerous environmental threshold. Robust decision-making, more computationally intensive than related approaches, nonetheless provides a quantitative decision-analytic framework for using statistical forecasts, adaptive and agent-based simulations, and other simulations. This may help decision-makers identify robust near-term policies in the face of deep uncertainty about environmental, socio-economic, and other factors affecting the long-term future.

References

Aubin, Jean-Pierre. 1991. *Viability Theory.* Boston, MA: Birkhäuser.

Aubin, Jean-Pierre, and Patrick Saint-Pierre. 2007. An Introduction to Viability Theory and Management of Renewable Resources. In *Advanced Methods for Decision Making and Risk Management in Sustainability Science,* edited by Jürgen Kropp and Jürgen Scheffran, 43–80. New York: Nova Science.

Axelrod, Robert M. 1984. *The Evolution of Cooperation.* New York: Basic Books.

———. 1997. *The Complexity of Cooperation: Agent-Based Models of Competition and Collaboration.* Princeton, NJ: Princeton University Press.

Ben-Haim, Yakov. 2001. *Information-Gap Decision Theory: Decisions Under Severe Uncertainty.* New York: Academic Press.

Billari, Francesco, Thomas Fent, Alexia Fürnkranz, and Jürgen Scheffran, eds. 2006. *Agent Based Computational Modelling.* Heidelberg: Springer/Physica.

Bradfield, Ron, George Wright, George Burt, George Cairns, and Kees Van Der Heijden. 2005. The Origins and Evolution of Scenario Techniques in Long Range Business Planning. *Futures* 37 (8): 795–812.

Braumoeller, Bear F., and Anne E. Sartori. 2004. The Promise and Peril of Statistics in International Relations. In *Models, Numbers, and Cases: Methods for Studying Interna-*

tional Relations, edited by D. F. Sprinz and Y. Wolinsky-Nahmias, 129–151. Ann Arbor, MI: University of Michigan Press.

Breitmeier, Helmut, Oran R. Young, and Michael Zürn. 2006. *Analyzing International Environmental Regimes: From Case Study to Database.* Cambridge, MA: The MIT Press.

Bruckner, Thomas, Gerhard Petschel-Held, Ferenc L. Toth, Carsten Helm, Marian Leimbach, and Hans-Joachim Schellnhuber. 1999. Climate Change Decision-Support and the Tolerable Windows Approach. *Environmental Modeling and Assessment* 4 (4): 217–234.

Carbone, Jared C., Thomas F. Rutherford, and Carsten Helm. 2003. Coalition Formation and International Trade in Greenhouse Gas Emissions. Mimeo, June 12–14. Presented at the Sixth Annual Conference on Global Economic Analysis at Scheveningen, The Hague, Netherlands.

Carraro, Carlo, and Jerzy A. Filar, eds. 1995. Control and Game-Theoretic Models of the Environment. *Annals of the International Society of Dynamic Games.* Boston, MA: Birkhäuser.

Cedermann, Lara Erik. 2001. Agent-Based Modeling in Political Science. *The Political Methodologist* 10 (1): 16–22.

Dasgupta, Susmita, Benoit Laplante, Hua Wang, and David Wheeler. 2002. Confronting the Environmental Kuznets Curve. *The Journal of Economic Perspectives* 16 (1): 147–168.

Deacon, Robert T., and Catherine S. Norma. 2004. Is the Environmental Kuznets Curve an Empirical Regularity? Working Paper, Department of Economics, University of California, Santa Barbara. Available at http://www.econ.ucsb.edu/papers/wp22-03.pdf, accessed 5 March 2009.

de Cooman, Gert, Terrence L. Fine, and Terry Seidenfeld. 2001. *Proceedings of the Second International Symposium on Imprecise Probabilities and Their Applications.* The Netherlands: Shaker Publishing.

Eisenack, Klaus, Jürgen Scheffran, and Jürgen Kropp. 2006. Viability Analysis of Management Frameworks for Fisheries. *Environmental Modeling and Assessment* 11 (1): 69–79.

Ellsberg, Daniel. 1961. Risk, Ambiguity, and the Savage Axioms. *Quarterly Journal of Economics* 75 (4): 643–669.

Epstein, Joshua, and Robert Axtell.1996. *Growing Artificial Societies: Social Science from the Bottom Up.* Cambridge, MA: MIT Press.

Finus, Michael. 2001. *Game Theory and International Environmental Cooperation.* Cheltenham, UK: Edward Elgar.

Galeotti, Marzio, Alessandro Lanza, and Francesco Pauli. 2006. Reassessing the Environmental Kuznets Curve for CO_2 Emissions: A Robustness Exercise. *Ecological Economics* 57 (1): 152–163.

Gaylord, Richard J., and Louis D'Andria. 1998. *Simulating Society—A Mathematica Toolkit for Modeling Socioeconomic Behavior.* Berlin: Springer/Telos.

Georghiou, Luke, Jennifer Cassingena Harper, Michael Keena, Ian Miles, and Rafael Popper. 2008. *The Handbook of Technology Foresight: Concepts and Practice.* Cheltemham, UK: Edward Elgar.

Göbeler, Frank, and Jürgen Scheffran. 2002. Extended Power Values and Dynamic Coalition Formation. In *Tenth International Symposium on Dynamic Games and Applica-*

tions. Proceedings, Vol. I, edited by Leon Petrosjan, Nikolay A. Zenkevich, 338–340. International Society of Dynamic Games, St. Petersburg.

Gordon, Theodore J., and Olaf Helmer. 1964. *Report on a Long-Range Forecasting Study.* Santa Monica, CA: RAND P-2982.

Grossman, Gene M., and Alan B. Krueger. 1991. Environmental Impacts of a North American Free Trade Agreement. *National Bureau of Economic Research Working Paper Series* No. 3914.

Groves, David, Debra Knopman, Robert Lempert, Sandra Berry, and Lynne Wainfan. 2007. *Presenting Uncertainty About Climate Change to Water Resource Managers*, Santa Monica, CA: RAND TR-505-NSF.

Groves, David G., and Robert J. Lempert. 2007. A New Analytic Method for Finding Policy-Relevant Scenarios. *Global Environmental Change.* 17 (1): 73–85.

Harbaugh, William T., Arik Levinson, and David Molloy Wilson. 2002. Reexamining the Empirical Evidence for an Environmental Kuznets Curve. *The Review of Economics and Statistics* 84 (3): 541–551.

Haurie, Alain, and Laurent Viguier, eds. 2005. *Coupling Climate and Economic Dynamics.* Berlin: Springer.

Helbing, Dirk. 1995. *Quantitative Sociodynamics—Stochastic Methods and Models of Social Interaction Processes.* Boston: Kluwer.

Heston, Alan, Robert Summers, and Bettina Aten. 2006. *Penn World Table: Real GDP per Capita*. Version 6.2. Center for International Comparisons of Production, Income and Prices, University of Pennsylvania.

Huang, Wei Ming, Grace W. M. Lee, and Chih Cheng Wu. 2008. GHG Emissions, GDP Growth and the Kyoto Protocol: A Revisit of Environmental Kuznets Curve Hypothesis. *Energy Policy* 36 (1): 239–247.

Hughes, Barry B. 1999. *International Futures: Choices in the Face of Uncertainty (Dilemmas in World Politics)*, 3rd edition. Boulder, CO: Westview Press.

Janssen, Marco A., and Elinor Ostrom. 2006. Empirically Based, Agent-Based Models. *Ecology and Society* 11 (2): 37.

Kemfert, Claudia. 2004. Climate Coalitions and International Trade: Assessment of Cooperation Incentives by Issue Linkage. *Energy Policy* 32 (4): 455–465.

Kilgour, D. Marc, and Yael Wolinsky-Nahmias. 2004. Game Theory and International Environmental Policy. In *Models, Numbers, and Cases: Methods for Studying International Relations*, edited by Detlef F. Sprinz and Yael Wolinsky-Nahmias, 317–343. Ann Arbor, MI: University of Michigan Press.

Knight, Frank H. 1921. *Risk, Uncertainty, and Profit.* Boston, MA: Houghton Mifflin.

Lempert, Robert. 2007. *Creating Constituencies for Long-Term, Radical Change*, John Brademas Center for the Study of Congress, Research Brief—Number 2.

Lempert, Robert J. 2002. A New Decision Sciences for Complex Systems. *PNAS* 99(3): 7309–7313.

Lempert, Robert J., and Myles T. Collins. 2007: Managing the Risk of Uncertain Threshold Response: Comparison of Robust, Optimum, and Precautionary Approaches. *Risk Analysis* 27 (4): 1009–1026.

Lempert, Robert J., David G. Groves, Steven W. Popper, and Steven C. Bankes. 2006. A General, Analytic Method for Generating Robust Strategies and Narrative Scenarios. *Management Science* 52 (4): 514–528.

Lempert, Robert J., Michael E. Schlesinger, and Steve Bankes. 1996. When We Don't

Know the Costs or the Benefits: Adaptive Strategies for Abating Climate Change. *Climatic Change* 33 (2): 235–274.

Lempert, Robert J., Nebojsa Nakicenovic, Daniel Sarewitz, Michael Schlesinger. 2004. Characterizing Climate-Change Uncertainties for Decision-Makers. *Climatic Change* 65 (1–2): 1–9.

Lempert, Robert J., Steven W. Popper, and Steven C. Bankes. 2002. Confronting Surprise. *Social Science Computing Review* 20 (4): 420–440.

———. 2003. *Shaping the Next One Hundred Years: New Methods for Quantitative, Long-Term Policy Analysis.* Santa Monica, CA: RAND, MR-1626-CR.

Macal, Charles M., and Michael J. North. 2005. *Tutorial on Agent-Based Modeling and Simulation.* Proceedings of the 37th conference on 2005 Winter Simulation.

Martinez-Zarzoso, Inma, Aurelia Bengochea-Morancho, and Rafael Morales-Lage. 2007. The Impact of Population on CO_2 Emissions: Evidence from European Countries. *Environmental and Resource Economics* 38 (4): 497–512.

McLean, Elena V., and Randall W. Stone. 2006. The Kyoto Protocol: Two-Level Bargaining or Hegemonic Leadership? Unpublished manuscript, Department of Political Science, Texas A&M, Texas; and University of Rochester, Rochester, NY.

Meadows, Donella H., Dennis L. Meadows, and Jorgen Randers. 1993. *Confronting Global Collapse, Envisioning a Sustainable Future.* White River Junction, VT: Chelsea Green Publishing Co.

Mitchell, Ronald B. 2002. A Quantitative Approach to Evaluating International Environmental Regimes. *Global Environmental Politics* 2 (4): 58–83.

Morgan, Granger, and Max Henrion. 1990. *Uncertainty: A Guide to Dealing With Uncertainty in Quantitative Risk and Policy Analysis.* Cambridge, UK: Cambridge University Press.

Morgan, M. Granger, with advice and contributions from Hadi Dowlatabadi, Max Henrion, David Keith, Robert Lempert, Sandra McBride, Mitchell Small, and Thomas Wilbanks. 2008. *Best Practice Approaches for Characterizing, Communicating, and Incorporating Scientific Uncertainty in Decisionmaking.* Synthesis and Assessment Product 5.2. U.S. Climate Change Science Program. Available at http://www.climatescience.gov/Library/sap/sap5-2, accessed 5 March 2009.

Ostrom, Elinor. 2000. Collective Action and the Evolution of Social Norms. *The Journal of Economic Perspectives* 14 (3): 137–158.

Panayotou, Theodore. 1997. Demystifying the Environmental Kuznets Curve: Turning a Black Box into a Policy Tool. *Environment and Development Economics* 2 (4): 465–484.

Patt, Andrew, and Bernd Siebenhüner. 2002. Agent Based Modeling and Adaptation to Climate Change. *Vierteljahrshefte zur Wirtschaftsforschung (Quarterly Journal of Economic Research)* 74 (2): 310–320.

Petschel-Held, Gerhard, Hans Joachim Schellnhuber, Thomas Bruckner, Ferenc L. Toth, and Klaus Hasselmann. 1999. The Tolerable Windows Approach. *Climatic Change* 41 (3–4): 303–331.

Ringquist, Evan J., and Tatiana Kostadinova. 2005. Assessing the Effectiveness of International Environmental Agreements: The Case of the 1985 Helsinki Protocol. *American Journal of Political Science* 49 (1): 86–102.

Roberts, J. T., and P. E. Grimes. 1997. Carbon Intensity and Economic Development 1962–91: A Brief Exploration of the Environmental Kuznets Curve. *World Development* 25 (2): 191–198.

Scheffran, Jürgen. 2002. Conflict and Cooperation in Energy and Climate Change. The Framework of a Dynamic Game of Power-Value Interaction. In *Yearbook New Political Economy* 20, edited by Manfred Holler, Hartmut Kliemt, Dieter Schmidtchen and Manfred E. Streit, 229–254. Tübingen: Mohr Siebeck.

———. 2006a. The Formation of Adaptive Coalitions. In *Advances in Dynamic Games: Applications to Economics, Management Science, Engineering, and Environmental Management,* edited by Alain Haurie, Shigeo Muto, Leon A. Petrosjan and T. E. S. Raghavan, 163–178. Heidelberg: Springer/Birkhäuser.

———. 2006b. Tools in Stakeholder Assessment and Interaction. In *Stakeholder Dialogues in Natural Resources Management and Integrated Assessments: Theory and Practice,* edited by Susanne Stoll-Kleemann and Martin Welp, 153–185. Berlin: Springer.

———. 2008a. Adaptive Management of Energy Transitions in Long-Term Climate Change. *Computational Management Science* 5 (3) May: 259–286.

———. 2008b. Preventing Dangerous Climate Change-Adaptive Decision-making and Cooperative Management in Long-term Climate Policy. In *Global Warming and Climate Change,* edited by Velma I. Grover, 449–482. Enfield, NH: Science Publishers.

Schmalensee, Richard, Thomas M. Stoker, and Ruth A. Judson. 1998. World Carbon Dioxide Emissions: 1950–2050. *The Review of Economics and Statistics* 80 (1): 15–27.

Selden, Thomas M., and Daqing Song. 1994. Environmental-Quality and Development—Is There a Kuznets Curve for Air-Pollution Emissions? *Journal of Environmental Economics and Management* 27 (2): 147–162.

Schneider, Stephen H. 2004. Abrupt Non-Linear Climate Change, Irreversibility and Surprise. *Global Environmental Change,* Part A. 14 (3): 245–258.

Schweitzer, Frank, ed. 1997. *Self-Organization of Complex Structures: From Individual to Collective Dynamics,* Vol. II, London: Gordon and Breach.

Sprinz, Detlef F. 2004. Environment Meets Statistics: Quantitative Analysis of International Environmental Policy. In *Models, Numbers, and Cases: Methods for Studying International Relations,* edited by Detlef F. Sprinz and Yael Wolinsky-Nahmias, 177–192. Ann Arbor, MI: University of Michigan Press.

———. 2007. Die neue Agenda: Zukünftige Forschung zur Effektivität Internationaler Institutionen [The Next Wave: Future Research on the Effectiveness of International Institutions]. Politische Vierteljahresschrift—Sonderheft Politik und Umwelt 39/2007: 60–72.

Stern, David I. 2003. *The Environmental Kuznets Curve.* Available at http://www.ecoeco.org/pdf/stern.pdf, accessed 17 March 2008.

Svirezhev, Yuri M., Werner von Bloh, and Hans Joachim Schellnhuber. 1999. "Emission game": Some Applications of the Theory of Games to the Problem of CO2 Emission. *Environmental Modelling and Assessment* 4 (4): 235–242.

Underdal, Arild. 2002. Conclusions: Patterns of Regime Effectiveness. In *Environmental Regime Effectiveness: Confronting Theory with Evidence,* authored by Edward L. Miles, Arild Underdal, Steinar Andresen, Jørgen Wettestad, Jon Birger Skjærseth and Elaine M. Carlin, 433–465. Cambridge, MA: The MIT Press.

Weber, Michael. 2004. A Multi-Actor Dynamic Integrated Assessment Model (MADIAM). *Reports on Earth System Science* 3/04. Hamburg: Max Planck Institute for Meteorology.

Weber, Michael, Volker Barth, and Klaus Hasselmann. 2005. A Multi-Actor Dynamic Integrated Assessment Model (MADIAM) of Induced Technological Change and Sustainable Change Economic Growth. *Ecological Economics* 54 (2–3): 306–327.

Weidlich, Wolfgang. 2000. *Sociodynamics—A Systematic Approach to Mathematical Modelling in the Social Sciences.* Amsterdam: Harwood Academic Publishers.

Weisbach, David, and Cass R. Sunstein. 2008. Climate Change and Discounting the Future: A Guide for the Perplexed. Working Paper 08–19. Aug 2008.

Weitzman, Martin L. 2007. Role of Uncertainty in the Economics of Catastrophic Climate Change, AEI-Brookings Joint Center Working Paper No. 07-11.

World Resources Institute. 2009. *Climate Analysis Indicators Tool (CAIT): CO_2 per Capita.* Version 6.0. Washington, D.C.: World Resources Institute.

Wooldridge, Jeffrey M. 2002. *Econometric Analysis of Cross Section and Panel Data.* Cambridge, MA: MIT Press.

———. 2009. *Introductory Econometrics—A Modern Approach*, 4th edition. Mason, OH: Thomson South-Western.

Yandle, Bruce, Madhusudan Bhattarai, and Maya Vijayaraghavan. 2004. *Environmental Kuznets Curves: A Review of Findings, Methods, and Policy Implications* PERC Research Study 02-1, update. Available at http://www.perc.org/pdf/rs02_1a.pdf, accessed 5 March 2009.