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Risk management and climate change

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The selection of climate policies should be an exercise in risk management reflecting the many relevant sources of uncertainty. Studies of climate change and its impacts rarely yield consensus on the distribution of exposure, vulnerability or possible outcomes. Hence policy analysis cannot effectively evaluate alternatives using standard approaches, such as expected utility theory and benefit-cost analysis. This Perspective highlights the value of robust decision-making tools designed for situations such as evaluating climate policies, where consensus on probability distributions is not available and stakeholders differ in their degree of risk tolerance. A broader risk-management approach enables a range of possible outcomes to be examined, as well as the uncertainty surrounding their likelihoods.

The scientific understanding of climate change and its impacts has increased dramatically in recent years, but several interacting sources of uncertainty mean that future climate change and its impacts will not be known with precision for the foreseeable future. Some uncertainties involve the path of global socioeconomic development, the way it affects the commitment by countries to use energy-efficient technologies and how greenhouse-gas emissions might respond to specific climate-related policies. Other uncertainties involve internal variability and incomplete understanding of the climate system and broader Earth-system feedbacks. Still other uncertainties involve the way that changes in climate translate to impacts such as changes in water availability, agricultural production, sea-level rise or heat waves in different parts of the world. A final set involves the evolution of assets at risk (exposure) both in physical and in monetary terms and the level of protection that can be undertaken to reduce their vulnerability to potential losses (that is, adaptation measures). The implication of these interacting sources of uncertainty is that choosing among climate policies is intrinsically an exercise in risk management.

A principal purpose of risk management is to evaluate strategies for responding to an uncertain threat. To illustrate this point in the context of a simple example, consider a coastal community in Florida deciding whether land 3 metres above sea level is a suitable location for construction of a new residential facility to be occupied for most of the current century. Suppose that the best estimate of the maximum storm surge plus sea-level rise over this period is 2 metres. In this case, the project looks safe. But if there is a chance of a storm surge plus sea-level rise that is substantially greater, it is less attractive. So a forecast of 2 metres is very different from a forecast of 1 to 4 metres with 2 metres as the most likely outcome. Key decision-makers in the community need to know the range of possible outcomes so they can determine the robustness of policy decisions. The final decision on whether to build the residential facility, and the maximum it is sensible to pay for the land, will be influenced by the characterization of the risk.

For decisions regarding climate policy, the central importance of uncertainty has long been recognized. Schneider[1] and colleagues were pioneers in posing policy questions in the context of risk and in introducing conceptual frameworks for managing that risk. Recent research takes a more formal approach, highlighting the importance of specifying uncertainty as a key policy input. Worst-case scenarios — the possibility of extremely costly outcomes with small but positive probabilities — can have massive impacts on the cost–benefit analysis of climate change mitigation, and on the perspectives of key decision-makers. These low-probability high-consequence events have motivated a focus on the tail of the distribution of outcomes[2,3]. For example, a 5% chance of a truly unacceptable temperature increase may have a significant impact when evaluating the expected benefits and costs of climate adaptation and mitigation policies.

So far, much of the focus in assessments of climate change and its impacts has been on central tendencies. Uncertainty in future climates is most often represented as the range of outcomes generated by different climate models run for a range of scenarios. There are, however, numerous physical grounds and some observational ones for suspecting that such ensembles of opportunity may not account for all sources of uncertainty. Some of the open issues relate to the ways the models are calibrated. Others reflect incomplete understanding of important feedbacks, like those involving the carbon cycle.

Relatively few studies systematically explore the uncertainty in climate model parameters or structure. Those studies that have fall into two categories. One set undertakes a large number of runs using simplified climate models: these typically produce rather broad ranges of uncertainty, but this may simply reflect the difficulty of using observations to constrain simple models[4,5,6]. The other set uses more complex models but much smaller ensembles: these typically give narrower ranges that may simply reflect inadequate exploration of parameter and structural uncertainty (see refs 7,8 for more details on these complex models with smaller ensembles). The few studies that use large ensembles and complex models[5,6] have found relatively broad ranges.

Many impact studies use climate forcing from multiple climate models or multiple climate scenarios but few provide a probability distribution of possible impacts for a given climate forcing scenario. The result is a striking gap between the available information and the demand for information framed in the context of risk and uncertainty that form the essential lens through which the entire issue must be viewed. One possible response to this gap is a greater emphasis on characterizing well-defined probability density functions (PDFs) as a foundation for policy advice. There have been many attempts to do this, for example Kolstadt[9], Fisher and Narain[10], or for a survey, Heal and Kristrom[11]. An alternative is a fundamental change in the focus of future research and the communication of uncertainty as it relates to climate change, with increased emphasis on probabilities based on subjective likelihoods of various outcomes[12]. The problem with proposing these probabilities, however, is that they may be divorced from the data available and may thus seem to be arbitrary.

A third option, the focus of this paper, is to take advantage of available tools for decision support that do not depend on information about the entire PDFs for each scenario. Some of the approaches that evaluate alternatives, such as expected utility theory, cannot deal with situations with limited or no information on probabilities.

Incorporating uncertainty in climate risk management

The challenge in evaluating alternative strategies for addressing climate change issues is that many risk assessments and climate impact studies provide ranges of outcomes, but with relatively little information on probability distributions. For example, the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report presents most of its climate model projections based on multi-model ensembles[13]. For line or bar charts, uncertainty is represented variously as the 5% to 95% range, means ±1 standard deviation, mean plus 60% to mean minus 40%, and results of all models plotted individually. For maps of projected precipitation, multi-model means are shown only where at least 66% of the models agree on the sign of the change, with stippling indicating areas where 90% of the models agree on the sign of the change.

A recent report of the IPCC (ref. 14) presents extremes of temperature and precipitation in terms of future return intervals for the regionally most extreme value in 20 years, showing the median and the range across 50% and 100% of the models that participated in the multi-model intercomparison project. Although this is a major advance in the presenting probabilistic outcomes, it is still far from providing complete PDFs.

In the absence of complete PDFs, one way to specify information about the tails of the distribution is to leave off extremes when the likelihood of an outcome is sufficiently small that key decision-makers feel that they can ignore its consequences. For example, if climate scientists agree that it is highly unlikely that the global average temperature increase will exceed 6 °C by 2050, then the consequences of this possible outcome would not be considered in choosing between alternatives. More generally, this process entails specifying a threshold probability and removing outcomes with lower likelihoods of occurrence when determining risk management strategies for dealing with climate change.

Insurers and reinsurers use this approach in determining the amount of coverage that they are willing to offer against a particular risk. They diversify their portfolio of policies to keep the annual probability of a major loss below some threshold level (for example, 1 in 1,000)[15]. This behaviour is in the spirit of Roy's classic paper on safety-first behaviour[16].

Consider our example of the coastal community in Florida reviewing a development at 3 metres above sea level. One way of evaluating this is to undertake a benefit–cost analysis delineating climate change scenarios where the construction costs, operating expenses and restoration costs should it be flooded exceed the expected benefits. If the cumulative probability of these scenarios is below the required safety level, the facility should be constructed at 3 metres. If these criteria are not met, then one could repeat the benefit–cost analysis for alternative adaptation measures such as elevating the facility so its foundation is at 4 metres above sea level. If there is no adaptation measure where the expected benefit–cost ratio exceeds 1 and also meets the safety first criteria, then the community may not want to build the facility.

Risk Management and Ambiguity

In contrast with risk situations where the probabilities are known, ambiguous (or imprecise) situations are ones in which the uncertainty about possible outcomes cannot be objectively characterized by a single well-defined PDF. Individuals and institutions are ambiguity-averse and will pay a premium to reduce the ambiguity that they face[17–19]. For example, estimates of the PDF of equilibrium climate sensitivity (ECS, or multi-century time-scale warming in response to a doubling of atmospheric CO_2) differ greatly among approaches and data sets. To illustrate this point, representative PDFs of ECS are depicted in Fig. 1. Estimates of the probability of ECS exceeding 4.5 °C range from less than 2% to over 50% in different studies[20]. Millner, Dietz and Heal use this example to show that the impact of such imprecision on decision processes can be substantial[21].

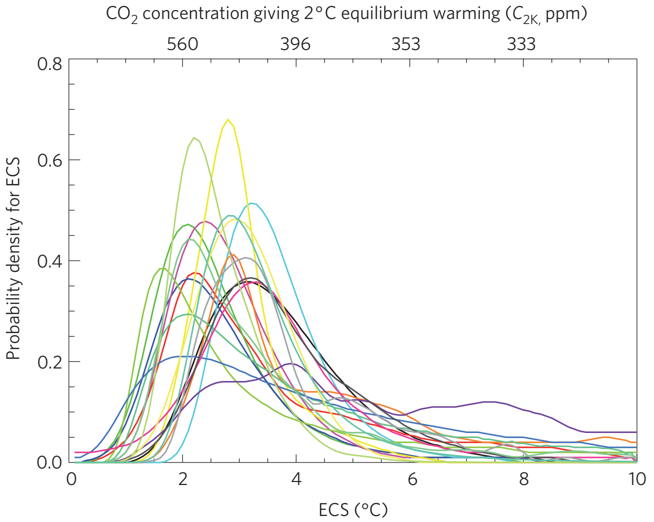

Figure 1 | Estimated probability distributions for ECS (bottom axis) from various published studies collated by ref. 20, and corresponding concentrations of CO_2 (top axis) consistent with a long-term CO_2-induced warming T_{max} of 2 °C (ref. 30), given by the expression $C_{2k} = C_{preindustrial}\exp(-\ln(2)T_{max}/\text{ECS})$. Current concentrations are 397 ppm.

Suppose emissions decay exponentially at an average rate r, and f is the average future airborne fraction (circa 45% over recent decades). Concentrations of CO_2 would then increase by a further f/r times current emissions E_0 of about 10 Gt C yr^{-1} (equivalent to 4.7 ppm atmospheric CO_2). Limiting CO_2-induced warming to 2 °C would therefore require emissions to fall at an average rate of 1.3% yr^{-1} if ECS is 2 °C and 4.4% yr^{-1} if ECS is 3 °C, a major difference. Uncertainty matters in this range of ECS values. As shown in Fig. 1, there is, however, a high level of consensus across studies that the probability of ECS>3 °C is 50% or more.

Meeting the 2 °C goal for any value of ECS much greater than 3 °C, would require either offsetting the impact of CO_2 with other forcings and/or deploying large-scale negative CO_2 emission measures in the future. The scale of these measures will depend not only on the trajectory of emissions but also on changes in the airborne fraction and climate system response[22], which will only become clear when emissions start to fall. Hence the steps required today to meet the 2 °C goal are not qualitatively affected by ambiguity in the shape of the distribution for ECS above 3 °C.

Modelling decision-making under ambiguity requires a framework for rational choice in the absence of well-defined probabilities. Several have been proposed in the last two decades (see Gilboa[23] for a review). Millner, Dietz and Heal[21] work with the framework developed by Klibanoff *et al.*[24] that separates preferences and subjective beliefs, a hallmark of expected utility theory. Their model allows one to consider the distributions forecast by several approaches, for example, the ECS distributions in Fig. 1. Millner, Dietz and Heal demonstrate that aversion to ambiguity, given the different predictions, leads to a greater willingness to invest in climate change mitigation.

Non-Probabilistic Models for Making Choices

Non-probabilistic approaches to decision-making — including minimax regret[25] and maximin[26] criteria, described in more detail below — can be applied when the probabilities of possible outcomes are not known.

The minimax regret approach requires the analyst to identify the regret associated with any policy. The regret is the difference between the value of the best policy in each state of the world and the value under the policy actually chosen. The optimal policy choice is that which minimizes, over all policy choices, the maximum regret (over all states) associated with a policy choice. Formally, if S is a state, and P a policy choice, let P*(S) be the best policy choice conditional on S being the state, and V(S,P) the value of choosing policy P if the outcome is S. Then the goal is:

$$\mathrm{Min}_{\mathrm{P}}\mathrm{Max}_{\mathrm{S}}[V(S,P^*(S))-V(S,P)]$$

Consider the application of this idea to the example of the Florida community determining whether or not to permit construction of a residential facility on the coast. To determine the optimal choice when using the minimax regret model, one first selects possible amounts of storm surge plus sea-level rise and calculates the optimal design of the residential facility for each of these scenarios. Suppose there are n climate scenarios, and the optimal facility design for scenario j is labelled j^*, $j = 1\ldots n$. For every other possible design of the facility, calculate how far its outcome diverges in present value from the optimal choice for each climate scenario: this is the regret for that scenario. The maximum regret is the largest possible divergence between the outcome from the optimal choice j^* for scenario j and the actual outcome over all possible scenarios if j^* is chosen. The chosen option is the one that gives the lowest value of the maximum regret.

The maximin criterion[26] is far simpler: it involves ranking policies by their worst-case outcomes; the optimal policy is the one that has the best worst-case outcome. There is no concept of regret here and so no need to measure the differences between outcomes, but merely to rank them. It is more demanding to use the minimax regret criterion in that it requires us to compare differences between outcomes; however, one gains information in the process. Crucially, neither approach requires relative probabilities to be assigned to the different climate scenarios, although some threshold would be required to avoid results being dominated by entirely implausible outcomes.

Robust Decision-Making

Robust decision-making is a particular set of methods and tools developed over the last decade to support decision-making and policy analysis under conditions of ambiguity. It uses ranges or, more formally, sets of plausible probability distributions to describe deep uncertainty in evaluating alternative strategies for today and the future. In contrast to expected utility theory, robust decision-making assesses different strategies on the basis of their robustness rather than their optimality. In the context of the design of a facility to reduce the likelihood of damage from storm surge and sea-level rise, choosing Design 1* may be optimal based on a specific set of estimates of the likelihood of each scenario $j = 1\ldots n$ occurring. However, Design 2* may have a higher expected loss than Design 1* but much less variance in its outcomes, and thus be a preferred choice by the community.

Lempert *et al.*[27] review the application of a range of robust approaches to decisions with respect to mitigating or adapting to climate change. The World Resources Institute summarizes several applications of robust decision/non-probabilistic approaches, each using various types of climate information[28]. These applications include the Thames River Barrier, energy production in the Niger Basin, water management in Yemen and flood risk management in a large southeast Asian metropolis. The examples illustrate how climate information[28] can be used to identify various thresholds, or bounding cases, beyond which certain policies will fail. In some situations robust decision methods generate probability thresholds for certain scenarios above which a decision-maker might choose a different risk management strategy. This threshold can then be compared to one or more probabilistic estimates from the literature, such as the study by Hall *et al*[29].

Conclusions

Studies by the climate science and climate-change impacts communities have provided a range of possible outcomes of climate change. Formal approaches, such as the maximization of expected utility or benefit-cost analysis, are difficult to apply in the presence of ambiguity with respect to the distribution of future climate scenarios. For most issues relevant to policy choices, the solution is to use more robust approaches to risk management that do not require unambiguous probabilities. Risk management strategies designed to deal with the uncertainties that surround projections of climate change and their impacts can thus play an important role in supporting the development of sound policy options.

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Howard Kunreuther and Geoffrey Heal provided the conceptual framework for this Perspective. After sharing a preliminary draft with Myles Allen, Ottmar Edenhofer, Chris Field and Gary Yohe, all authors contributed equally.

Additional information
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Competing financial interests
The authors declare no competing financial interests.