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Does climate adaptation policy need probabilities?

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Abstract

Estimating the likelihood of future climate change has become a priority objective within the research community. This is the case because of the advancement of science, because of user demand and because of the central role played by climate prediction in guiding adaptation policy. But are probabilities what climate policy really needs? This article reviews three key questions: (1) Why might we (not) need probabilities of climate change? (2) What are the problems in estimating probabilities? (3) How are researchers estimating probabilities? These questions are analysed within the context of adaptation to climate change. Overall, we conclude that the jury is still out on whether probabilities are useful for climate adaptation policy. The answer is highly context dependent and thus is a function of the goals and motivation of the policy analysis, the unit of analysis, timescale and the training of the analyst. Probability assessment in the context of climate change is always subjective, conditional and provisional. There are various problems in estimating the probability of future climate change, but reflexive human behaviour (i.e. actions explicitly influenced by information) is largely intractable in the context of prediction. Nonetheless, there is considerable scope to develop novel methodologies that combine conditional probabilities with scenarios and which are relevant for climate decision-making.

Keywords: Climate policy; Climate change; Probabilities; Uncertainty; Prediction; Adaptation; Scenarios

> *To combat global warming, we must first assess just how likely it is to occur* (Schneider, 2001).
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> *We need to research all the potential* [emissions] *outcomes, not try to guess which is likeliest to occur* (Grubler and Nakicenovic, 2001).
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> *Climate change strategy needs to be robust* (Lempert and Schlesinger, 2001).
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> *Without* [quantitative] *estimates, engineers and planners will have to delay decisions or take a gamble* (Pittock *et al*., 2001).

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1. Introduction

There has been a growing discussion amongst climate change researchers, crosscutting all three Working Groups of the Intergovernmental Panel on Climate Change (IPCC), about whether the likelihood of quantified amounts of climate change throughout the coming century can be estimated. This lively debate re-emerged after the IPCC Third Assessment Report (TAR) was published with a commentary on 'What is 'dangerous' climate change?' by Schneider (2001), which was followed up by three subsequent responses (see initial quotes). Parallel discussions surrounding the issue of uncertainty in climate change projections also had a forum in other journals (Allen *et al*., 2001; Reilly *et al*., 2001; Schneider, 2002). Though this topic is not new, the questions raised can no longer be ignored because of the substantial advancement in climate change science as demonstrated by the IPCC TAR (2001c), because of the upcoming Fourth Assessment Report, and because of the sharpening of climate policy discussions relating both to mitigation and adaptation (IPCC, 2001b).

In his initial paper, Schneider (2001) argues that policy analysts need probability estimates to assess the seriousness of the implied impacts of climate change. He is particularly concerned that in a 'probability vacuum' users will select arbitrary scenarios which compound through a cascade of uncertainties to produce a 'frequency' of future climate impacts. While he acknowledges the difficulty of assigning subjective probabilities to different development pathways, he would rather trust IPCC authors than, say, particular interest groups. In their reply, Grubler and Nakicenovic (2001) disagree with Schneider's suggestion of assigning subjective probabilities to emissions scenarios because, according to them, the future is unknown, each future is in any case 'path-dependent' and it requires knowledge of how the variables interact, which is also currently unknown. As a result, they argue that we should research all the potential outcomes and not try to guess which is the likeliest to occur. Lempert and Schlesinger (2001) suggest that in conditions of deep uncertainty, such as those surrounding the estimation of subjective probabilities for future greenhouse gas (GHG) emissions, decision-makers need to rely on robustness. That is to say, policy solutions should be based on strategies that work reasonably well for all possibilities (Lempert and Schlesinger, 2000). In their reply, Pittock *et al*. (2001) propose a risk-management approach that estimates the likelihood of exceeding a certain impact threshold (Jones, 2001). They argue that the probability of threshold exceedance is much less sensitive to input assumptions than the probability of climate change per se (Jones, 2004). Therefore, they conclude that to allow optimal and focused adaptation plans it is more appropriate to establish cumulative probability distributions of threshold exceedance.

Elsewhere, Reilly *et al*. (2001) commented on the shortcoming of the uncertainty analysis presented in the IPCC TAR. They grouped methods for estimating likelihood into model-based and expert elicitation-based, though overlap was acknowledged. Noting that expert judgement was widely used in the TAR, Reilly *et al*. (2001) criticized the lack of documentation on how judgements were reached or whose estimates were reflected. These authors also note that while some statements in the TAR have attached likelihoods, other more crucial ones do not, e.g. projected global mean temperature change over the next century. In their reply, Allen *et al.* (2001) pointed out three reasons why this last point could not be achieved in the IPCC TAR: the difficulty of assigning reliable probabilities to future development paths; the difficulty of getting consensus ranges for certain climate parameters, e.g. climate sensitivity (Keith, 1996; Paté-Cornell, 1996a); and the possibility of non-linear response to very high GHG concentrations. Nevertheless, they expected estimating probabilities to be a major feature of climate research over the coming years and noted that numerous groups are already working towards this goal.

This review is divided into five sections. Section 2 examines why it is proposed that we need estimates of likelihood of future climate change and why some would argue that these are not necessary. The focus here is on the needs of climate adaptation policy. Section 3 identifies some of the problems associated with estimating probabilities. Section 4 reviews efforts in trying to overcome these problems. We conclude by drawing some lessons from the review on the implications of probabilities of climate change for research, assessment and adaptation policy.

2. Why might we (not) need estimates of likelihood for climate change?

The ultimate objective of the United Nations Framework Convention on Climate Change (UNFCCC) is to prevent dangerous anthropogenic interference with the climate system (Article 2). This purposely ambiguous political objective has been translated by the scientific community into the notion of 'dangerous' climate change (see, e.g., Swart and Vellinga, 1994; Parry *et al.*, 1996). This notion combines aspects of both mitigative and adaptive nature, and spans global to local scales. A corollary of conceiving of some climate change as 'dangerous', is that some climate change may be regarded as 'safe'. In fact, the Convention stipulates that a 'safe' level should 'allow ecosystems to adapt naturally, food production not to be threatened and economic growth to proceed in a sustainable manner'.

Danger is clearly related to risk, the most basic and uncontroversial definition of which is 'probability times consequence' (Schneider, 2002). Similarly, the IPCC (2001a) considers risks associated with climate change a function of the probability and magnitude of different types of impacts. The natural hazards literature considers risk to be the 'probability of climate hazard times vulnerability'. Likelihood or probability can therefore be argued to be at the core of determining the risk that climate change poses to systems. This can be traced back to one plausible interpretation of the Convention's ultimate objective of avoiding danger, but other interpretations exist (see, for example, Dessai *et al.*, 2004).

2.1 Climate adaptation policy

In the realm of adaptation to climate change, there are a large number of studies that deal with Impact and Adaptation Assessments (IAAs) of climate change. These have become increasingly sophisticated in the last few years, but few have been able to provide robust information for decision-makers and risk managers. According to Burton *et al.* (2002) this occurs because of: (1) the wide range of potential impacts (issue of uncertainty); (2) the mismatch of resolution between global climate models and adaptation measures (usually local or site specific; issue of scale); (3) impact assessments not designed to consider a range of adaptation options; (4) adaptation incorporated as an assumption rather than explored as a process; (5) IAAs being initially developed for the scientific purpose of understanding impacts.

The majority of IAAs have taken a prediction-oriented 'top-down' approach (Figure 1) that considers a single or a range of scenarios of world development, whose greenhouse gas emissions serve as input to global climate models (GCMs), whose output serves as input to impact models (Parry and Carter, 1998). Some studies do not consider adaptation (the 'dumb farmer' hypothesis) while others assume arbitrary adaptation (e.g. the 'clairvoyant farmer'); others include adaptation based on observation (analogues) or try to model adaptation (Tol *et al*., 1998; Reilly and Schimmelpfennig, 2000). Anticipatory adaptation strategies are then considered within a certain decision-making framework based on the physical impacts of climate change on the exposure unit being examined with some consideration for the context.

2.1.1 The case for probabilities

In order to elaborate the point that probabilities might be required for climate adaptation policy, we shall focus on a particular IAA, the US national assessment (NAST, 2001). This assessment was a major exercise devised to evaluate and summarize the potential consequences of climate variability and change for the USA over the next l00 years. In order to do so, the best available information was provided in order to conduct a risk-based analysis of the potential consequences of climate change. Three approaches were used to develop this information: historical record (e.g. the Dust Bowl period); results from GCMs; and through sensitivity analysis designed to explore vulnerability.

By and large, the use of GCMs was the most prevalent approach in the report. After careful consideration, the assessment team decided to use two GCMs: the Canadian model and the Hadley Centre model. Broadly speaking both models' control runs provided a general agreement with the observed record of the USA, although the accurate simulation of precipitation in mountainous areas remained problematic. For the whole of the USA, the temperature scenarios for the 21st century from both models were broadly consistent, with the Canadian model showing a greater warming. There was much less agreement in the precipitation projections, except for increased rainfall in the southwest. The Canadian model projected a decrease in annual precipitation across the southern half of the nation east of the Rocky Mountains. Particularly large decreases were projected for eastern Colorado and western Nebraska. In the Hadley model, virtually all of the USA was projected to experience increases in precipitation.

In the case of eastern Colorado, these divergent results render a risk-based analysis extremely difficult because stakeholders are left wondering whether they should be prepared for more drought-like conditions or for wetter conditions. This will lead to suboptimal adaptation strategies closer to 'adaptation screening' than 'robust solutions'. From a water resources management perspective, Stakhiv (1998) concluded that 'the GCM scenarios produce such widely varying results that it is simply impossible to develop a tailored, cost-effective adaptation strategy'. From this, one could infer that systems should be as flexible as possible to allow for any sort of adaptation. Limited national or local resources would render this strategy unrealistic, even if robust.

From this example it becomes clear that if we had probabilities of climate change then we could determine the likelihood of drying and wetting conditions, which would better fit a risk assessment framework. Such a framework would not yield predictions because we are dealing with conditional and subjective probabilities, but would manage uncertainties (Jones, 2000b), leading to more informed decision-making. As Paté-Cornell (1996b) has noted, 'the reason for quantifying risk is to make coherent risk management decisions under uncertainties and within resource constraints'. Furthermore, this type of information would allow decision-makers to hedge the risk of climate change by balancing the risks of waiting against premature action. Hedging-oriented methods have the additional advantage of keeping uncertainties within the bounds of credibility for decision-makers (Rotmans and van Asselt, 2001). A long-range climate derivatives market, following the weather derivative or insurance market – 'a contract between two parties that stipulates how payment will be exchanged between the parties depending on certain meteorological conditions during the contract period' (Zeng, 2000) – is also likely to emerge in the future and would require probabilistic information.

It is also important to recognize that several communities – for example water resource managers and engineers – already use probabilities, though of a different kind, to minimize the impacts of climate variability on their activities. These communities are therefore very receptive to probabilities and in fact tend to demand them from the climate modelling community. Turnpenny *et al*. (2004) reported that various users of climate information would like a better treatment of information, e.g. one of the users said 'we want a probabilistic understanding of future changes to inform business decisions'.

It is important, however, to note the different nature of the probabilities being discussed here. Water managers and engineers frequently use probabilities based on historical records, for example, to determine the return period of the 100-year flood. These types of probabilities are called *frequentist* (or classical) because they are determined by long-run observations of the occurrence of an event (Stewart, 2000). In contrast, climate change probabilities are *subjective* (or Bayesian) because they are based on the degree of belief that a person has that an event will occur, given all the relevant information currently known to that person (Morgan and Henrion, 1990). Thus while these particular user communities would like frequentist probabilities to facilitate adaptation, only subjective (and highly conditional) probabilities can be delivered, as section 3 explains.

2.1.2 The case against probabilities

In contrast to the above views, there is a growing literature that argues that scenarios of climate change, least of all probabilities of climate change, are not needed for climate adaptation policy. Instead, a strategy of resilience and adaptive environmental management that enhances coping capacity is preferred (Pielke, 1998; Adger, 1999; Barnett, 2001; Burton *et al.*, 2002; Clark and Pulwarty, 2003). These authors argue that in the face of the considerable uncertainty over climate change projections and its impacts, one is better off adapting to the present day (or recent historic) climate variability, as this is assumed to be a good proxy for near-term climate change. These so-called 'bottom-up' approaches (see Figure 1) have been tremendously useful for understanding society's vulnerability to present-day climate and also the underlying causes of vulnerability. In particular, social vulnerability scholars are concerned with the capacity of individuals or social groups to respond to (i.e. to cope with, recover from or adapt to) any external stress placed on their livelihoods and well-being; this method of analysis emerged from the work of Sen (1981), Blaikie *et al.* (1994) and others.

Other approaches use so-called 'analogues' to learn from past climate adaptation experiences (e.g. Pulwarty and Melis, 2001) because their basis in actual experience is viewed as an advantage over modelled quantitative scenarios (Meyer *et al*., 1998). However, history may not be the best guide in viewing how adaptation will unfold with future changes in hazard exposure, though it is certainly an important one (Yohe and Dowlatabadi, 1999). There are two fundamental limitations to the use of analogues in climate-society research: analogues between cases are never perfect, and analogues can say little about long-term climate change (Meyer *et al*., 1998). Future climate change is a result of unique global forcing and is likely to produce non-analogue impacts. Therefore, while analogues can be extremely useful to calibrate our understanding of how the system works, they are limited by the unique and transient nature of future climate change.

Nevertheless, this school of thought would argue that probabilistic results are not very useful because they do not reveal anything about the underlying adaptive capacity of the system(s) in study. Some of these scholars are more concerned with the underlying causes of social vulnerability (e.g. poverty, institutional structures, and inequality) and therefore any type of adaptation to future changes in climate will necessarily have to tackle these underlying processes in the present. Such a perspective would indeed render scenarios, and consequently probabilities, of climate change irrelevant for climate adaptation policy.

2.1.3 Why is there a bifurcation in the literature?

Two opposing views on the need for probabilities of climate change for climate adaptation policy have been exposed (Figure 1). This does not mean that the two approaches are contradictory; in fact, they are complementary in terms of informing policy, but they clearly have different climate information requirements. In this article we call them, respectively, *biophysical* and *social* vulnerability approaches, consistent with Cutter (1996), who reviewed the confused lexicon of meanings and approaches to understanding vulnerability to environmental hazards (she calls them, respectively, vulnerability as pre-existing condition and vulnerability as tempered response). Several factors underlie these differing perspectives.

First is the type and scale of the unit of analysis being considered. Social vulnerability scholars appear to prefer social exposure units such as households, communities (Adger, 1999), or in some cases small nations (Barnett, 2001) or all nations (Brooks and Adger, 2004). The focus is more centred on the social and economic well-being of society. Conversely, biophysical vulnerability scholars are more concerned with physical or natural exposure units (e.g. watersheds, ecosystems, irrigation projects, buildings, etc.). In order to reduce and simplify the problem they break it down to discernible component parts and processes (also known as reductionism), usually removing the human element which is hard to predict. In essence, the first group tackles the problem with humans and largely disregards physical exposure, while the second group ignores humans and only considers physical exposure. Although a simplification, this caricature reveals why biophysical vulnerability scholars would prefer probabilities more than their social counterparts do.

Another important factor is the issue of timescale and planning horizons. Social vulnerability scholars mainly focus on the past and present conditions to inform policy-making today and in the near future. Biophysical vulnerability scholars have traditionally focused on the mid- and long-term future (e.g. 2050s or 2080s), which again leads to a mismatch of information requirements. Planning horizons are also important because if the exposure unit being considered has a long planning horizon (e.g. dams, bridges or roads), then estimates of likelihood of climate change could help strategic adaptation decision-making, especially to prevent irreversible damages. Many social exposure units have short planning horizons or turnover times and these do not require probabilities of climate change; for example, governmental, institutional or business policy horizons mostly focus on the short-term.

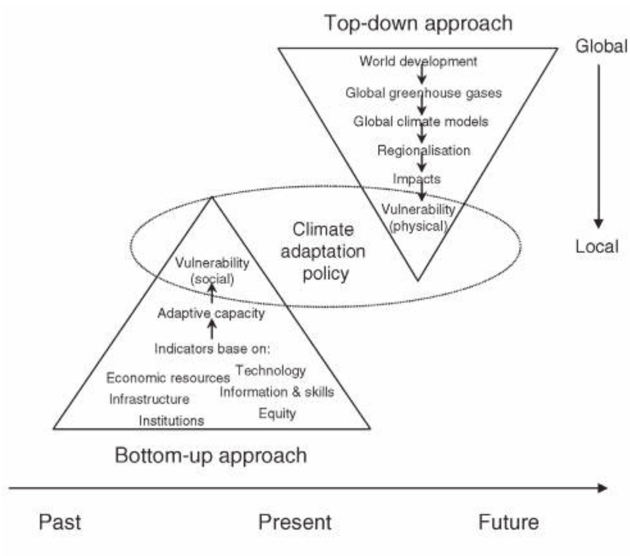

Figure 1. 'Top-down' and 'bottom-up' approaches used to inform climate adaptation policy

A third important factor is the development status of the region or country. Most developed countries are perceived as being more resilient (less vulnerable) to climate variability and change than developing countries are. Because of this perception, it is easy to understand why vulnerability-based studies in developed countries have been largely neglected relative to prediction-oriented studies (for an exception see O'Brien *et al*., 2004). On the other hand, because numerous developing countries are presently vulnerable to climate variability (Bangladesh is cited as a typical example), it makes more sense to look at the processes that create this vulnerability rather than make predictions of the (long-term) future.

Furthermore, some of the seasonal climate forecasting literature suggests that developing countries do not make good use of probabilistic information (Broad and Agrawala, 2000; O'Brien *et al*., 2000), although this is contested (Ogallo *et al*., 2000; van Aalst *et al*., 2000). Many developing countries with extreme levels of poverty, corruption, civil strife and political instability are ill-equipped to make use of such information effectively (Agrawala *et al*., 2001). This is due to the limited financial and human resources of poor developing countries to digest and interpret complex probabilistic information on climate. Even in developed countries, probabilistic climate forecasts have been of limited use in water resources (Rayner *et al*., 2002), power utilities (Changnon *et al*., 1995) or salmon management (Pulwarty and Redmond, 1997). There is also some evidence that some developed country decision-makers (in this case water resource planners in the UK) have not found climate change scenarios useful for planning. Instead they have used past drought conditions as worst-case scenarios for planning (Subak, 2000).

Fourth, different types of adaptation will require different types of climate information. Throughout this article, we follow the Burton et al. (2002) definition of climate adaptation policy as 'actions taken by governments including legislation, regulations and incentives to mandate or facilitate changes in socio-economic systems aimed at reducing vulnerability to climate change'. According to the IPCC (2001a) this type of adaptation would be characterized as anticipatory, planned and strategic, and usually undertaken by public decision-makers. Probabilities of climate change could potentially be very helpful for this sort of adaptation. On the other hand, autonomous, responsive, instantaneous adaptations undertaken mainly by private decision-makers (e.g. behavioural changes), are a different type of adaptation that will also take place under a changing climate. This sort of adaptation would probably not benefit from probabilities of climate change because it is based on experiencing climate hazards and responding to them, rather than planning in advance based on probabilistic information. These adaptations refer mainly to human and managed ecological systems. It is also clear that probabilities will be irrelevant for adaptation in unmanaged ecological systems.

Finally, the different perspectives on probabilities also originate from the training and philosophy (i.e. the epistemological orientation) of the researchers doing the policy analysis; hence the conceptual division between biophysical and social vulnerability scholars that can be traced back to the division between the natural and the social sciences. Malone and Rayner (2001) note that there are two styles of research that tend towards highly disparate scales and standpoints, which they argue to be irreconcilable. Descriptive-style researchers see themselves as objective observers outside the environment they analyse, which lends to research at the macro level and to global analysis based on large data sets and aggregated numbers. With the increase in computational power this has arguably led to the emergence of predicting the future in terms of probabilities. Interpretative-style researchers, however, see themselves as at the centre of the environment, experiencing it from within, a participant-observer of society, which lends itself to micro-level research, to richly detailed local analyses that are difficult to generalize from, and for which probabilistic climate information is superfluous.

Furthermore, the motivation for the analysis (the goals) is also very important. For example, social vulnerability scholars are more interested in the processes underlying vulnerability, which once identified and improved could facilitate adaptation to climate change. Biophysical vulnerability scholars are interested in modelling the impacts of climate change to the highest degree of precision possible, which certainly requires probabilities (or some explicit representation of uncertainty), and then devising adaptation strategies to reduce exposure to the increased hazard.

3. What are the problems of estimating probabilities?

Probabilities are an important ingredient in determining the risk of climate change by quantifying the likelihood of a certain event or hazard, be it climate change itself or the impacts thereof. The large range of the IPCC global mean temperature projection originates from both *incomplete* and *unknowable* knowledge (Hulme and Carter, 1999). In a general context these have been classified as *epistemic* (or subjective, type B, reducible, and state of knowledge) and *stochastic* uncertainty (or aleatory, type A, irreducible, ontic and variability) (Helton and Davis, 2002). Epistemic uncertainty originates from incomplete knowledge of processes that influence events. In relation to climate change, this type of uncertainty includes unknown values for the climate sensitivity, the rate of heat uptake by the deep ocean or the parameterization of an impact model. Unknowable knowledge derives from the indeterminacy of human systems and the unpredictability of the climate system. Because global greenhouse gas emissions depend on human behaviour, they are inherently uncertain; e.g. the uncertainty of the future fertility rate. The climate system is also stochastically unpredictable to a certain extent because of its chaotic nature, i.e. small differences in the initial conditions of a global climate model can yield very different results (Lorenz, 1993; Smith, 2002).

It is the representation of uncertainty in terms of likelihood that has been so controversial, as the four quotes introducing this article illustrate. We argue that in the context of climate change, incomplete knowledge matches perfectly the concept of epistemic uncertainty in that by collecting more information, this type of uncertainty can be reduced, although it is also possible that uncertainty increases with more research (as shown in section 5.1). For complex systems, like climate change, it is more likely than with simple well-constrained systems that this type of uncertainty grows at first with more research and then starts converging as the science matures. Representing epistemic uncertainty in a probabilistic fashion has been relatively widely accepted, either through probability distributions based on scientific evidence or expert judgements, although the aggregation of expert opinions is still controversial (see Clemen and Winkler, 1999, for a review). Nonetheless, in the past, scientists have been uncomfortable with the notion that there was a subjective element to their analysis (Moss, 2000; but for a successful example see Vaughan and Spouge, 2002). This has sometimes led these uncertainties to be ignored – by overlooking available techniques for improving subjective assessments of probability and confidence levels – and sometimes under-reported, especially in public policy studies of controversial or politically sensitive issues, such as climate change (Paté-Cornell, 1996b). Examples of this type of uncertainty are given in section 4, including constraining certain climate parameters with the use of climate observations (Forest *et al*., 2002) or the use of expert judgement (Morgan and Keith, 1995).

In the case of climate change, unknowable knowledge does not translate solely into stochastic uncertainty. This is where a split between natural and social scientists is most noticeable. Stochastic (or aleatory) uncertainty stems from variability in known (or observable) populations and, therefore, represents randomness in samples (Paté-Cornell, 1996b). This type of uncertainty arises when we try to predict weather and climate, which climate scientists are overcoming with so-called ensemble simulations (Mitchell et al., 1999). Though not fully probabilistic, because of computational constraints, it is expected that this type of stochastic uncertainty will be better represented in the future as computational power increases (Allen, 1999; Stainforth *et al*., 2002). Dealing with stochastic uncertainty in the social sciences has been more problematic and so attaching probabilities to world development paths and emissions of greenhouse gases has been hotly debated (Grubler and Nakicenovic, 2001). These authors argue that probabilities in the natural sciences are different from probabilities in the social sciences. Schneider (2002) provides a rebuttal of this argument, which we support, but will not repeat here.

Instead, we emphasize the notion of 'reflexivity', which some scientists call 'human volition', 'agency' or 'feedback'. Humans are capable of reflecting critically on the implications of their behaviour and making adjustments in the light of experience (Berkhout *et al*., 2002). In a climate change context, if we as scientists state that global temperature will increase between 1.4 and 5.8°C by 2100 (with or without a probability distribution), society will surely react. By critically reflecting upon this information, society will create a perception of the problem (is it good? is it bad? will it affect me or my children?) and act upon it (even if it means doing nothing or business as usual).

If there is a reaction then it can conventionally take two forms: mitigating the problem by reducing greenhouse gas emissions and enhancing sinks, and/or adapting to the problem by devising and enhancing coping strategies to deal with the impacts of a changing climate. By mitigating (or adapting to) the problem, people are changing the future, which would render the scientist's original statement incorrect had he or she attached an estimate of likelihood. Thus, within the unknowable knowledge sphere it is appropriate to introduce a new category of *reflexive* uncertainty, which together with stochastic uncertainty provides a comprehensive picture of unknowable knowledge in the context of climate change. Reflexive uncertainty only applies to human systems because natural systems are not reflexive to information about the future (predictions). For example, it could be argued that the publication of the four SRES storylines has already made a B1-type world more likely than an A2-type world. However, if we then perceived we were living in a B1 world we may become complacent with regard to policy and thus move towards a more A2-like world. This crude example shows the significant reflexive uncertainty that social systems exhibit.

The fact that humans are part of the system being researched therefore makes uncertainty irreducible in the context of prediction; it makes all probabilities 'provisional'. According to Slaughter (1994) predictions (with explicit or implicit probability evaluations) are useless in the context of social systems where qualitative phenomena relating to human choice are dominant. In the case of climate change Sarewitz *et al*. (2003) we should note that the process of prediction for decision-making is hindered by the fact that 'relationships that inform expert probabilities are themselves highly non-stationary and perhaps influenced by the predictions themselves'.

Table 1 tries to summarize the different types of uncertainty introduced in this section. Reflexivity is in our view the major obstacle to estimating the likelihood of climate change. Modelling reflexivity (iterative human behaviour) is fundamentally complex and, some would argue, logically impossible to

Table 1. Characteristics of different types of uncertainty in the context of climate change

Type of knowledge	Type of uncertainty	Possible to represent with probabilities
Incomplete	Epistemic	Yes, but limited by knowledge
Incomplete-Unknowable	Natural stochastic	Yes, but with limits
Unknowable	Human reflexive	No, scenarios required

predict. Nonetheless, there are a range of efforts, such as integrated assessment or agent-based modelling, that try to do just this, even if integrated assessment has neglected adaptation almost entirely (Toth, 2000) and agent-based modelling is still immature in its application to climate change (see Ziervogel *et al*., 2004, for an application to seasonal climate forecasting). Though we might see reflexivity as a problem, we do not think it should preclude us from attempting to estimate the probability of climate change by using a combination of probabilities (to represent epistemic and natural stochastic uncertainty) and formal scenario methods of the 'what if' type of questions (to represent human reflexive uncertainty). These probabilities will remain highly conditional on the assumptions made, because it is impossible to estimate how much uncertainty remains unquantified. Such a hybrid approach can then be used simultaneously as a heuristic social learning tool – for organizing inquiry, identifying interdependencies, and developing a better overall understanding of complex issues (Rotmans and Dowlatabadi, 1998) – as well as a potential guide for policy-making based on scenario-independent assessments.

4. What has been done so far?

We next review the numerous efforts that are contributing to estimation of the likelihood of various magnitudes of climate change, with particular attention to probability-based studies.

4.1 Key drivers of greenhouse gas emissions

Uncertainty in certain key drivers of GHG emissions have been explored in probabilistic terms, namely population growth (Lutz *et al.*, 2001) and technological change (Gritsevskyi and Nakicenovic, 2000). However, these have rarely been combined to produce probabilistic greenhouse gas emissions, mainly because the probability distribution functions (*pdfs*) for a number of key drivers (e.g. per capita income, hydrocarbon resource use and land-use change) are unavailable/unknown and the interconnection between drivers is complex. One exception is a study that developed a consistent set of emissions scenarios with known probabilities based on a computable general equilibrium model of the world economy (Webster *et al*., 2002), who performed a sensitivity analysis to identify the most important parameters, whose uncertain *pdfs* were constructed through expert elicitation (by five in-house economists) and drawing from the literature. The uncertainty of the eight independent sets of input parameters (e.g. labour productivity growth, autonomous energy efficiency improvement rate, and several sources of GHGs) was propagated into the model. Through a Monte Carlo simulation, *pdfs* of GHG emissions for each time period were produced. An earlier study performed something rather similar to this, but went beyond it by constraining the global energy model according to observations of energy consumption and carbon emissions through a Bayesian technique (Tsang and Dowlatabadi, 1995).

4.2 Global climate

Most of the work on probabilities has been performed at the global climate system level, particularly looking at key uncertainty parameters such as the climate sensitivity, heat uptake by the oceans or aerosol forcing. One of the earliest studies that explored the uncertainty of key climate variables (e.g. climate sensitivity) was that of Morgan and Keith (1995), who interviewed a number of US climate experts to elicit *pdfs*. Their results showed a diversity of expert opinion, which led them to conclude that the overall uncertainty of climate change is not likely to be reduced dramatically in the next few decades (a prediction so far borne out). Using a number of different methods, researchers have run their previously deterministic climate models in a probabilistic manner (Zapert *et al.*, 1998; Visser *et al*., 2000; Webster and Sokolov, 2000; Dessai and Hulme, 2001; Wigley and Raper, 2001). It is important to note that within this approach the output likelihood is dependent on the subjective prior *pdfs* attached to uncertain model parameters (these are mostly based on expert judgement).

While a probabilistic approach could be applied to simple and intermediate complexity climate models, there is simply not enough computational power (yet – but this is now changing) to perform this in a GCM. Therefore, uncertainty in GCMs has been mainly explored through means of intercomparison and validation statistics between model results and observed climatology (Lambert and Boer, 2001). There are also a few examples of evaluating GCM output with impact models (Williams *et al.*, 1998). However, there is an ambitious project (Allen, 1999; Stainforth *et al.*, 2002) to perform a Monte Carlo climate forecast by means of running a large ensemble simultaneously on thousands of personal computers, which will allow much of the uncertain parameter space to be sampled. This project (see http://climateprediction.net) is expected to provide a better handle on uncertainty in global climate predictions. Another strand of research that complements earlier efforts and attempts to reduce uncertainty is the method of constraining certain climate parameters by using recent observed changes in the climate system (Tol and de Vos, 1998; Allen *et al.*, 2000; Andronova and Schlesinger, 2001; Forest *et al*., 2002; Gregory *et al*., 2002; Knutti *et al.*, 2002; Stott and Kettleborough, 2002). This is essentially a Bayesian approach, which will prove most useful as more observed data are gathered in the future.

4.3 Global impacts

The likelihood of global impacts such as sea level rise (Patwardhan and Small, 1992; Titus and Narayanan, 1996), the collapse of the West Antarctic Ice Sheet (Vaughan and Spouge, 2002), the global carbon cycle (Craig and Holmen, 1995; Shackley *et al*., 1998; Jones *et al*., 2003), global economic impact (Nordhaus, 1994), and the overturning of the thermohaline circulation (Mastrandrea and Schneider, 2001; Vellinga and Wood, 2002) have been the subject of some research and much media attention (the last two studies do not estimate likelihood, but explore a ‘forced’ temporary collapse). These approaches have relied heavily on expert judgement techniques because of the difficulty in quantifying low probability/high impact events. There are numerous other studies that deal with global impacts such as the large-scale eradication of coral reef systems, biome migration or changes in ENSO, but few have represented uncertainty explicitly through probabilities.

4.4 Regional climate

At the level of regional climate, probabilities have been less explored because the compounding of uncertainty from the global level is large and not well quantified, and the number of GCM runs is still small. Thus, validation statistics (e.g. mean, standard deviation, pattern correlation, etc.) have traditionally been used to explore regional uncertainties in future climate (Kittel *et al*., 1998; Giorgi *et al*., 2001). This has led to a new summary measure, which calculates average, uncertainty range, and reliability of regional climate changes from GCM simulations, being proposed by Giorgi and Mearns (2002), named the Reliability Ensemble Averaging method. Some researchers, however, have looked at probabilistic methods for regional climate. New and Hulme (2000) used a simple climate model to sample uncertainty in the global climate and then used the ‘pattern-scaling’ technique to propagate this uncertainty to the regional level using 14 runs of GCMs as a 'super-ensemble'. Räisänen and Palmer (2001) ignored the upstream uncertainties and considered 17 GCMs a probabilistic multimodel ensemble projection of future regional climate. Giorgi and Mearns (2003) extended their Reliability Ensemble Averaging method to calculate the probability of regional climate change exceeding given thresholds using nine GCM simulations under SRES A2 and B2. This method goes beyond previous studies by using the reliability factor to estimate the probability of future regional climate change.

The most important caveat with these probabilistic approaches is likely to be the limited number of GCM runs sampled. Hopefully this will be overcome in the future (Stainforth *et al.*, 2002), but in the meantime these studies are important methodological additions to the representation of uncertainties in regional climate change projections. Allen and Ingram (2002) have suggested that once the new generation of climate experiments is underway, it might be possible to constrain regional climate with the combined use of observed global-mean temperature and the hydrologic cycle, though the latter could be a weak constraint. Other important uncertainties that need further attention from probability methods include spatial downscaling and the impact of land-use change and landscape dynamics on regional climate.

4.5 Regional/local impacts

There are a plethora of impact studies that have used one or a few more climate change scenarios to represent uncertainties from climate projections (IPCC, 2001a). This is clearly insufficient (see Katz, 2002, for a review of uncertainty techniques in this area), but few studies have ventured into the probabilistic realm for the same reasons as given earlier, in particular the compounding and management of uncertainty. Similarly, Schimmelpfennig (1996) noted that uncertainty has been poorly represented in the economic models of climate change impacts, suggesting that a full probabilistic analysis be conducted. Because quantification of uncertainty in climate assessments is problematic, Risbey (1998) performed a qualitative sensitivity analysis that showed that water-planning decisions were sensitive to uncertainty in the range of GCMs simulated for the Sacramento basin in California. Though only a few GCMs were used and a simple scenario matrix approach taken for adaptation decisions, this study is nonetheless ground-breaking because it links future climate with planning decisions of today under a range of plausible scenarios. Most of the other local impact studies reviewed lack this important component – *the sensitivity of adaptation decisions to upstream uncertainties* – even though uncertainty is sometimes quantified in terms of probability.

However, in most studies, uncertainty is not comprehensively covered, especially with respect to climate change scenarios. Perhaps the most ambitious approach is provided by Jones (2000a), who used a similar approach to New and Hulme (2000), but extended this to numerous impact models using critical impact thresholds. In Jones and Page (2001) an uncertainty analysis was carried out to assess the contribution of global warming vis-à-vis other components, as well as a Bayesian analysis to test the sensitivity of the results to initial assumptions. For the water resources of the Macquarie river catchment, 25% of the uncertainty originates from global warming whereas precipitation changes contribute 64%. The Bayesian analysis showed that the risk of threshold exceedance is rather insensitive to changes in the input assumptions for rainfall or global warming.

5. Concluding remarks

This literature review cannot provide an unambiguous answer to the question, 'Does climate adaptation policy need probabilities?'. The answer depends on the goals of the policy analysis, in particular regarding timescale and type of exposure unit being considered, but also the context where adaptation (and/or mitigation) is being undertaken, the training of the policy analyst, and the motivation of the policy-focused research. There are numerous problems associated with estimating the probability of climate change, but the most serious is the fact that human reflexive uncertainty is unquantifiable (in terms of probabilities) in the context of prediction. This suggests that a combination of scenario- and probability-based approaches is desirable. We have shown that there are a number of research efforts underway trying to estimate the likelihood of climate change. We draw some insights from this review on the role of probabilities for the future of research, assessment and policy in the context of adaptation to climate change.

5.1 Research

Attaching probabilities to future climate change will remain a scientific challenge for years to come. Section 4 showed that research is already well under way into numerous aspects of this ambitious goal. Some might even argue that the essential methods are already in place, but value judgements and a plurality of frameworks remain. It is important to recognize that science will not deliver an uncontested estimate of likelihood of future climate change. The Fourth Assessment Report of the IPCC may well need to respect the plurality of frameworks, rather than compressing all uncertainty into a single *pdf* of future global warming.

To illustrate this point, Figure 2 shows the cumulative distribution function of climate sensitivity for a number of recent studies (lines) as well as the state-of-the-art GCMs used in the IPCC TAR (diamonds).

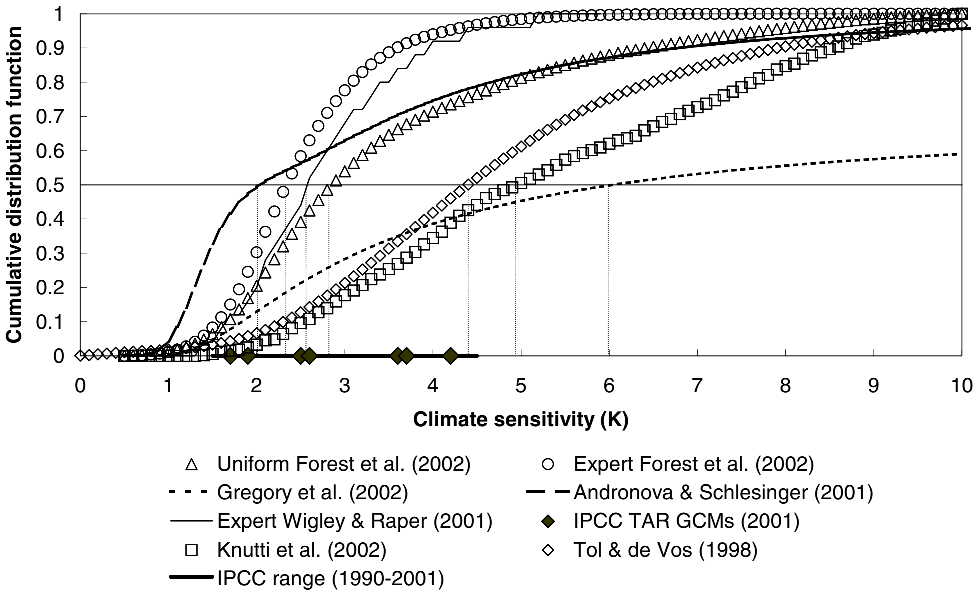

Figure 2. Cumulative distribution functions of climate sensitivity (the equilibrium response to global surface temperature change to a doubling of equivalent CO_2 concentration) for a number of studies reviewed in section 4.2. On the bottom axis the climate sensitivity of individual GCMs used in the IPCC TAR (diamonds) is indicated and also the IPCC 'consensus' range (thick black line). The thin black line intersects each study at its most likely value (50% chance)

Essentially, different value judgements about which techniques to use (e.g. optimal fingerprinting, bootstrapping, or Bayesian techniques), which models to employ, or which parameters to include (e.g. sulphate aerosols, solar forcing, ocean temperatures) yield significantly different curves. Probabilities of climate change will remain subjective – there is no such thing as 'true' probabilities – so it is extremely important for researchers to be as explicit as possible about their assumptions.

As Morgan and Keith (1995) anticipated, the overall uncertainty surrounding climate sensitivity has not reduced in the last decade. In fact, Figure 2 shows that there is a considerable chance that the climate sensitivity lies outside the IPCC consensus range of 1.5–4.5ºC. Van der Sluijs *et al.* (1998) have also noted that this consensus estimate for climate sensitivity has remained unchanged for two decades, operating as an 'anchoring device' in 'science for policy'. The use of probabilities to represent uncertainties in climate sensitivity is likely to challenge this view. This is a case where more research has actually increased uncertainty significantly compared with IPCC 'consensus science', which according to Pielke (2001) can only provide an illusion of certainty. This author concludes that

> science and technology will contribute more effectively to society's needs when decision-makers base their expectations on a full distribution of outcomes, and then make choices in the face of the resulting – perhaps considerable – uncertainty.

Because of unquantifiable uncertainties, science cannot deliver a full distribution of outcomes when it comes to climate change projections or impacts. This reasoning led Clark and Pulwarty (2003) to argue that

> probabilistic climate projections can mislead decision-makers by actually obscuring the real range of futures they face and by appearing to provide a greater degree of certainty about the future than is warranted.

This is a real danger that only scientists involved in the research can prevent by proper communication of uncertainty. It is important to emphasize that these subjective probabilities are highly conditional upon the assumptions made; again the need to be as explicit and transparent as possible cannot be emphasized enough. Our view on conditional probabilities is that we should not wait for perfect information (e.g. a single *pdf*) before providing decision-makers with the best available scientific information for their questions. A combination of conditional probabilities and scenarios will be required. Bounding the questions with decision-makers could further truncate the considerable uncertainty that may result from using conditional probabilities.

One important robust result apparent in Figure 2 is that the climate sensitivity is very unlikely to lie below 1 ºK, with the most likely values ranging from 2 to 6 ºK. The combination of this result with the sensitivity study of Caldeira *et al*. (2003) has important policy implications as it precludes considerable carbon emissions increases during this century if we aspire to stabilize the climate.

This review has also showed that determining the probability of climate change cannot be resolved within what Funtowicz and Ravetz (1993) call 'normal' science (i.e. routine puzzle-solving by experts, whose knowledge serves as a base for policy decisions) or what Morgan *et al.* (1999) call 'conventional tools for policy analysis' (e.g. utility theory, cost-benefit analysis, statistical decision theory and contingent valuation). This is the case because climate change has numerous characteristics of 'post-normal science': uncertainty is pervasive, values are disputed, stakes are high, decisions are urgent and the system is 'reflexively complex'. For post-normal science, the decision-making process is as important as the research product. Consequently, researchers need to further investigate the nature of decision-making in the context of probabilities and climate policy.

In the context of adaptation to climate change, the main focus of this article, the following questions deserve further attention. How sensitive is a particular system to changing probabilities in climate? How sensitive are adaptation decisions (of this system) to upstream uncertainties (from emission scenarios, global and regional climate modelling and impact modelling)? What is the value of probabilistic information for climate adaptation decision-making? These questions emphasize the importance of sensitivity analysis (Saltelli *et al.*, 2000), which is sometimes forgotten in the rush for prediction.

If a system is not sensitive to alternative climate futures then no action (in terms of adaptation) is required; i.e. climate change is not a problem. If sensitivity is low, perhaps autonomous adaptation will suffice to cope with the impacts of changing climate. If sensitivity is high, then planned adaptation may be required, and thus probabilities need more in-depth investigation, for uncertainty analysis for example (see also Willows and Connell, 2003). Also, we should not forget that options for coping with climate change must be considered in the context of multiple stressors (Scheraga and Grambsch, 1998). The application of climate change probabilities needs to be considered together with other environmental and socio-economic scenarios, such as a co-evolutionary approach that integrates socio-economic and climate change scenarios (Lorenzoni *et al*., 2000), the concept of double exposure to climate change and globalization (O'Brien and Leichenko, 2000), or the construction of 'non implausible' climate and economic scenarios (Strzepek *et al*., 2001).

Probabilities are being used because there are significant uncertainties associated with estimates of future changes in the climate. However, it is important to remember that all of these are subjective and highly conditional probabilities. Where possible, uncertainty needs to be quantified, but this depends on the type of uncertainty being considered. Epistemic uncertainty can be quantified and regularly updated as science progresses, but its range depends on the amount of knowledge available. Natural stochastic uncertainty is only semi-quantifiable in the sense that there are limits to predictability (of the climate system for example) even if we had perfect knowledge, which we do not have. We believe that human reflexive uncertainty is largely unquantifiable in probabilistic terms in the context of prediction, so scenario approaches have to be used to represent this type of uncertainty (see section 3).

Once the total quantifiable uncertainty has been combined with the different scenarios (to represent human reflexive uncertainty) it is possible to link these various uncertainties with specific adaptation decisions. Figure 3 shows a hypothetical example of changing probabilities according to four different development paths and numerous quantifiable uncertainties in the context of water resources. The challenge is to find robust adaptation strategies that are scenario-independent, i.e. options that will be beneficial to

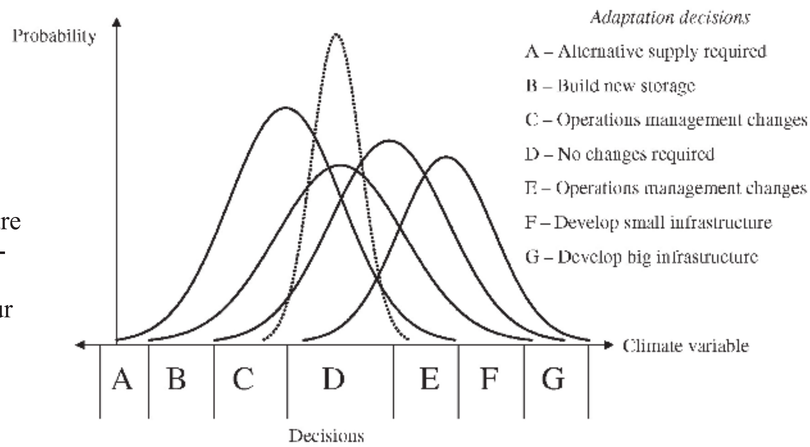

Figure 3. Hypothetical example of changing probabilities in a water resources context. The dotted line represents the probability of current climate (e.g. 1961–1990) and the full lines represent the probability of future climate (including quantifiable uncertainties such as climate and impact model uncertainties) according to four different 'futures'. Depending on the probability of occurrence of a certain climate variable specific adaptation decisions are listed (A–G)

society no matter what world development path we follow in the future. These robust solutions will have to be explored within a post-normal science framework that includes active input from all the relevant stakeholders. Lessons from previous assessments have shown that a regional approach with the inclusion and participation of stakeholders has the best potential to advance the assessment and implementation of adaptation options. Stakeholders are crucial ingredients of what is proposed because they are the people whose decisions must take account of climate change (and other environmental stresses), who hold the specialized practical knowledge needed to evaluate adaptation options, and who are the primary source of technological and managerial activities needed to implement them (Parson *et al*., 2003). However, it is unclear how public involvement will be incorporated in national climate change assessments (Wolfe *et al.*, 2001); this remains a considerable challenge for the scientific and policy communities. A further benefit of separating and managing uncertainties as described is that it enables research managers to identify and strategically invest in research areas where large and reducible uncertainty remains.

5.2 Assessment

Policy-focused assessment is an ongoing process that engages both researchers and end-users to analyse, evaluate and interpret information from multiple disciplines to draw conclusions that are both timely and useful for decision-makers (Scheraga and Furlow, 2001). This is the general aim of most national and regional climate change vulnerability and adaptation assessments (sometimes these are integrated) as well as the broader IPCC assessment reports. Moss and Schneider (2000) tried to introduce a common approach for assessing, characterizing and reporting uncertainties in the IPCC TAR. This was half-heartedly followed by the various chapters of each Working Group, with some conforming to the framework more closely than others. With a potential increase in the use of probabilities – and other forms of representing uncertainty, either qualitatively or quantitatively – in climate assessments in the near future, it could become an incommensurable task to maintain consistency in future assessments. This will certainly prove a challenge for the forthcoming Fourth Assessment Report of IPCC, especially with regard to the contrasting scientific subcultures represented across the three Working Groups.

The major implication of this is that researchers need to be explicit about the assumptions made to represent uncertainties, either using probabilities or other forms of expression. Schneider (1997) has emphasized the ‘critical importance of making value-laden assumptions highly transparent in integrated assessment modelling of global climate change’. If the use of probabilities, as an attempt to quantify uncertainties in climate change projections, is made explicit and transparent then there will be little scope to criticize the results as biased or misleading. Already users of climate change information are requesting that ‘context and uncertainties be clearly expressed’ (Turnpenny *et al.*, 2004). Risbey *et al*. (2000) argue that a formal method to represent uncertainty should have the following characteristics:

> In order to produce a traceable account of the method, each step in the process should be made as explicit as possible. The various assumptions employed should be articulated, along with the elements of judgement. For transparency, the methods should be coherent and consistent with the science. Judgements that need to be made should be tractable and meaningful. Further, where there is a range of disagreement in making judgements based on reasonable arguments, that range should be captured in representing the judgements.

5.3 Policy

Assessments are useful to the extent that they can inform policy and resource management decisions (Scheraga and Furlow, 2001). While this might be true, it is important to acknowledge that there are a myriad of other drivers of public policy. For example, limited financial resources are a major constraint on policy-making. This is actually an area where probabilities could be of added value to public policy because instead of adapting to any plausible climate realization, it would be possible to have focused, strategic adaptation polices, even though they are based only on the present range of quantifiable uncertainty. But, even if this were true, do we need 99.9% certainty to enact an adaptation policy? How different is a 0.6 from a 0.8 probability in policy terms? We need to investigate further how sensitive public policy is to changes in probability. We have already mentioned financial resources, but there are many other drivers of public policy such as culture, history, public awareness, self-interest, interest groups, power relationships, etc. If probabilities are ever to be effectively used in climate policy, this broader context of social and political processes where decisions are being made must be appreciated.

Finally, even if we start using probabilities in the near future for climate decision-making, the biggest constraint to their effective use is likely to be 'cognitive illusions'. These illusions lead us to errors which we are unaware of committing and arise from the considerable difficulty that people have in estimating and dealing with probabilities, risk and uncertainty (Nicholls, 1999). This is a well-known concept in the area of risk perception: presenting the same information about risk in different ways (e.g. a 2% chance as opposed to a 2 in 100 chance) alters people's perspectives and actions (Slovic, 1987). Furthermore, it has been shown that low probability/high consequences events are treated very differently to high probability/low consequences events (Patt and Schrag, 2003). This will clearly have considerable implications for the use of probabilities in any climate policy context. We need to understand these illusions better in order to communicate probabilities of climate change accordingly for appropriate use in public policy.

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