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Summary

Estimating the likelihood of future climate change has become a topical matter within the research community. This is the case because of the advancement of science, user demand and the central role played by prediction in guiding policy. But are probabilities what climate policy really needs? This paper reviews three key questions: (1) why might we need probabilities of climate change? (2) what are the problems in estimating probabilities? (3) how are researchers estimating probabilities? The first question is primarily analysed within the context of adaptation to climate change, but mitigation and integrated assessment are also briefly discussed. The second question explores the types and sources of uncertainties involved in estimating probabilities of climate change and how their characterisation can be controversial. For the third question, an extensive review of the literature is conducted on research that is creating the building blocks towards estimating the likelihood of climate change.

Overall, we conclude that the jury is still out on whether probabilities are useful for climate 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. There are various problems in estimating the probability of future climate change, but human reflexive uncertainty 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.

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

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 we can estimate the likelihood of quantified amounts of climate change throughout the coming century. 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 neglected because of the substantial advancement of climate change science as demonstrated by the IPCC TAR (2001d), in light of the upcoming Fourth Assessment Report, and because of the sharpening of climate policy discussions relating both to mitigation and adaptation (IPCC, 2001c).

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) disagreed 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) argued 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) proposed a risk-management approach that estimates the likelihood of exceeding a certain impact threshold (Jones, 2001). They argued that the probability of threshold exceedance is much less sensitive to input assumptions than the probability of climate change (Jones, 2003). Therefore, they concluded that it is more appropriate to establish cumulative probability distributions of threshold exceedance to allow optimal, focused adaptation plans.

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) criticised 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); 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.

Scott et al. (1999) have noted that four questions are evident when talking about uncertainty and climate change: How uncertain is global warming (what are the confidence intervals around key results)? What are the major sources of uncertainty (what individual parameters appear to really control overall uncertainty)? What is the form of information that could reduce this uncertainty and what would it be worth? What are robust policies that could be crafted to control damage from global warming despite the uncertainties involved? This paper explores the first two questions in detail and briefly touches upon the last two.

This review paper is divided into five sections. Section 2 takes a more in-depth look at why exactly it is proposed that we need estimates of likelihood of future climate change and why some would argue that these are not necessary. While the focus here is mainly on climate adaptation policy, we also touch upon probabilities in the context of climate mitigation policy and integrated assessment. 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 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, drafted by lawyers, not environmental scientists, has been largely translated by the scientific community into the notion of 'dangerous' climate change (see, e.g., Swart and Vellinga, 1994; Parry et al., 1996). This concept combines aspects of both mitigative and adaptive nature, and spans global to local scales. As in the IPCC, mitigation is referred to in this paper as the human capacity to reduce the root of the problem (e.g., by reducing greenhouse gas emissions or by enhancing sinks), whereas adaptation refers to the ability of systems (human and natural) to adjust (advertently or inadvertently) to climate change. Curiously, the UNFCCC and the IPCC have different definitions of climate change. The UNFCCC is solely concerned with human-induced climate change, whereas the IPCC considers both natural and anthropogenic climate change (see, e.g., Pielke Jr., 2003). 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".

In order to assess dangerous climate change for a certain unit of analysis – which could range from the whole planet to a certain species or economic sector in a particular location, down to the household level – one needs to find out what risk is posed by climate change to the exposure unit in question. As Schneider (2002) has pointed out, the most basic and uncontroversial definition of risk is "probability times consequence". For Morgan and Henrion (1990) risk involves an "exposure to a chance of injury or loss", which according to these authors leads directly to a need to describe and deal with uncertainty. 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., 2003).

In a survey of seven risk assessment frameworks, risk characterisation – i.e., the estimation of the magnitude and probability of consequences – emerges as one of the main common elements (Power and McCarty, 2002). This emphasis on risk assessment and quantification of uncertainty does not imply a return to conventional public policy analysis tools (e.g., cost-benefit analysis or decision analysis), as these have proven inadequate for global problems like climate change (Morgan et al., 1999). Instead, a combination of risk assessment techniques and other sophisticated global change tools (e.g., global climate models, earth-system models, integrated assessment models) will be required. For example, Jones (2001) developed an environmental risk framework to assess climate change impacts on individual exposure units. The framework is designed to simultaneously allow for the management of uncertainties (that propagate from climate change scenarios through a sequence of climate impacts) and provide extensive consultation within a broad setting of social decision-making. Particularly useful for research managers will be to distinguish between, and quantify, different types of uncertainty so that investments can be made in reducible uncertainty, useful policy insights can be drawn, and clarification made between what is known and what is not (Helton and Burmaster, 1996; Paté-Cornell, 1996b; Goodman, 2002).

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 initially developed for the scientific purpose of understanding impacts.

IAAs are national requirements for Parties who have ratified the UNFCCC. Most developed countries have performed this in one way or another. Recent examples include the US national assessment (NAST, 2001), the Canadian Country Study (Maxwell et al., 1997), the Assessment of Potential Effects and Adaptations for Climate Change in Europe (Parry, 2000) and Portugal's SIAM project (Santos et al., 2002). Examples from developing countries are less abundant, but include the numerous US country studies (Smith and Lazo, 2001) and the Dutch sponsored studies (NCCSAP, 2000). New studies are also being conducted under the AIACC programme (Assessments of Impacts and Adaptations to Climate Change) in multiple regions and sectors, which aims to support the development of scientific and technical capacity among developing country scientists to address gaps in knowledge about climate change impacts, vulnerability and adaptation (START, 2002).

The majority of IAAs have taken a prediction-oriented 'top-down' approach (Figure 1) that considers 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 (Carter et al., 1994; Parry and Carter, 1998). Some studies do not consider adaptation ('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 (Smith, 1997) 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 (see, for example, Mizina et al., 1999 for a typical example).

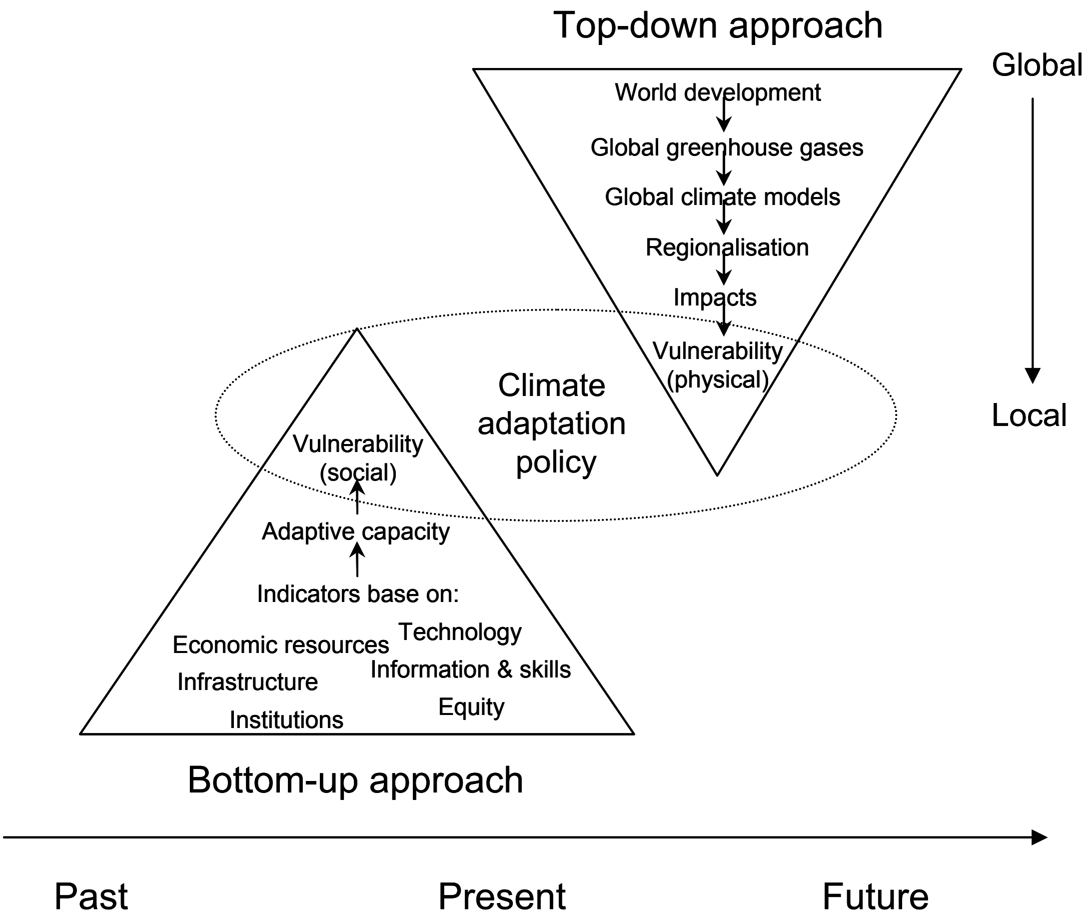

Figure 1: *"Top-down" and "bottom-up" approaches used to inform climate adaptation policy.*

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 recent IAA, the US national assessment (NAST, 2001).

This assessment was a major exercise devised to evaluate and summarise the potential consequences of climate variability and change for the US over the next l00 years. In order to do so, the best available information was provided 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 in the report. After careful consideration, the assessment team decided to use two GCMs: the Canadian model (Boer et al., 2000) and the Hadley Centre model (Johns et al., 1997). Broadly speaking both models' control runs provided a general agreement with the observed record of the US, although the accurate simulation of precipitation in mountainous areas remained problematic. For the whole US, 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 the US was projected to experience increases in precipitation.

In the case of eastern Colorado, these divergent results lend a risk-based analysis extremely difficult because stakeholders are left wondering if they should be prepared for more drought-like conditions or for wetter conditions. This will lead to sub-optimal adaptation strategies closer to 'adaptation screening' than 'robust solutions'. From a water resources management perspective, Stakhiv (1998) concluded "the GCM scenarios produce such a 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 it to make coherent risk management decisions under uncertainties and within resource constrains." 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 an additional advantage of keeping uncertainties within 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 recognise that several communities – for example water resource managers and engineers – already use probabilities, though of a different kind, to minimise the impacts of climate variability on their activities. These communities are therefore very receptive to probabilities and in fact tend to demand it from the climate modelling community. From a regional and state level perspective, Hickox and Nichols (2003) argue that adaptation planning will only be effective if climate scenarios describing a range of possible climates are available. Turnpenny et al. (2003) 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 it 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.

A final, more subtle, reason why probabilities are being vigorously pursued can be explained by history and the cultural aspects of science. Predictions have come to occupy a position of authority and legitimacy throughout history as a test of scientific understanding; "when expectations coincide with events, it lends support to the power of scientific understanding to explain how things work" (Sarewitz and Pielke Jr., 1999) Also, prediction has played an important role in guiding decision-making, which is also inherently forward looking. Sarewitz and Pielke (1999) have argued that the prediction of the behaviour of complex systems, such as the climate system, has been legitimised by the historical success of traditional reductionist predictive science. This has created a demand for climate prediction and, now, for probabilities of climate change. Since the 1970s, predictive tools in the form of GCMs have played a central and sometimes controversial role in climate policy (Shackley et al., 1998; Rayner, 2000). Some scientists have emphasised the considerable uncertainty and thus the need to improve prediction; Shackley et al (1998) called it the dogma "that great complexity equals greater realism, equals greater policy-utility". In view of this, some policy-makers have argued that sound policy cannot be developed without substantially reducing scientific uncertainty; thus the need to "get the science right". There is a reinforcing cycle (further explained in Pielke Jr. and Sarewitz, 2003) of providing better and better predictions from GCMs, which at present means estimating probabilities. In this logic there is an expectation that uncertainty will be reduced, which tackles one of the concerns of Burton et al. (2002), but not the others.

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 Jr., 1998; Adger, 1999; Handmer et al., 1999; Kelly and Adger, 2000; Barnett, 2001; Burton et al., 2002; Clark and Pulwarty, 2003; Tompkins and Adger, 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 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 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 place on their livelihoods and well-being; this method of analysis emerged from the work of Sen (1981), Blaikie et al. (1994) and others. Social vulnerability has been measured by developing a set of indicators of relative vulnerability, e.g., for a small rural community this could include poverty, the use of resources, the distribution of assets and income, institutional effectiveness, etc.

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 would unfold with future changes in hazard exposure, though it is certainly an important one (Yohe and Dowlatabadi, 1999). This is the case because there are two fundamental limitations of 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).

This school of thought would argue that probabilistic results are not very useful because they don't 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. Pielke and Sarewitz (2003) have used a metaphor to explain this: "It's as if the National Institutes of Health focused its research on making better projections of when people will die, rather than seeking practical ways to increase health and life expectancy". Interestingly, one climate modeller proposed a vulnerability assessment approach because in his view accurate prediction of climate variables beyond seasonal time scales may not be possible (Pielke Sr., 2002).

2.1.3 Why is there a bifurcation in the literature?

Two opposing views have been exposed on the need of probabilities of climate change for climate adaptation policy (Figure 1). This does not mean the two approaches are contradictory; in fact, they are complementary in terms of informing policy, but they have different climate information requirements. In this paper 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). The different climate information necessities of these two approaches seem to reside in a number of factors that we now examine.

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) and all nations (Brooks and Adger, 2003). The focus is more centred on the social and economic well-being of society (Kelly and Adger, 2000). 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 takes the humans out and only considers the physical exposure. Though a simplification, this caricature reveals why biophysical vulnerability scholars would prefer probabilities to their social counterparts. In a flooding context, Few (2003) notes the "differences of approach between those that see vulnerability in terms of variations in exposure to hazards and those that concentrate on variation in people's capacity to cope with hazards."

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 or business policy horizons mostly focus on the short-term.

A third important factor is the development status of the region or country (cf. Yohe and Schlesinger, 2002). Most developed countries are perceived to be more resilient (less vulnerable) to climate variability and change than developing countries. Because of this perception, it is understandable why vulnerability-based studies in developed countries have been largely neglected relative to prediction-oriented studies (for an exception see O'Brien et al., 2003). 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). According to Murphy et al. (2001), seasonal forecasting has good prospects for application to early warning of drought and flood hazards, with economic value in the developed world and a matter of life and death in the more vulnerable communities of the developing world. Nevertheless, 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. Patt and Gwata (2002) identified six constraints limiting the usefulness of forecasts: credibility, legitimacy, scale, cognitive capacity, procedural and institutional barriers, and available choices. 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 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 paper, 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 characterised 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 likely 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 of computational power this has arguably led to the emergence of predicting the future in terms of probabilities. Interpretative-style researchers 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 generalise 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 accuracy possible, which certainly requires probabilities (or some explicit representation of uncertainty), and then devise adaptation strategies to reduce exposure to the increased hazard.

2.2 Climate mitigation policy

While some aspects of climate adaptation policy could potentially reap benefits from probabilities attached to climate futures, the case does not appear to be so strong for climate mitigation policy. For example, whereas adaptation will have to be tackled at the sub-national (i.e., local) and regional levels, mitigation is a global 'commons' problem. Cooperation between states is arguably much more important than probabilities.

There is considerable scope to apply probabilities nonetheless. For example, by defining a dangerous level of climate change based on a certain global impact threshold one can probabilistically find out how much emission reduction will be needed to avoid this impact. One study used the large-scale eradication of coral reef systems and the disintegration of the West Antarctic Ice Sheet as dangerous thresholds and looked at different atmospheric stabilisation levels, but not in a probabilistic fashion (O'Neill and Oppenheimer, 2002). This approach is usually termed the policy optimisation model. The other approach is known as the policy evaluation model, of which Dessai and Hulme (2001) is a probabilistic example. These authors used probabilistic climate projections to show the impact of different global mitigation strategies based on the Kyoto Protocol and subsequent commitments. The aim here was to show decision-makers the impact of their choices in terms of global temperature change, but with estimates of likelihood attached to them. A hybrid approach is the "Tolerable Windows Approach", which defines the boundaries of tolerable change (with respect to their 'anthropogenic interferences') and then computes backwards the necessary economic, social, and political conditions which are consistent with the corridor of tolerable climates (Petschel-Held et al., 1999).

Climate mitigation policies have been dominated by international and national politics (Dessai, 2001). Amongst other reasons, the large uncertainties associated with climate change have been used to justify a wait-and-see approach to climate mitigation policy; the Bush Administration rejection of the Kyoto Protocol is cited as a typical example. We would argue that the use of probabilities, to represent uncertainties in climate change projections, will help policymakers make more *informed* decision about the management of the climate system, but these are by no means a prerequisite to devise and implement climate mitigation policies. For example, without any explicit definition of dangerous climate change, the UNFCCC adopted the Kyoto Protocol. As Pielke and Sarewitz (2003) have stated, "the focus on climate uncertainty has distracted us from the fact that there are plenty of reasons [environmental, health, security] to improve energy policy".

2.3 Integrated Assessment

According to Rotmans and van Asselt (2001), Integrated Assessment (IA) "is the practice of combining different strands of knowledge to accurately represent and analyse real world problems of interest to decision-makers." For Scott et al. (1999) "IA models for climate change assemble knowledge from a diverse set of sources, relevant to one or more aspects of the climate change issue, for the purpose of gaining insights that would not otherwise be available from traditional, disciplinary, research". Definitions of IA abound, but what is clear is that IA models have been important tools in the advancement of the science and policy of climate change (Rotmans, 1990; Dowlatabadi and Morgan, 1993). Uncertainty is a key issue in IA modelling that has either taken a secondary role or been completely neglected, though it has risen in prominence recently. In their review, Rotmans and van Asselt (2001), list a number of uncertainty approaches used in IA, including probabilities. Other approaches include sensitivity analysis, formal scenario analysis, hedging-oriented methods (i.e., seeks risk minimisation), validation, the NUSAP (Numeral, Unit, Spread, Assessment and Pedigree) method (see Funtowicz and Ravetz, 1990 or http://www.nusap.net/), and a new approach the authors called "pluralistic uncertainty management", which is further developed elsewhere (van Asselt and Rotmans, 2002). In this last approach, multiple perspectives are incorporated as a way to assess the most salient uncertainties, both in model quantities and structure. Rotmans and van Asselt (2001) note that probability-based methods ignore uncertainty in model structure, which makes them question whether probability distributions can adequately cover the range of possibilities. Researchers in applied statistics are currently investigating these issues (Craig et al., 2001; Kennedy and O'Hagan, 2001), and applying it to IA models of climate change (Challenor, 2002). It is not clear whether probabilities are the 'right' approach for IA modelling because of the multitude of available approaches, but they are certainly an important method, especially when used in conjunction with other approaches (e.g., scenario analysis or hedging methods).

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. Probability distribution functions are one of various methods to represent uncertainty of climate change projections. As noted earlier, probability is understood differently by different groups of scholars, but has mainly been divided into the frequentist and the subjective (or Bayesian) schools. Likewise, the concepts of 'risk' and 'uncertainty' have various meanings (other than the ones implied in this paper) because of the different communities and cultures using the terms. For example, Knight (1922) distinguished 'uncertainty', which he associated with a particularly radical type of 'not knowing', from a weaker sense of 'not knowing', which he associated with 'risk'. 'Ignorance' – "a condition under which it is possible neither to resolve a set of discrete set of probabilities along a scale of outcomes, nor even to define a comprehensive set of outcomes" (Stirling, 1998) – was introduced more recently.

Figure 2 tries to capture these elements where risk would encompass the first circle, mainly using frequentist probabilities, but sometimes also subjective probabilities; e.g., the question "what is the risk that it will rain tomorrow?" could be answered using climatology (frequentist probabilities) or numerical weather prediction (subjective probabilities). The middle ground is occupied by uncertainty, where subjective probabilities and scenario analysis are usually applied. A typical example is the IPCC TAR statement that globally averaged surface temperature is projected to increase by 1.4 to 5.8°C over the period 1990 to 2100. The calculation of these figures involved considering four different scenarios of world development until 2100. These "visions" or "futures" were converted to GHG emissions trajectories by several deterministic energy-economy-environment models (Nakicenovic and Swart, 2000). A simple climate model (Raper et al., 2001) that emulates several GCMs then converted GHG emissions into atmospheric concentrations, into "radiative forcing", and finally into global temperature change and sea level rise.

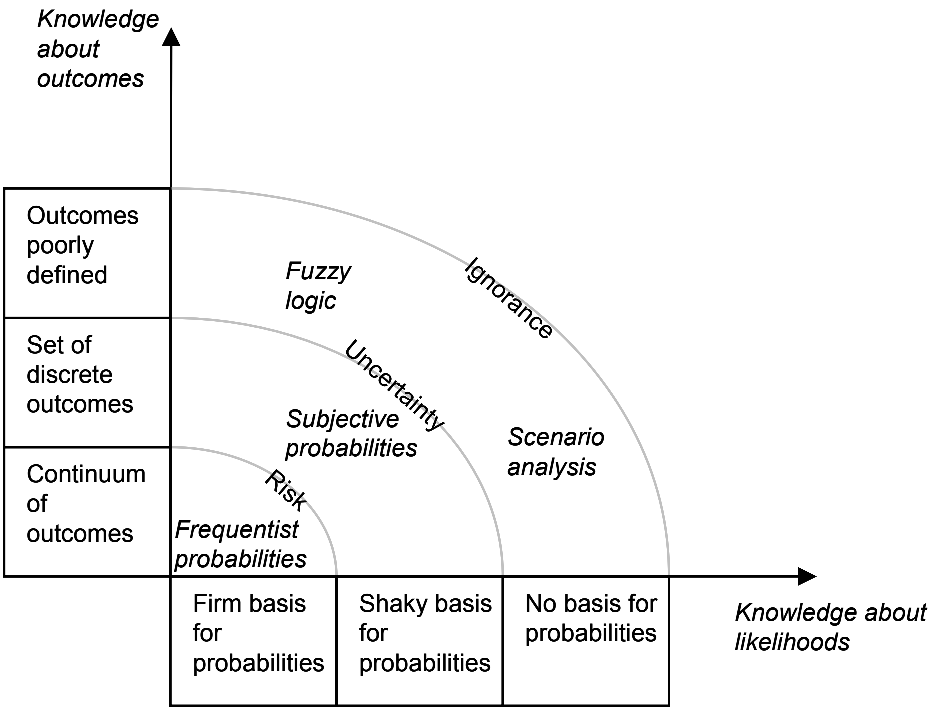

Figure 2: *The realm of probabilities and other methods to represent uncertainty when comparing the knowledge about outcomes with the knowledge about likelihoods. Modified after Stirling (1998).*

Finally, the area in the top right hand quadrant is occupied by ignorance, where there is no basis for probabilities and where we do not know the outcomes either. For example, what is the maximum atmospheric concentration of greenhouse gases that the planet can support without endangering life as we know it today? Ignorance is important because under such circumstances, there is often no credible basis for the many sophisticated techniques of probability theory (Stirling, 1998), although Dempster-Shafer theory is one attempt to overcome near-ignorance conditions (see, for example, Luo and Caselton, 1997). Other attempts to tackle ignorance include the concepts of 'imaginable surprise' (Schneider et al., 1998) and 'climate surprise' (Streets and Glantz, 2000). According to these authors, a surprise is the condition in which the event, process or outcome is not known or expected. These authors go on to explore different taxonomies of surprise and their policy usefulness.

There is no universal typology of uncertainty. At the very basic level, uncertainty is uncertainty and probabilities are probabilities; distinguishing types of uncertainty is done for the practical purposes of disentangling complex problems (Winkler, 1996). For example, Walker et al. (2003) classify uncertainty according to three dimensions: its 'location' (where it occurs; e.g., expert judgement, models, data), its 'level' (where uncertainty manifests itself on the gradual spectrum from determinism, through probability and possibility, to ignorance) and its 'nature' (whether uncertainty primarily stems from knowledge imperfection or is a direct consequence of inherent variability). While we take a holistic view of the term 'uncertainty' (which can range from a lack of absolute sureness to complete vagueness, thus encompassing the narrower 'risk', 'uncertainty' and 'ignorance' interpretations shown in Figure 2) we next examine the sources and types of uncertainty, which from a practical viewpoint can explain the problems of estimating the probability of climate change.

The large uncertainty of the IPCC global mean temperature projection range originates from '*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 Burmaster, 1996; 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 parameterisation 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 paper 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 (Parry, 1996), although it is possible that uncertainty increases with more research (as shown in Section 5.1). Representing epistemic uncertainty in a probabilistic fashion has been relatively 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; for an example see Vaughan and Spouge, 2002). This has led these uncertainties to be sometimes ignored – by overlooking available techniques for improving subjective assessments of probability and confidence levels (Moss, 2000) – 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 to this argument, which we support, but will not repeat here.

Instead, we emphasise a point that was not explicitly mentioned by Grubler and Nakicenovic (2001) or Schneider (2002) which we think is important and which completes the rest of the picture regarding unknowable knowledge, the notion of "reflexivity". 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).

This reaction in a collective form has traditionally taken 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 lend the scientists' 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 publications of the four SRES storylines have already made a B1-type world more likely than an A2-type world, in which the impacts of climate change would be much more pronounced. However, if we perceived we were following 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 social systems exhibit.

The fact that humans are part of the system being researched in the case of the climate change problem therefore makes the 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) note that the process of prediction for decision 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 summarise the different types of uncertainty introduced in this section. "Reflexivity" is in our view the major obstacle for estimating the likelihood of climate change. Modelling "reflexivity" (iterative human behaviour) is fundamentally complex and some would argue logically impossible. 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 questions (to represent human reflexive uncertainty). These probabilities will remain highly conditional on the assumptions taken 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 organising 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.

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

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

4. What has been done so far?

In his paper, Schneider (2001) argues that the IPCC should embrace the challenge of estimating the probability of climate change. While we hope the IPCC takes on this challenge, we do recognise some limitations to what can be achieved (see Section 3). We next review the numerous efforts, by a wide-ranging research community, that are contributing or leading to the estimation of the likelihood of climate change with a particular, but not exclusive, emphasis on probability-based studies. The problem of climate change cuts across many different areas, therefore we discuss the literature in subject areas rather than by individual 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., 1997; Lutz et al., 2001) and technological change (Gritsevskyi and Nakicenovic, 2000). However, rarely have these 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). They 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). Another recent study estimated global CO_2 emissions until 2100, using a Monte Carlo method that draws on *pdfs* based on historic data (calculate using regression analysis) or expert assessments (Leggett et al., 2003). From 2500 runs, Leggett et al. (2003) concluded that it is highly unlikely that CO_2 emissions would more than triple over this century, with 95% probability bounds that ranged from 10-20 Gigatonnes of carbon (GtC) with a median of 14.1 GtC. Webster et al. (2002) performed a Monte Carlo simulation with 10,000 runs, where 5-95% of the results stayed in the range 7-39 GtC, with a median of 20 GtC. Interestingly, neither of these studies span the whole IPCC SRES range (3.3-36.8 GtC) at the 95% confidence level.

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) 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 proposal (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 is almost ready to start (see http://climateprediction.net) and is expected to provide a better handle on uncertainty in global climate predictions. Other similar efforts with fewer runs are currently being undertaken (Barnett et al., 2003; Murphy et al., 2003). 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; Forest et al., 2000; Andronova and Schlesinger, 2001; Forest et al., 2001; Forest et al., 2002; Gregory et al., 2002; Knutti et al., 2002; Stott and Kettleborough, 2002; Jones et al., 2003; Knutti et al., 2003). This is essentially a Bayesian approach that will prove most useful as more observed data are gathered in the future.

In the context of detection and attribution of climate change, Allen (2003) has even proposed the usage of a “net likelihood-weighted liability” for the purposes of climate change litigation (see Grossman, 2003 on tort-based climate change litigation). It will never be possible to say, at any confidence level, that human influence has contributed X% to an actual weather event. Instead, Allen (2003) argues that we will be able to say that past GHG emissions are likely to have increased the risk of that event over its pre-industrial value. However, there are substantial uncertainties involved in attributing responsibility to global temperature change to individual countries, as den Elzen and Schaeffer (2002) have shown. Uncertainties in climate change detection and attribution have also been articulated and quantified using a formal probabilistic protocol (Risbey et al., 2000; Risbey and Kandlikar, 2002).

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 high impact/low probability nature of the 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.

Titus and Narayanan (T&N) (1996) developed probability-based projections of future sea level rise using a combination of Delphic and Monte Carlo techniques. The Monte Carlo experiment was divided into two parts. In part one, T&N (1996) developed a simplified model (based on Wigley and Raper, 1992) for estimating sea level rise as a function of 35 major uncertainties, where the probability distributions for each parameters were derived from the existing literature, and performed 10,000 simulations. In part two, the results from part one were circulated to the Delphic panel of approximately two dozen experts (including climatologists, oceanographers, and glaciologists) who reviewed T&N’s assumptions and suggested their own subjective probability distributions (which were treated as equally likely), with which they re-ran 10,000 simulations. They estimated that global temperatures are most likely (50% probability) to rise 2ºC and sea level rise of 35cm by 2100, which is somewhat lower than previous IPCC assessments. The numbers here are not important, but the fact that coastal managers and engineers can include the risk of sea level rise in engineering design and land-use planning regulation shows that probabilities of climate change can be useful for policy.

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 been traditionally used to explore regional uncertainties in future climate (Kittel et al., 1998; Giorgi and Francisco, 2000; Giorgi et al., 2001b), and a new summary measure, which calculates average, uncertainty range, and reliability of regional climate changes from GCM simulations has been proposed by Giorgi and Mearns (2002), named 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. Benestad (2003) produced probabilistic regional temperature scenarios for northern Europe based on spatially interpolated empirically downscaled trends, derived using a multi-model GCM ensemble as well as various downscaling options. Goodess et al. (2003) have developed a sophisticated method to estimate the probability of future extreme weather events. They applied this to short and long drought frequency in the UK as a function of global mean temperature change, computed by scaling observed time series means and distribution shapes according to relationships fitted to a GCM and a regional climate model. Giorgi and Mearns (2003) extended their Reliability Ensemble Averaging method to calculate the probability of regional climate change exceeding given thresholds using 9 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.

One specific problem of the Giorgi and Mearns (2003) study is that it conflates different types of uncertainties by associating a likelihood to emissions scenarios (in this case SRES A2 and B2 had equal weight). 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 mean time 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.

A particular regional uncertainty that has been consistently overlooked by assessments, and thus is far from any type of probabilistic treatment, is the impact of land-use change and landscape dynamics on regional and global climate (Pielke Sr., 2002). Marland et al. (2003) suggest that this human disturbance could have important implications for climate mitigation policy so they suggest a 'regional climate change potential' (as opposed to the Kyoto Protocol's global warming potentials) as a new metric useful for developing a more inclusive protocol.

Another problematic issue in dealing with regional climate uncertainty is the issue of spatial downscaling. The mismatch between the coarse resolution of GCMs (hundreds of kms) and local or regional impact applications has led to the development of a plethora of downscaling techniques (Wilby and Wigley, 1997; see Appendix 10.4 in Giorgi et al., 2001a for a list of examples). These include dynamical downscaling, which describe the fine atmospheric processes nested within the GCM outputs, the so-called Regional Climate Models (RCMs) (e.g., Jones et al., 1995; Giorgi et al., 1998); and statistical downscaling, including weather typing (e.g., Wilby, 1994), stochastic weather generators (see Wilks and Wilby, 1999 for a review) and neural networks (e.g., Trigo and Palutikof, 1999). Both New and Hulme (2000) and Raisanen and Palmer (2001) used 'raw' GCM data (sometimes called 'unintelligent' or 'simple' downscaling since it only involves interpolation of the output) in their probabilistic studies whereas Benestad (2003) and Osborn et al. (2003) applied some downscaling techniques to the GCM data. Managing downscaling uncertainties will prove particularly difficult because of the various techniques being developed and the conflation of scales (global to local), which makes the appropriateness of techniques highly context dependent. At present, validation statistics are being used to explore downscaling uncertainty in a number of settings (e.g., water and agriculture), between statistical downscaling and raw GCM output (e.g., Wilby et al., 1999), between statistical methods (e.g., Wilby et al., 1998), between RCMs and statistical downscaling (e.g., Mearns et al., 1999; Wilby et al., 2000). Several on-going projects are now comparing the results of different RCM simulations (PRUDENCE, 2002) and comparing between RCM and statistical downscaling techniques (STARDEX, 2002). Like the global climate, representation of uncertainty in spatial downscaling in probabilistic terms is constrained by computational power, but Katz (2002) and Prudhomme et al. (2002) suggest that statistical downscaling, in terms of conditional stochastic processes, could be particularly useful for uncertainty analysis, rather than empirical methods. Downscaling has become a large enterprise within climate change science, but these techniques are very dependent on the GCM outputs they utilise – downscaling cannot correct for model inaccuracies (Mitchell and Hulme, 1999).

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 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. For example, Woodbury et al. (1998) used four different GCMs to derive what they call a "probabilistic climate change scenario", Venkatesh and Hobbs (1999) used four climate scenarios, while Scherm (2000) used a fuzzy scenario. The most comprehensive approach is provided by Jones (2000a) who has a similar approach to New and Hulme (2000), but extends 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. In the Great Lakes region, Hobbs et al. (1997) used decision trees and Bayesian analysis to assess climate change risk to two specific investment decisions. They found that beliefs about climate change can affect optimal decision. Without using probabilities of climate change, Risbey et al. (1999) examined farming decision-making under the uncertainty of climate variability and change for Australia. At the micro-scale (farm level) they constructed a simple model to compare the performance of hypothetical farmers operating under a variety of possible behaviours – e.g., a hedge farmer who is risk averse or a predictive farmer who uses forecast information – with the performance of a clairvoyant farmer. This study showed that using climate forecast information has substantial benefits over decision rules based on historical trends, but this cannot be generalised because of the simplicity of the model. The study also showed that the model is sensitive to the shape of the crop response surface used. Morgan et al. (2001) determined subjective probability distributions of the impact of a doubling CO_2 climate change on forest ecosystems through the elicitation of experts. For one single climate change scenario various non-climate key factors and processes of forest ecosystems were explored, e.g., human land use, physical disturbance, soil properties, etc.

A recent study combined the results of New and Hulme (2000; i.e., 25,000 climate scenarios randomly generated by a Monte Carlo simulation using several GCMs, SRES-98 emission scenarios and climate sensitivities) with a hydrological model to quantify uncertainties of climate change impact on the flood regime of five small catchments in Great Britain (Prudhomme et al., 2003). The analysis showed a large variation of results (varying by a factor of 10), but most scenarios showed an increase in both the magnitude and frequency of flood events, generally not greater than natural variability (which in this study constituted 95%-confidence intervals of historical data). The largest uncertainty was attributed to the GCM used rather than emissions scenarios or climate sensitivity, though the former starts playing a larger role by the 2080s. Uncertainties in the hydrological model itself or downscaling were not explored so it is not possible to make definitive recommendations on where further research should be targeted.

4.6 Integrated assessment for climate change

Some of the studies reviewed in previous sections (e.g., Webster et al. 2002; Legett et al. 2003) are modules of larger integrated assessment models (IAMs). Various IAMs of climate change have represented uncertainty explicitly (e.g., Dowlatabadi and Morgan, 1993; Hope et al., 1993; Chao, 1995; Peck and Teisberg, 1996; Nordhaus and Popp, 1997; Scott et al., 1999), which Weyant et al. (1996) have called ‘uncertainty-based models’ in their overview of the literature. They counted ten of these models in 1996, some of which we review next.

Nordhaus and Popp (1997) estimated that the value of early information (assuming decision-makers act optimally once the information is known) is between one and two billion dollars for each year that resolution of uncertainty is moved forward in time. They estimate that damages of climate change and the costs of reducing greenhouse gas emissions are the most important uncertain variables when estimating the value of scientific knowledge. On the other hand, subsequent improvements to Dowlatabadi and Morgan (1993) found that uncertainties in climatic/geophysical parameters dominate policy outcomes. Hope et al. (1993) found that adaptation to climate change might be cheaper than mitigation, but the results were sensitive to various parameters including climate sensitivity, mitigation costs, etc. Within probabilistic-based methods, the treatment of uncertainty in IAMs has taken a number of methodological approaches including Latin hypercube sampling (e.g., Nordhaus and Pop, 1997; Scott et al. 1999), method of probabilistic collocation (e.g., Webster et al. 2003) or Monte Carlo simulation (e.g., Roughgarden and Schneider 1999). However, as discussed in section 2.3, there are other approaches to treat uncertainty in IA. Van der Sluijs (1996) has explored the problems of uncertainty management in IAMs of climate change and concluded that a methodology based on the NUSAP method (Funtowicz and Ravetz, 1990) is most appropriate to disentangle the uncertainty problem in IAMs.

Though some results might be probabilistic, the treatment of adaptation in IA models is still very simplistic, if at all existent (Toth, 2000). This is implicitly done using damage functions that remain considerably uncertain mainly because they use global mean temperature as an indicator of impacts (see e.g., Smith and Hitz, 2003). In order to explore this particular uncertainty, Roughgarden and Schneider (1999) used an IAM (Nordhaus and Popp, 1997) to explore several alternate published estimates (e.g., Fankhauser, 1995) and opinions (Nordhaus, 1994) of the possible damages from climate change. They showed that incorporating alternate damage estimates results in a significantly more aggressive optimal policy than using a single damage function, thus emphasising the need to consider estimates of uncertainty of the various parameters of IAMs.

Scott et al. (1999) performed sensitivity and uncertainty analysis in their previously deterministic IAM. The sensitivity analysis showed that market damages are much more sensitive to variables relating to economic activity or emissions than climate sensitivity. For example, an increase of the index of labour productivity in the developing world by 50% would increase global temperature by 1.24ºC by the year 2100 and market damages by 290%. A 50% increase of income elasticity of demand for energy in the developing world would increase temperature by over 2.54ºC. Climate sensitivity is ranked fourth out of 74 variables of importance for market damages. The uncertainty analysis showed that the income elasticity of demand of energy in the developing world is the single largest uncertainty for either emissions, temperature change, market damage or non-market damage in the year 2100.

These results have considerable implications on where research investment should be targeted if the aim is to reduce uncertainties associated with climate change.

Toth et al. (2003) performed uncertainty analysis in four decision variables to explore the effects of policy/target-related uncertainties on the shape of the emission corridors. Impact constraints, climatic constraints (such as the magnitude and rate of the global mean temperature increase) and aerosol emission scenarios had an important influence in the emission corridors. In a similar effort and without using probabilities, Caldeira et al. (2003) showed how uncertainty in climate sensitivity propagates to uncertainty in allowable carbon emissions for a specified climate change scenario, arbitrarily chosen to be a stabilisation to 2ºC global mean warming after the year 2150. Estimated allowable carbon emissions later this century could be less than 0 GtC or 13 GtC per year depending on whether climate sensitivity is 4.5ºC or 1.5ºC respectively. These authors conclude that even if climate sensitivity is low, a considerable transition to CO_2 emission-free technologies will be required (see Hoffert et al., 2002).

Webster et al. (2003) have recently combined probabilistic GHG emissions (Webster et al., 2002) with constrains on climate parameters from observations (Forest et al., 2002). They found that in the absence of policy intervention their 95% probability range of global mean temperature change for 2100 is 1.0 to 4.9ºC, with a mean of 2.4ºC. The policy scenario reduces (mean of 1.7ºC in 2100), but doesn't eliminate the chance of substantial warming. While this approach is certainly pioneering in terms of climate change uncertainty analysis, there remain important caveats surrounding the issue of policy versus no-policy scenarios. Where does reflexivity fit with these scenarios? This study used arbitrary climate policy and no-climate policy scenarios (Reilly et al., 1999), however, unlike the SRES scenarios little information is given about the "worlds" that underlie these scenarios, which limits the use of the results. Also, these results might be useful to evaluate a certain mitigation strategy, but in terms of adaptation it is not because one could envisage millions of policy scenarios; adaptation researchers want to know which is the likeliest to occur.

5. Concluding remarks

This literature review cannot provide an unambiguous answer to whether climate policy needs probabilities or not. This will depend 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 gravest 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 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 underway into numerous aspects of this ambitious aim. 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 recognise that science will not deliver an uncontroversial 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 compress all uncertainty into a single *pdf* of future global warming.

To illustrate this point, Figure 3 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. 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.

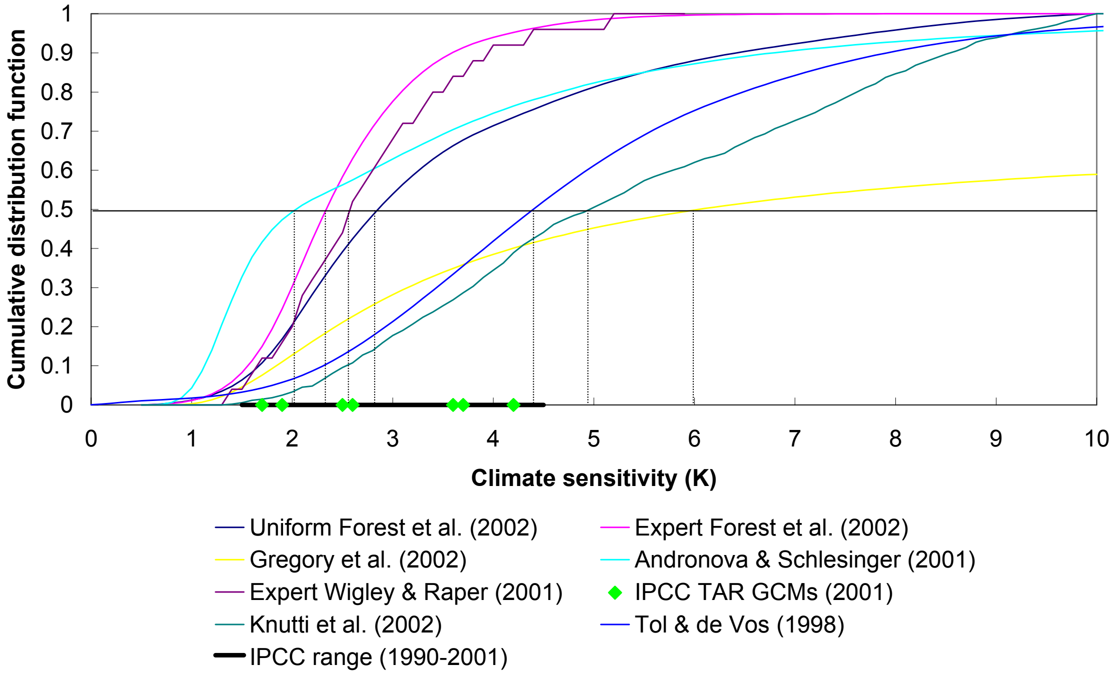

Figure 3: *Cumulative distribution functions of climate sensitivity (K) for a number of studies reviewed in section 4.2, individual GCMs used in the IPCC TAR (green diamonds) and thick black line representing the IPCC "consensus" range. The thin black line intersects each study at its most likely value.*

It is interesting to note that as Morgan and Keith (1995) had anticipated, the overall uncertainty surrounding climate sensitivity has not reduced in the last decade. In fact, Figure 3 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 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 to IPCC 'consensus science', which according to Pielke Jr. (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".

From this review, it is clear that 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 emphasise that these subjective probabilities are highly conditional upon the assumptions made; again the need to be as explicit and transparent as possible cannot be emphasised enough. Our view on conditional probabilities is that we should not wait for perfect information (e.g. a single *pdf* since this is not attainable because of unquantifiable uncertainties) 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. A particularly robust result that decision-makers can take from the studies shown in Figure 3 is that there is little chance that climate sensitivity lays below 1ºK, with the most likely value ranging from 2-6ºK. 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 a stabilisation of climate.

This review has also showed that determining the probability of climate change cannot be resolved within what Functowicz 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 contigent 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, it is important for researchers 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 paper, this review has identified some questions that 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 emphasise the importance of sensitivity analysis (Saltelli et al., 2000), which is sometimes forgotten in the dash for predictions.

If the system is not sensitive to alternative climate futures then no action (in terms of adaptation) is required. If sensitivity is low, perhaps autonomous adaptation will suffice to cope with the impacts of changing climate. In the case of high sensitivity, planned adaptation may be required, and thus probabilities need more in-depth investigation (see also, Willows and Connell, 2003). Sensitivity analysis of adaptation decisions will tell us whether these decisions are indeed sensitive to changes in the climate. If not, then climate change will not be a problem. If the decisions are highly sensitive, then probabilities of climate change may well be necessary in order to perform an uncertainty analysis to determine the sources of uncertainty in making adaptation decisions. 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 (see, e.g., Carter et al., 2001), 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 globalisation (O'Brien and Leichenko, 2000) or the construction of 'not-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 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. Human reflexive uncertainty is 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 4 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 society no matter what world development path we follow in the future.

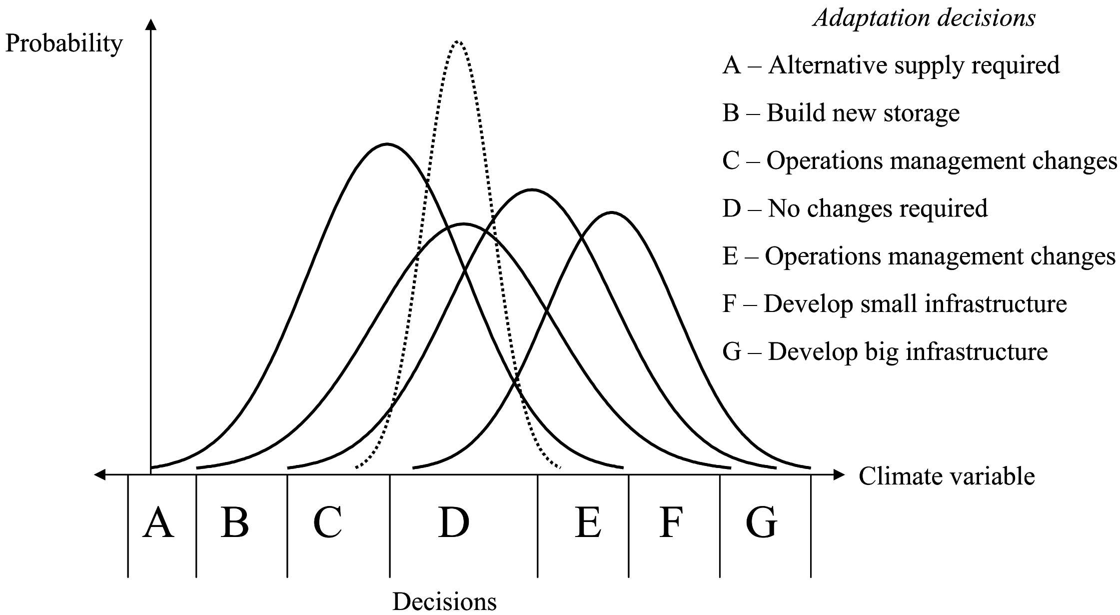

Figure 4: *Hypothetical example of changing probabilities in a water resources context. The dotted line represents the probability of current climate (e.g., 1961-90) and the full lines represent the probability of future climate according to four different 'futures' that include quantifiable uncertainties such as climate and impact model uncertainties. Depending on the probability of occurrence of a certain climate variable specific adaptation decisions are listed (A-G).*

These robust solutions will have to be explored within a post normal science framework that includes 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 specialised 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 areas of large and reducible uncertainty.

5.2 Assessment and policy

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, characterising and reporting uncertainties in the IPCC TAR. This was half-heartedly followed by the various chapters of each Working Group, with some abiding 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 sub-cultures 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 emphasised 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 criticise the results as biased or misleading as has been done in the past (see, e.g., Soon et al., 2001; and subsequent replies by Risbey, 2002; Karoly et al., 2003). Already users of climate change information are requesting that "context and uncertainties be clearly expressed" (Turnpenny et al., 2003). 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."

Like Moss and Schneider (2000), Toth (2000) attempted to introduce decision analysis and management frameworks (DAMFs) to the TAR, i.e., "analytical techniques aimed at synthesising available information from many segments of the climate problem in order to help policymakers assess consequences of various decision options in their own jurisdictions". DAMFs are crucial because much of the climate policy debate emanates from differing or contradicting results from different DAMFs or from the same DAMF formulated differently (Toth, 2000). In essence, DAMFs represent the bridge between assessments and policy, but the boundaries between these domains are very blurred. Again, this emphasises the importance of being explicit; analysts need to document their application-specific assumptions along with the pedigree of the adopted DAMFs. While a whole chapter was devoted to DAMFs in IPCC TAR (2001b) Working Group III on mitigation decisions, Working Group II on impacts, adaptation and vulnerability hardly made any mention to the DAMFs. This could be related to the pervasive uncertainty involved in estimating the impacts of climate change. However, with the potential use of climate change probabilities, DAMFs will have to be made more transparent and explicit to policymakers and stakeholders. In fact, the DAMFs being used will determine whether probabilities of climate change are useful or indeed necessary. For example, decision analysis or risk analysis would likely benefit from using probabilities, whereas multi-criteria analysis or sociological perspectives would not. It will be important to further investigate DAMFs in the context of adaptation decisions to cope with climate variability and change.

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 realisation, 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 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 we are unaware of committing and arise from the considerable difficulty 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. 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 optimal use in public policy.

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