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Modelling climate change impacts for adaptation assessments

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6.1 Introduction

Climate change is one of the most pressing global problems of our time. Two major responses have emerged to deal with this issue: mitigation and adaptation. In general, climate policy has mostly focused on mitigation – i.e., the reduction of greenhouse gas (GHG) emissions and/or the enhancement of sinks – with instruments such as the Kyoto Protocol. While there is a wide consensus among climate experts and policy makers that mitigation of climate change is and should remain the prime focus of climate policy, it is increasingly recognized that adaptation to climate change has become unavoidable. The Intergovernmental Panel on Climate Change (IPCC) has shown that even under optimistic assumptions for the success of present-day mitigation efforts and policies, human activity is likely to lead to further climate change with possibly severe impacts (IPCC, 2007a). The Stern review noted that adaptation is the only response available for the impacts that will occur over the next several decades before mitigation measures can have an effect (Stern, 2007).

Also important here is the understanding that even if atmospheric GHG concentrations are kept constant at today's levels, temperature would still continue to rise because

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the thermal inertia of the oceans causes the realized warming to lag several decades behind changes in radiative forcing[1] from GHGs. Moreover, temporary aerosol cooling masks part of the greenhouse warming, but aerosols are short-lived and their impact is highly regional.

IPCC scenario studies show that without additional mitigation climate policies, global mean temperature change could range from 1.1° C to 6.4° C by the end of the century compared to 1980–99 (IPCC, 2007b). These circumstances make adaptation to climate change – i.e., the adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects – unavoidable (IPCC, 2001; Parry et al., 1998; Pielke Jr., 1998; Pielke Jr. et al., 2007).

The impacts of projected climate change are expected to be manifold. Because of limited understanding of many feedback loops in the complex Earth system and inherent limitations to the predictability of climate on the local and regional spatial scales, uncertainties in climate projections are very large and partly irreducible. Effects can become manifest gradually but also abruptly as a singular event and the processes of change can be linear or non-linear. Gradual changes include the increase of temperature, sea level rise, melting of glaciers, increase in length of the growth season, increase in precipitation and increase of extreme weather events such as heatwaves and tropical cyclones. These gradual changes can be manifest in extreme singular events (e.g. a storm surge or an extreme precipitation event). Examples of non-linear effects are the possible strong reduction or even shutdown of the so-called thermohaline circulation in the oceans (which could lead to a cooling of North and North-West Europe), disintegration of gas hydrates in melting permafrost and in the oceans (which leads to massive emissions of the greenhouse gas methane), disintegration of the West Antarctic Ice Sheet or strongly increased melting of the Greenland Ice Sheet which may lead to several meters of sea level rise in the long term.

The IPCC has defined adaptation as an adjustment in ecological, social, or economic systems in response to actual or expected climatic stimuli and their effects or impacts (Smit et al., 2001). Adaptation is therefore made up of actions throughout society by individuals, groups and government (Adger et al., 2005). In essence, adaptation is a complex societal process of activities, actions, decisions and attitudes that reflect existing social norms and processes. Adaptation is often reactive, induced by observed extreme weather events and their impacts (see also McKenzie-Hedger, 2005). Societies, organizations and individuals have been adapting to changing conditions for centuries, but the advent of climate change brings new challenges. Some of the challenges are brought about by issues related to the rate (and magnitude) of change of climate, the potential for non-linear changes and the long time horizons. All these issues are plagued with substantial uncertainties, which makes anticipatory adaptation difficult.

6.1.1 Climate impact assessment

Climate impact assessment is one of a family of interdisciplinary studies that focus on the interaction between nature and society, drawing theory, methods and tools from the biophysical, social-behavioural and engineering sciences. Kates (1985) conceptualized the interaction between climate and society into two sets of nested models: impact models and interaction models (Figure 6.1).

[1] Radiative forcing is the change in the net (downward minus upward) irradiance (expressed in watts per square metre) at the tropopause due to a change in an external driver of climate change, such as a change in the concentration of carbon dioxide or the output of the Sun (IPCC, 2007b).

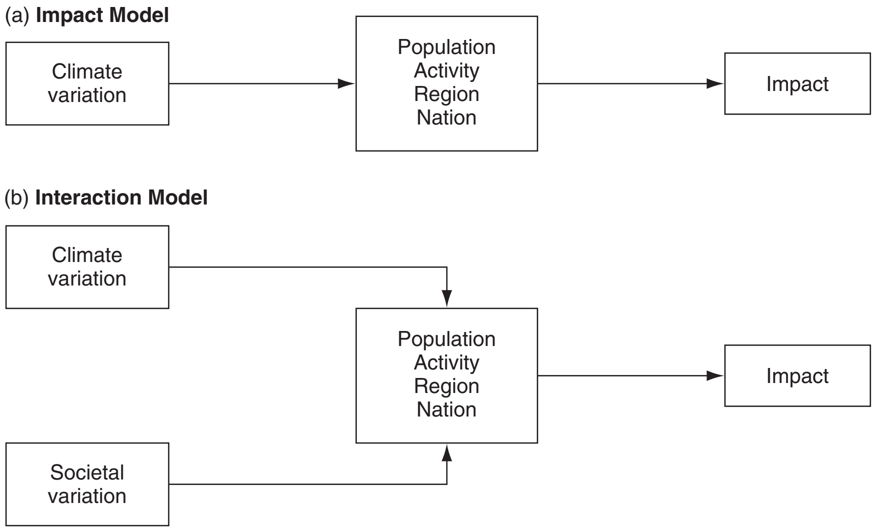

Figure 6.1 Schematics of (a) impact and (b) interactive models (Kates, 1985). Reproduced with permission from Wiley, UK.

In the simplest of assumed relationships, the impact model (Figure 6.1(a)), variation in one or more aspects of climate affects a defined population, activity, sector, region or nation and 'causes' impacts – changes in state that would not have occurred in the absence of the variation in climate state (Kates, 1985). The impact model, which assumes direct cause and effect, can be further divided into ordered (first, second, third) impacts – for example, meteorological drought (first impact), hydrological drought (second impact), socio-economic drought (third impact) – and multiple impacts – for example, a heat-wave causing heat-related deaths and forest fires at the same time. The interaction model (Figure 6.1(b)) recognizes that impacts are joint products of the interaction between climate and society and that similar climatic variations will yield different impacts under different sets of social conditions (Kates, 1985). Recognizing that climate impacts will induce responses in the form of adaptations or adjustments, Figure 6.2 presents a more comprehensive interactive model where responses act functionally to change either the biophysical or the societal characteristics of the interaction, or the underlying processes of nature and society.

Since these schematics of climate–society interactions were published, 25 years ago, both impact and interaction models have grown increasingly complex and sophisticated. On the whole, impact models are more prevalent in the literature than interaction models, perhaps because the latter require further interdisciplinary endeavour (particularly with social scientists) and are therefore more complex. The treatment of uncertainty has also improved in climate impact assessment (Hulme and Carter, 1999; Katz, 2002) but it remains a thorny issue given the breath of disciplines involved (and therefore different traditions of uncertainty management) and the different models or components (global climate model, hydrological model, etc.) used in such assessments.

A 'cascade' or 'explosion' of uncertainty arises when conducting climate change impact assessments for the purposes of making national and local adaptation decisions using a linear, top-down approach (Figure 6.3). For example, there are uncertainties

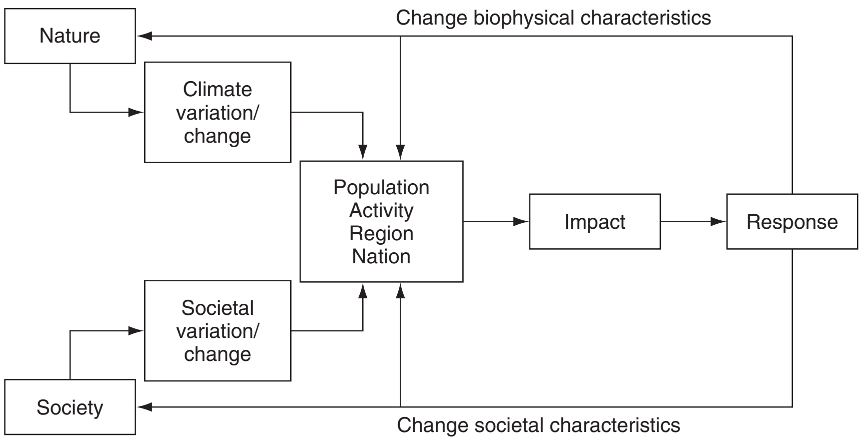

Figure 6.2 *Interactive model that includes feedback to underlying physical and social processes and structures (Kates, 1985). Reproduced with permission from Wiley, UK.*

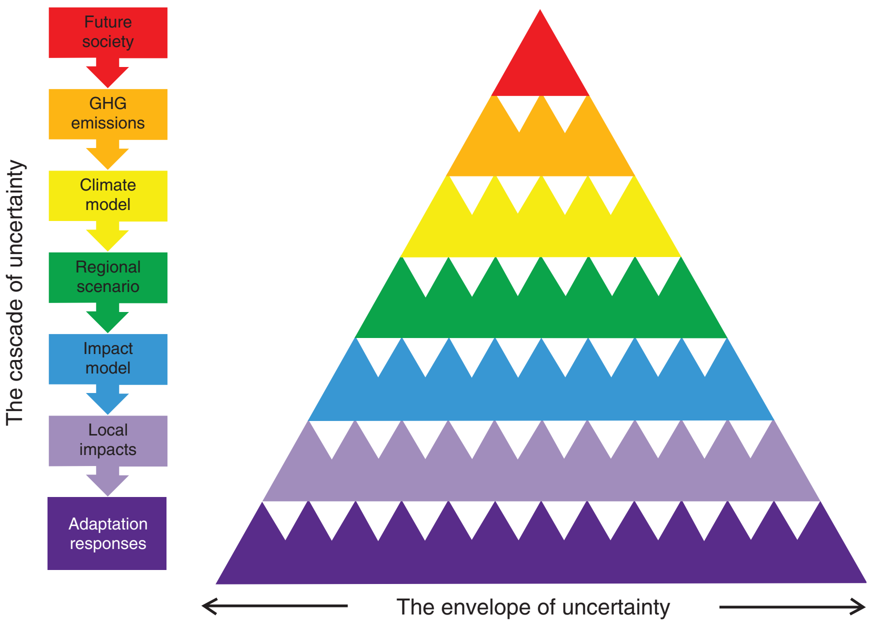

Figure 6.3 *A cascade of uncertainty proceeds from different socio-economic and demographic pathways, their translation into concentrations of atmospheric greenhouse gas concentrations, expressed climate outcomes in global and regional models, translation into local impacts on human and natural systems, and implied adaptation responses. The increasing number of triangles at each level symbolize the growing number of permutations and hence expanding envelope of uncertainty (Wilby and Dessai, 2010). Reproduced with permission from Wiley, UK.*

associated with future emissions of GHGs and sulphate aerosols, uncertainties about the response of the climate system to these changes at global and local scales, uncertainties associated with the impact models and the spatial and temporal distributions of impacts. Climate change impacts such as changes in temperature, precipitation, runoff or crop yield are therefore characterized by major uncertainties regarding their magnitude, timing and spatial distribution, sometimes having opposite signs (e.g., some projections show more precipitation whereas others show less). These uncertainties pose major challenges for planners taking decisions on adaptation measures. Gagnon-Lebrun and Agrawala (2006) note that the level of certainty associated with climate change and impact projections is often key to determining the extent to which such information can be used to formulate appropriate adaptation responses. There are also uncertainties associated with the assessment of adaptation options. Uncertainties also exist when trying to understand current vulnerabilities to the impacts of climate variability and change for the purpose of identifying adaption responses. These uncertainties can potentially be quite large, but there has been little research in this area.

The nature of uncertainty is multi-dimensional: it includes statistical uncertainty, scenario uncertainty and recognized ignorance in observed data, in climate models, in climate impacts, in policy context, and on all these locations uncertainties are both epistemic (imperfect knowledge) and stochastic (intrinsic variability in the climate system) (Dessai and Hulme, 2004; Janssen et al., 2005; Walker et al., 2003).

This chapter reviews the various stages involved in the modelling of climate change impacts for adaptation assessments from emissions of GHGs to local impacts (e.g., on hydrology) with a particular focus on uncertainty quantification and management. It is important to note that adaptation to climate change does not happen in isolation – there are multiple stresses and stimuli occurring at the same time as climatic stimuli, which are the main focus of this chapter.

6.2 Modelling climate change impacts: From world development paths to localized impacts

6.2.1 Greenhouse gas emissions

Anthropogenic climate change is being caused by an increase in the atmospheric concentration of GHGs (IPCC, 2007b). In order to determine how climate will change in the future it is crucial to know how atmospheric concentrations of GHGs (carbon dioxide, methane and nitrous oxide, among others) will vary in the future (it is also important to know how other agents with significant radiative forcing properties will vary – e.g., ozone, black carbon and aerosols). Future atmospheric concentrations of GHGs depend mainly on the amount of GHGs emitted by society over previous decades and how much will be emitted in the future (from burning of fossil fuel, deforestation, etc.). Despite uncertainties in monitoring and estimating past GHG emissions, it is future emissions of GHGs that suffer from deep uncertainties as they depend on multiple drivers such as demographic change, social and economic development, and the rate and direction of technological change (all of which are heavily modulated by human choice).

Integrated assessment models of energy-economy-environment have been used to explore how future emissions could vary until the end of the century. Most of this literature has characterized uncertainty in emissions by using scenarios – e.g., IPCC (1992) and Nakicenovic et al. (2000), known in the literature as IPCC SRES (Special Report on Emissions Scenarios). Scenarios are alternative images of how the future might unfold and are an appropriate tool with which to analyse how driving forces may influence future emission outcomes and to assess the associated uncertainties (Nakicenovic et al., 2000). The presence of deep uncertainties, such as 'human reflexive uncertainty' (Dessai and Hulme, 2004), justify the use of scenarios.

Uncertainty in certain key drivers of GHG emissions has been explored in probabilistic terms, namely population growth (Lutz et al., 1997, 2001) and technological change (Gritsevskyi and Nakicenovic, 2000). However, rarely have these been combined to produce probabilistic projections of GHG 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 or unknown and the interconnection between drivers is complex. One exception is a study that developed a consistent set of anthropogenic emissions projections 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). A few recent studies have started examining the uncertainty associated with key drivers of GHG emissions within scenarios, thus creating probabilistic estimates of GHG emissions conditional on storylines about future development patterns. O'Neill (2004) developed probabilistic projections of population conditional on the storylines used in the SRES scenarios. Through simple linear scaling (with per capita emissions rates derived from the SRES scenarios), O'Neill (2004) developed conditional probabilistic emissions scenarios, using the IPCC SRES scenarios as a basis. Van Vuuren et al. (2008) have conducted a similar study using an energy model (TIMER) to combine the scenario approach with formal uncertainty analysis. They sampled uncertainties on 26 input parameters on the basis of a sensitivity analysis performed on the model (see van der Sluis, 2005b). The Latin hypercube sampling technique was used to estimate CO_2 emissions based on 750 runs for each SRES scenario. Figure 6.4 shows the results for annual global carbon emissions, which have a wide range in 2100 from 4 to 40 gigatonnes of carbon (GtC).

Van Vuuren et al. (2008) conclude that conditional probabilistic scenario analysis can be used as a way to introduce statistical methods of uncertainty analysis, while recognizing deep uncertainties. It bridges the gap between scenario approaches and probabilistic approaches. Van Vuuren et al. (2008) note that the probabilistic approach operates from the positivist engineering/control paradigm, whereas the scenario approach positions itself more in a constructivist social science tradition.

Another method that has tried to bridge the scenario probability gap is the imprecise probability approach. Fuzzy set theory deals with the inherent vagueness in linguistic statements. Hall et al. (2007) applied fuzzy set theory to deal with SRES emission scenarios. They also proposed a non-probabilistic approach to dealing with the problem of aggregating different emissions scenarios. Imprecise probability theory can be thought of as a generalization of probability and fuzzy sets and has been used to deal with climate model uncertainties while avoiding the strong assumptions of recent probabilistic

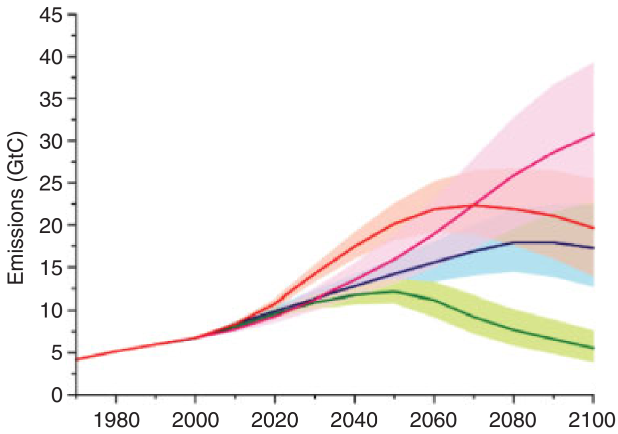

Figure 6.4 Carbon dioxide emissions 1970–2100 using the SRES scenario storylines and uncertainty quantification. In red is the A1 scenario, in pink the A2, in green the B1 and in blue the B2. (Reprinted from Global Environmental Change*, 18(4), D.P. van Vuuren, B. De Vries, A. Beusen and P. Heuberger, Conditional probabilistic estimates of 21st century greenhouse gas emissions based on the storylines of the IPCC-SRES scenarios, 635–654, © 2008, with permission from Elsevier.)*

interpretations of ensemble experiments (Duong, 2003; Hall et al., 2007; Kriegler and Held, 2005).

Van der Sluijs (2005a; 2005b) applied the Numeral Unit Spread Assessment Pedigree (NUSAP) method, an analytical and notational system to qualify quantitative information proposed by Funtowicz and Ravetz (1990), to the TIMER B1 emission scenario. The NUSAP system for multidimensional uncertainty assessment (Funtowicz and Ravetz, 1990; van der Sluijs et al., 2005a) aims to provide an analysis and diagnosis of uncertainty in science for policy. The basic idea is to qualify quantities by using the five qualifiers of the NUSAP acronym: numeral, unit, spread, assessment, and pedigree. NUSAP complements quantitative analysis (numeral, unit, spread) with expert judgement of reliability (assessment) and systematic multi-criterion evaluation of the different phases of production of a given knowledge base (pedigree). Pedigree criteria can be: proxy representation, empirical basis, methodological rigour, theoretical understanding, and degree of validation. In the application to the TIMER model and its B1 scenario, a global sensitivity analysis was combined with a systematic pedigree analysis of the 40 (out of 300) most sensitive model parameters. The pedigree analysis was done interactively in a workshop involving 18 experts. This was the first test of NUSAP on a model of such complexity, and the authors show that the method can be usefully applied to such models. A discussion of methods to ensure the pedigree of complex decision processes is provided by Davis and Hall (2003).

The climate change research community has recently embarked on a new approach of scenario construction that attempts to move away from a sequential approach (as described in Figure 6.3) to a parallel process whereby socio-economic and climate scenarios are constructed in parallel. This process begins with the identification of radiative forcing characteristics that support modelling of a wide range of possible future climates. To this end, Moss et al. (2010) selected representative concentration pathways (RCPs) from

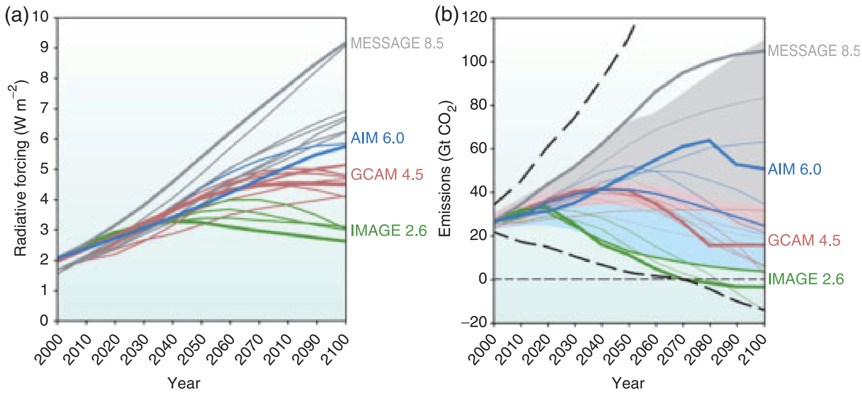

Figure 6.5 (a) Changes in radiative forcing relative to pre-industrial conditions. Bold coloured lines show the four RCPs; thin lines show individual scenarios from approximately 30 candidate RCP scenarios. (b) Energy and industry CO_2 emissions for the RCP candidates. The range of emissions in the post-SRES literature is presented for the maximum and minimum (thick dashed curve) and 10th to 90th percentile (shaded area). The blue shaded area corresponds to mitigation scenarios; the grey shaded area corresponds to reference scenarios; the pink area represents the overlap between reference and mitigation scenarios (Moss et al., 2010).

the literature (see Figure 6.5) to provide inputs of emissions, concentrations and land use/cover for climate models. In parallel with the development of climate scenarios based on the RCPs, new socio-economic scenarios (some consistent with the radiative forcing characteristics used to identify the RCPs and some developed to explore completely different futures and issues) will be developed to explore important socio-economic uncertainties affecting both adaptation and mitigation. It is expected that such integrated scenarios will explore adaptation, mitigation and other issues such as feedbacks, using consistent assumptions, thus providing insights into the costs, benefits and risks of different climate futures, policies and socio-economic development pathways (Moss et al., 2010).

In summary, a multitude of tools and techniques have been used to characterize uncertainty in emissions of GHGs. The most prevalent approach is the use of scenarios given the deep uncertainties surrounding the key drivers. The next generation of scenarios proposed by Moss et al. (2010) should encourage a greater appreciation for interactive models (see Section 6.1.1) in climate impact assessment.

6.2.2 Climate models

Emissions of GHGs are converted into atmospheric concentrations and then into radiative forcing using models, thus adding further uncertainties, before serving as input to climate models. Challenor and Tokmakian (Chapter 5, this volume) describe the types of climate models – simple, intermediate complexity and coupled atmosphere/ocean general circulations models (AOGCMs) – and their uncertainties – aleatoric/stochastic and epistemic, which is further divided into structural and input uncertainty. They discuss the trade-offs between simplicity and complexity as a function of spatial resolution, improved physics and large ensembles. This section explains how uncertainty has been managed in climate models.

One of the earliest studies that explored the uncertainty of key climate variables was that of Morgan and Keith (1995), who interviewed a number of US climate experts to elicit subjective PDFs of climate sensitivity. 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 (Dessai and Hulme, 2001; Visser et al., 2000; Webster and Sokolov, 2000; Wigley and Raper, 2001; Zapert et al., 1998). 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). Likelihoods also depend on the ability of the energy balance models to emulate the global mean temperature series of GCMs.

Another strand of research that complements earlier efforts and attempts to reduce uncertainty is the method of constraining certain climate parameters – in particular, climate sensitivity – by using recent observed changes in the climate system (Allen et al., 2000; Andronova and Schlesinger, 2001; Forest et al., 2001, 2000, 2006, 2002; Frame et al., 2005; Gregory et al., 2002; Jones et al., 2003; Knutti et al., 2002, 2003; Stott and Kettleborough, 2002; Tol and de Vos, 1998). This is essentially a Bayesian approach that will prove most useful as more observed data are gathered in the future. Palaeoclimate data have also been used to constrain climate sensitivity (Annan et al., 2005; Hegerl et al., 2006; Schneider von Deimling et al., 2006). Uncertainties in climate change detection and attribution have also been articulated and quantified using a formal probabilistic protocol (Risbey and Kandlikar 2002; Risbey et al., 2000).

Due to computational constraints in the recent past, uncertainty in GCMs has been explored by 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, with computational power on the increase there are a few studies that have started to run large ensembles of GCMs in order to quantify uncertainty in the climate response (Murphy et al., 2004; Stainforth et al., 2005). Murphy et al. (2004) performed a local sensitivity analysis for a selection of parameters of the HadAM3 climate model (an atmospheric general circulation model coupled to a 'slab' ocean) to generate a PDF for climate sensitivity. They based parameter selection, and the range over which they varied parameters, on expert elicitation.[2] In constructing the climate sensitivity PDF, a 'climate prediction index' that weights ensemble members according to degree of correspondence with observations was applied. Their 95% confidence range for climate sensitivity was 2.4–5.4° C. The Stainforth et al. (2005) study uses the same model but runs many more simulations (over 2000) and does not attempt to constrain the results. They found climate sensitivities that ranged from less than 2° C to more than 11° C.

Figure 6.6 shows PDFs of climate sensitivity as constrained by past historical transient evolution of surface temperature, upper air temperature, ocean temperature, estimates of the radiative forcing, satellite data, proxy data over the last millennium or a subset thereof. There is agreement in the lower bound that climate sensitivity is very unlikely below 1.5° C; there is less agreement in the upper bound because of a nonlinear relationship

[2] To the knowledge of the authors, no formal protocol of elicitation – as in Morgan and Keith (1995) or Risbey et al. (2000) – was followed to, for example, 'de-bias' experts.

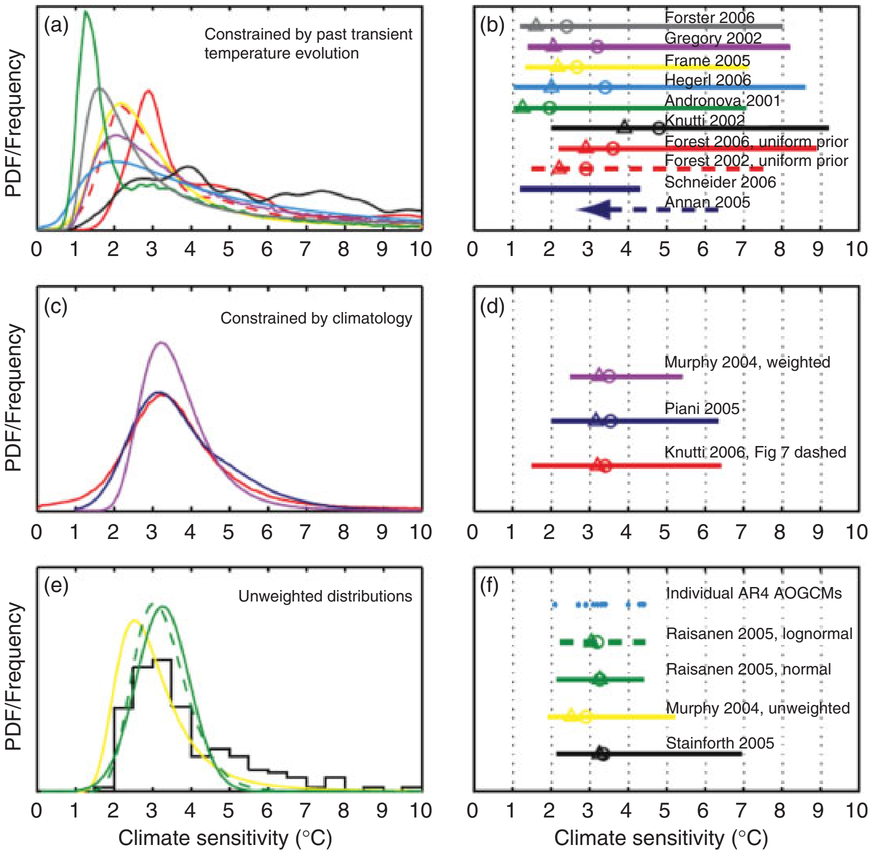

Figure 6.6 *(a) PDF or frequency distributions constrained by the transient evolution of the atmospheric temperature, radiative forcing and ocean heat uptake. (b) as in (a) but 5–95% ranges, medians (circles) and maximum probabilities (triangles). (c) and (d) As (a) and (b), but using constraints from present-day climatology. (e) and (f) Unweighted or fitted distributions from different models or from perturbing parameters in a single model (Meehl et al., 2007).*

between climate sensitivity and the feedbacks such as enhanced release of terrestrial carbon due to rising soil temperatures, and such agreement is further hampered by the limited length of the observational record and uncertainties in the observations, which are particularly large for ocean heat uptake and for the magnitude of the aerosol radiative forcing (Meehl et al., 2007).

Missing or inadequately parameterized processes in climate models (e.g., atmospheric chemistry or land use) remain a difficult uncertainty to tackle as it is not clear how it could broaden the current simulated range of future changes (Meehl et al., 2007). The IPCC noted that different methods show consistency in some aspects of their results, but differ significantly in others. They could not recommend a preferred method yet for characterizing uncertainty in climate models, but they emphasized that assumptions and limitations underlying the various approaches, and the sensitivity of the results to these, should be communicated to users (Meehl et al., 2007).

Since the publication of the IPCC Fourth Assessment Report (AR4), a large number of studies have been exploring uncertainty in climate change projections (cf. Collins, 2007) using a range of methods including: perturbed physics ensembles (Harris et al., 2010), multi-model ensembles (Knutti et al., 2010b; Tebaldi and Knutti, 2007), statistical emulators (Rougier and Sexton, 2007) or a combination of approaches (Murphy et al., 2007, 2009). There is still no consensus on a 'best' approach to quantify uncertainty in climate projections, but the IPCC has recently published a good practice guidance paper on assessing and combining multi-model climate projections (Knutti et al., 2010a), where it provides a number of recommendations, including criteria for decision making concerning model quality, and performance metrics, model weighting and averaging.

6.2.3 Downscaling

The compounding of uncertainty at the global climate model level is already considerable (see Section 6.2.2 and Figure 6.3). Given the coarse resolution of most AOGCMs – of the order of hundreds of kilometres – downscaling is often used for impact and adaptation assessments. The two main approaches are dynamical and statistical downscaling. Dynamical downscaling uses high-resolution climate models, often called regional climate models (RCMs), with the boundary conditions of observed or lower-resolution AOGCM data. Dynamical downscaling has the potential to capture meso-scale nonlinear effects and provide coherent information among multiple climate variables. These models are formulated using physical principles and they can credibly reproduce a broad range of climates around the world, which increases confidence in their ability to realistically downscale future climates. The main drawbacks of dynamical models are their computational cost and that in future climates the parameterization schemes they use to represent sub-grid scale processes may be operating outside the range for which they were designed. Statistical downscaling methods start by establishing a relationship between large-scale atmospheric variables (predictors) and local/regional climate variables (predictands) using observed records.[3] This relationship is then applied to AOGCM results to estimate future changes at the local/regional scale. Statistical downscaling methods have the advantage of being computationally inexpensive, able to access finer scales than dynamical methods and applicable to parameters that cannot be directly obtained from the RCM outputs. They require observational data at the desired scale for a long enough period to allow the method to be well trained and validated. The main drawbacks of statistical downscaling methods are that they assume that the derived cross-scale relationships remain stable when the climate is perturbed, they cannot effectively accommodate regional feedbacks and, in some methods, can lack coherency among multiple climate variables. There are numerous RCMs available[4] and various statistical downscaling algorithms. Like the IPCC TAR, AR4 concluded that each downscaling approach has distinctive strengths and weaknesses, and that the methods are comparable (Christensen et al., 2007). For a review of new developments in the downscaling field specifically for hydrological impacts, see Fowler et al. (2007). These authors propose a method that links probabilistic climate

[3] Statistical downscaling methods can be further classified into three groups: regression models, weather typing schemes and weather generators.

[4] See, for example, http://prudence.dmi.dk/ and http://ensembles-eu.metoffice.com/

change scenarios to a weather generator downscaling method. Goodess et al. (2007) provides a useful discussion of local decision making with probabilistic climate information. The latest set of UK climate projections (UKCP09) combine regional climate simulations with an ensemble of GCM simulations (Murphy et al., 2007, 2009) to provide probabilistic climate change projections on individual 25 km grid squares (and predefined aggregated areas) for seven 30-year time periods (compared to a 1961–90 baseline) under three emissions scenarios. These projections estimate annual, seasonal and monthly climate averages. Further temporal and spatial downscaling of these projections was deemed necessary, so a weather generator was constructed to provide synthetic time series of weather variables at 5 km resolution, which are consistent with the underlying climate projections (Jones et al., 2009). Numerous methodologies exist for the treatment of uncertainty in downscaling. This step further adds uncertainty to climate impact assessment given the multiple available routes (statistical and dynamical downscaling) and methods.

6.2.4 Regional/local climate change impacts

Climate change impact studies have been conducted in numerous sectors such as water, health, ecosystems and agriculture. Such studies use both process-based models (see Hall, Chapter 8, this volume) as well as data-based models (e.g., Dessai, 2003). 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, 2001). A growing number of studies have attempted to quantify uncertainty consistently from emissions of GHGs to climate change impacts – see references in Carter et al. (2007). Given the breadth of potential affected sectors by climate change, this subsection focuses on a selection of UK water resources studies as an example of how uncertainty has been managed and quantified. One could argue that water resources are one of the earliest and most sophisticated sectors using uncertain climate change information (cf. Vicuna and Dracup, 2007).

Prudhomme et al. (2003) combined the results of New and Hulme (2000) – 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 in 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 to play 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 based on this study.

Wilby and Harris (2006) estimated future low flows in the River Thames by combining information from four GCMs, GHG emission scenarios, two statistical downscaling techniques, two hydrological model structures, and two sets of hydrological model parameters (see Wilby, 2005, for an exploration of the last uncertainty). The GCMs and the hydrological model structures and parameters were weighted by performance whereas the emission scenarios and downscaling methods were unweighted. The framework was implemented using the Monte Carlo approach. The results were most sensitive to uncertainty in the GCMs and the downscaling.

Dessai and Hulme (2007) assessed the robustness of a water company's Water Resource Plan[5] in the East of England against numerous climate change uncertainties in a probabilistic framework. A local sensitivity analysis (a 'one-at-a-time' experiment) was performed on the various elements of the modelling framework (e.g., emissions of GHGs, climate sensitivity and global climate models) in order to determine whether or not a decision to adapt to climate change is sensitive to uncertainty in those elements. Water resources are found to be sensitive to uncertainties in regional climate response (from GCMs and dynamical downscaling), in climate sensitivity and in climate impacts.

Manning et al. (2009) use a Bayesian approach to combine projections by weighting and generate probability distributions of local climate change from an ensemble of RCM outputs. A stochastic weather generator produces corresponding daily series of rainfall and potential evapotranspiration, which are input into a catchment rainfall–runoff model to estimate future water abstraction availability in the Thames.

Lopez et al. (2009) use a large perturbed physics ensemble of climate models (from climateprediction.net) with a rainfall–runoff model and a water resource model to assess climate change impacts and adaptation strategies in the Wimbleball water resource zone in the South West of England. Their approach includes downscaling and bias correction techniques to adjust GCM monthly time series to daily input for the hydrological model.

Some studies have started appraising hypothetical adaptation strategies within a modelling framework (Whitehead et al., 2006), while others have focused on combining a number of increasingly complex models in the cascade of a climate change impact assessment (Wilby and Harris, 2006). Overall, there seems to be some evidence (Dessai, 2005; Dessai and Hulme, 2007; Wilby and Harris, 2006) to show that the largest climate change uncertainties from an impact/adaptation perspective come from the AOGCMs, followed by the downscaling method.

The Monte Carlo method (in various guises) has been the most predominant method used to quantify uncertainties in the hydrological impacts of climate change in the UK. Other methods such as the Bayesian framework have also been applied. Various different methods are currently being tried and tested in numerous case studies around the world. For example, a study in the Mahanadi River in India has applied Dempster–Shafer evidence theory to predict hydrologic drought under climate change (Raje and Mujumdar, 2010).

6.3 Discussion

Section 6.2 has reviewed the multiple stages of modelling climate change impacts for adaptation assessments with an emphasis on uncertainty management. Methodologically, one of the conclusions that emerges is the lack of a consistent treatment of uncertainty across the various stages. This may not be a surprise given the breadth of the multiple stages (from world development paths to local impacts) and the number of disciplines and traditions (including social scientists, economists, natural scientists and engineers) involved in quantifying uncertainties across these scales. This section puts the review in a wider context of simplicity and complexity in modelling. Section 6.3.1 examines the multiple routes that have been taken in managing the uncertainties of climate change impact studies. Section 6.3.2 discusses the trade-offs between simplicity and complexity.

[5] Their adaptation strategy to cope with climate change and various other risks and uncertainties over the next 25 years.

6.3.1 Multiple routes of uncertainty assessment

Table 6.1 shows how a selection of climate change impact studies (described in Section 6.2.4) have sampled parts of the uncertainty space. Partly this is due to the fact that each study was asking a slightly different research question, but also due to computational constraints, pragmatism and scientific tradition. Each study has gone in depth at a particular stage(s) of the cascade of uncertainty (as shown in Figure 6.3). For example, Dessai and Hulme (2007) explored 'upstream' uncertainties in GHG emissions and climate sensitivity extensively but had simple assumptions on 'downstream' uncertainties such as hydrology. Wilby and Harris (2006) focused much more on the downstream uncertainties (downscaling and hydrology) than the upstream uncertainties. Lopez et al. (2009) arguably conducted the most extensive quantification of uncertainty in climate system response (AOGCM), which most studies identify as the largest source of uncertainty in climate change impact assessments. Furthermore, the Lopez et al. (2009) study goes further downstream than the other studies by examining multiple adaptation scenarios (Dessai and Hulme (2007) only assess the merit of one adaptation plan). Manning et al. (2009) thoroughly explore the 'middle' stage uncertainties by using a Bayesian framework to combine projections by weighting.

The studies described in Table 6.1 demonstrate that there is no simple and clear method of managing uncertainty in climate change impact assessment. Instead, multiple routes of uncertainty assessment exist, thus giving rise to a plurality of approaches to dealing with uncertainty (cf. Parker, 2006, in the context of climate modelling). Given the wide variety of scientific disciplines involved in this field it is unlikely that a universally accepted uncertainty management approach will ever emerge.

6.3.2 What is the appropriate balance between simplicity and complexity?

Table 6.1 demonstrates some of the trade-offs between simplicity and complexity within particular studies. Given limited computational power, adding more complexity to the assessment often prohibits a comprehensive uncertainty analysis (e.g., uncertainty in RCMs has not yet been explored as fully as in coarse AOGCMs). Choosing simpler models allows comprehensive uncertainty analysis to be conducted but at the likely expense of precision (often either temporally and/or spatially) or the violation of known relationships (often linear relationships are assumed; e.g., in GCM pattern-scaling). The appropriate balance between simplicity and complexity in climate change impact assessments can only be answered in a particular decision context. Phillips (1984) introduced the notion of a requisite decision model as a model whose form and content are sufficient to solve a particular problem. Unfortunately, the upstream stages of a climate change impact assessment (above local impacts in Figure 6.3) are often done in a decision vacuum, therefore making it very difficult, if not impossible, to assess whether the scientific analysis is fit for purpose or requisite. With an increasing focus on adaptation to the unavoidable impacts of climate change, it may become possible to assess the appropriate balance between simplicity and complexity in modelling climate change impacts. This will depend on numerous factors such as the decision stakes, the decision environment, the degree of risk aversion of decision makers, and how important climate change is as a driver of the system under study. Under conditions of deep or severe uncertainty, characteristic of climate change impact assessments, it has been argued that a focus on identifying robust decisions

Table 6.1 Main characteristics of a selected number of climate change impact studies.

	New and Hulme (2000), Prudhomme et al. (2003)	Wilby and Harris (2006)	Dessai and Hulme (2007)	Lopez et al. (2009)	Manning et al. (2009)
GHG emissions	4	2	40	1 (SRES A1B)	4 (most results for SRES A2)
Carbon cycle response	1 model		1 model with uniform PDF		
Global climate sensitivity	Triangular PDF		Multiple PDFs from the literature		
AOGCM	7	4	9	21 + 1 (w/u[a] 246 simulations)	2
Downscaling		2 statistical downscaling	19 RCMs (dynamical downscaling, but not linked to above)	Bias correction and temporal downscaling using a gamma transform	14 RCMs + stochastic weather generator
Impacts	1 hydrological model	2 hydrological model structures + 2 sets of hydrological model parameters (w/u)	Simple linear transfer function	1 hydrological model (w/u) and water resource model	1 hydrological model (w/u)
Unit of assessment	Flood regime of 5 small catchments	Low flows in the Thames	Additional water required due to climate change in the East of England	Reservoir storage level and supply failure under a number of supply and demand scenarios	Abstraction availability in the Thames

[a] with uncertainty analysis

(i.e., decisions that are immune to large uncertainties) is preferable to postponing decisions until better model predictions are available (Dessai et al. 2009a,b).

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