



Uncertainty in regional climate modelling: A review

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Abstract

For geographers engaged in activities such as environmental planning and natural resource management, regional climate models are becoming increasingly important as a source of information about the possible impacts of future climate change. However, in order to make informed adaptation decisions, the uncertainties associated with their output must be recognized and taken into account. In this paper, the cascade of uncertainty from emissions scenario to global model to regional climate model is explored. The initial part of the discussion focuses on uncertainties associated with human action, such as emissions of greenhouse gases, and the climate system's response to increased greenhouse gas forcing, which includes climate sensitivity and feedbacks. In the second part of the discussion, uncertainties associated with climate modelling are explored with emphasis on the implications for regional scale analysis. Such uncertainties include parameterizations and resolutions, initial and boundary conditions inherited from the driving global model, intermodel variability and issues surrounding the validation or verification of models. The paper concludes with a critique of approaches employed to quantify or cater for uncertainties highlighting the strengths and limitations of such approaches.

Keywords

climate science, emissions scenario, greenhouse gases, regional climate modelling, uncertainty

1 Introduction

Anthropogenic climate change is now well established, with the latest report from the Intergovernmental Panel on Climate Change (IPCC) concluding with 'very high confidence' that human-induced warming of the atmosphere is taking place (IPCC, 2007: 3). In the event that emissions of greenhouse gases continue to increase, the likely impacts of continued anthropogenic warming could include extinction risks for plant and animal species (Thomas et al., 2004), and direct physical risks to people and communities, as well as economic risks. As such, climate change and climate uncertainty are relevant issues for a range of disciplines including biogeography and ecology (Diniz Filho

et al., 2009; Wiens et al., 2009), water resource management (Buytaert et al., 2009; Kay et al., 2009), oceanography (Good et al., 2009) and glaciology (Holland et al., 2010; Vizcaino et al., 2010). Additionally, decision-makers at all levels of governance must consider how the potential impacts of climate change can be lessened or managed.

While adaptation policy is developed at national level, differences in physical environment, land use and population make the task of

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implementing adaptation strategies a task best carried out at regional and local scale. To do this, planners require information about how human-induced warming may affect key climate parameters such as precipitation and temperature and what effects such changes will have in their region of interest. Dynamical computer models of climate, particularly regional climate models (RCMs), can provide this information. Yet their limitations must also be understood if their outputs are to be useful in developing meaningful adaptation policy, particularly if such policies are associated with costly infrastructure such as flood defences or reservoir construction.

The climate system is comprised of numerous complex processes and interactions and no model can ever be expected to perfectly simulate this. While many processes are represented in models by fundamental physical equations, parameterizations are also employed to approximate certain processes. The scientific knowledge on which such parameterizations are based comes from studying the current climate and proxy studies of past climate and, as such, their ability to simulate the climate under different forcing conditions may potentially be limited. Such limitations necessitate a greater understanding and awareness of the uncertainty surrounding climate model output. If such projections are to provide an effective basis for policy-making, then as much uncertainty as possible must be accounted for.

In an earlier paper in *Progress in Physical Geography*, Mitchell and Hulme (1999) described uncertainty in regional climate modelling as a 'cascade of uncertainty'. This description is still very appropriate ten years on. However, the sources of uncertainty that form the cascade have changed somewhat, due to advances such as the development of nested regional climate models (RCMs), perturbed physics ensembles (PPEs) and multimodel ensembles (MMEs). This review characterizes the various forms of uncertainty, discusses how they affect each stage of the modelling process and considers approaches to working with uncertainty.

II Defining uncertainty in climate modelling

The impacts associated with climate change are dependent on what degree of change emerges. This degree of change is unknown. In a system undergoing change, past observations are unlikely to be a robust estimator of future behaviour. For example, King (2004) notes that under higher emissions concentrations, flood levels that are currently expected every 100 years based on observational records could occur every three years. Therefore, long-term projections from climate models are needed to determine likely changes on which to base adaptation planning.

However, with less knowledge of possible outcomes, the basis for assigning probability becomes less firm (Figure 1). Where outcomes are poorly defined and knowledge about likelihoods is low, alternative approaches such as scenario analysis must be used, as there is no basis for probabilities. As the uncertainty surrounding the modelled output increases, confidence in the data decreases. In order to prepare strategies for managing climate risks, uncertainties must be accounted for as far as possible.

The 'types' of uncertainty commonly identified in the larger scientific community (eg, Tannert et al., 2007) are often referred to in climate science also. At its core, uncertainty in climate science is a case of 'imperfect knowledge' and what Gershon (1998) identifies as 'causes of imperfect knowledge' are all present. However, due to the complexity of the climate system and the modelling process, the relationships between uncertainty types must also be considered.

A typology of climate model uncertainties is described in Figure 2. The first division made is between uncertainty inherent in the climate system and uncertainty related to our ability to model it, which can be further categorized as epistemological or ontological.

Uncertainty in the climate system has two main sources. First, there is uncertainty over human action, including uncertainty due to

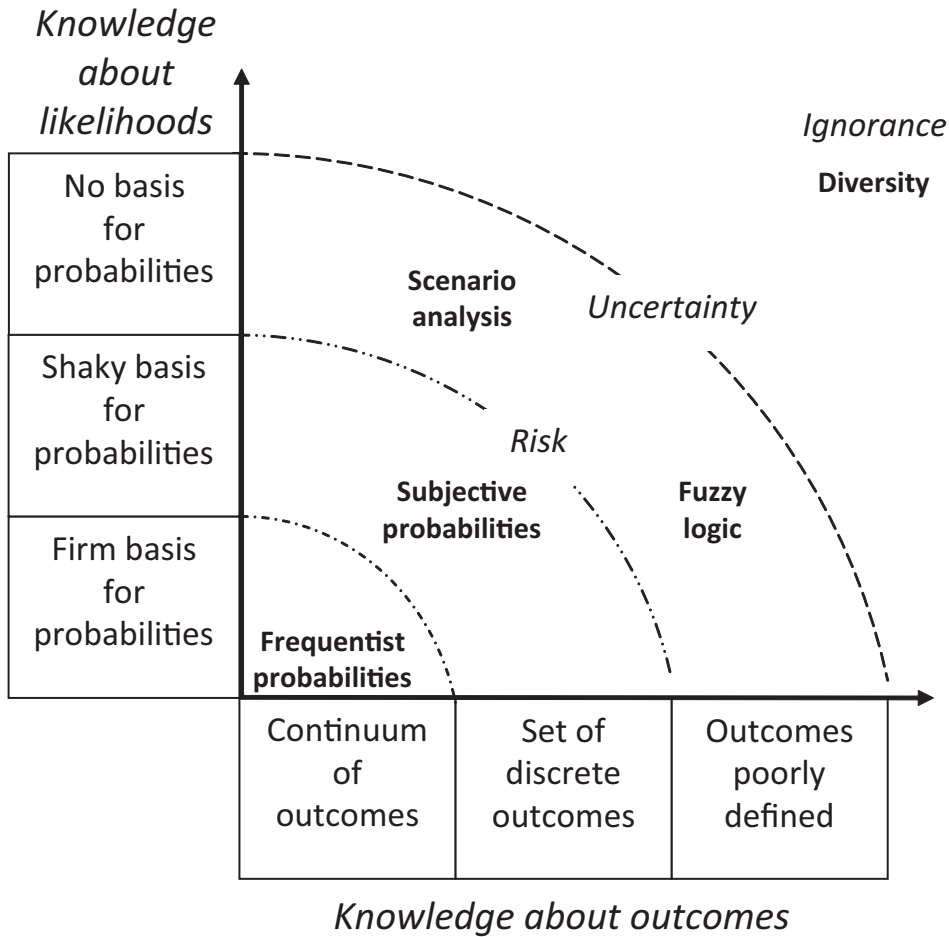


Figure 1. A scheme for defining ‘risk’, ‘uncertainty’ and ‘ignorance’
 Source: Stirling (1998)

unknown future emission concentrations of greenhouse gases and aerosols. Emissions-related uncertainties are what Schwierz et al. (2006) categorized as Type I uncertainties. This uncertainty is largely due to unknowable knowledge, and is inherently irreducible (Hulme and Carter, 1999). Second, there is uncertainty over how the climate system is likely to respond to our actions. Further research may reduce this uncertainty, but may also uncover previously unknown processes, thereby increasing uncertainty. Additionally, in a complex, non-linear system the existence of unknown states or the occurrence of ‘surprise’ events is also possible.

Uncertainty relating to our ability to model the climate system can be refined into two further categories. Epistemological uncertainty is that which is related to gaps in knowledge: what Hulme and Carter (1999) refer to as ‘incomplete’ knowledge. This gives rise to what Schwierz et al. (2006) called Type III uncertainties, and Jenkins and Lowe (2003) called science uncertainty. These uncertainties relate to issues with modelling specific processes, and also to the issue of finite computer resources.

Ontological uncertainty, as it relates to climate modelling, involves the variability of the climate system and climate models (van Asselt

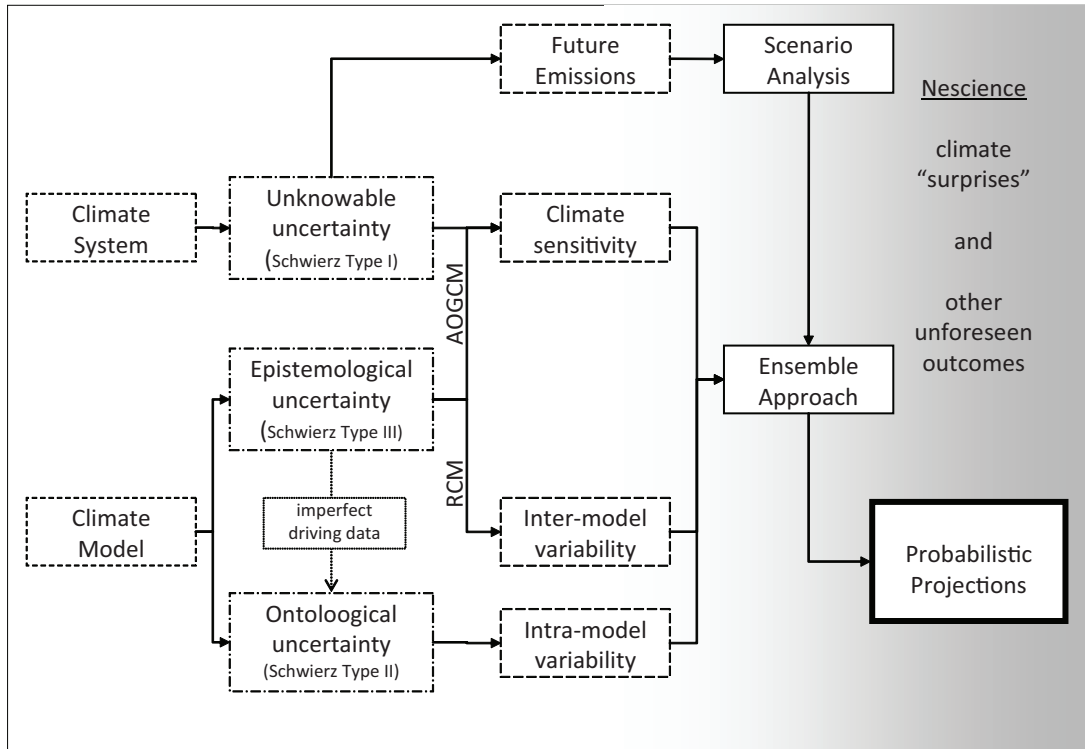


Figure 2. A taxonomy of climate model uncertainties

Source: Modified from Tannert et al. (2007)

and Rotmans, 2002; van der Keur et al., 2008), what Tannert et al. (2007) describes as ‘stochastic features of the situation’. The non-deterministic nature of the climate system (Mitchell and Hulme, 1999) gives rise to ontological uncertainty in climate modelling, which is characterized by a lack of predictability. Schwierz et al. (2006) refer to these uncertainties as Type II uncertainties. GCMs and RCMs share many of the same uncertainties and are affected to some degree by all types of uncertainty, though different sources emerge as key influencers.

III Uncertainty and the climate system

1 Emissions scenarios

The greatest uncertainty in climate modelling, which features in all climate downscaling techniques, stems from the unpredictability of future

anthropogenic greenhouse gas emissions and their resultant atmospheric concentrations. The IPCC Special Report on Emissions Scenarios (SRES; Nakicenovic et al., 2000) discusses several factors that impact on the atmospheric greenhouse gas concentrations projected over the present century: population growth, economic and social development, the development and utilization of carbon-free energy sources and technology and changes to agricultural practices and land use. The four storylines on which the SRES scenarios are based capture just some of the ways in which these driving forces might change.

The emissions scenarios quantify the emissions likely to be associated with each storyline. Historical knowledge about emissions and their driving forces can assist in scenario development. For example, it is known that emissions have historically increased as Gross Domestic

Product (GDP) increases (Heil and Selden, 2001). However, it is impossible to say with accuracy how all the driving influences will evolve as they depend upon human behaviour. This information is unknowable, and as such is an inherently irreducible uncertainty. Yet the degree of climate change experienced is inextricably linked to concentrations of GHGs. No climate projections can be made without first finding a way to represent this unknowable information. As the outcomes are so poorly defined, there can be no basis for assigning probabilities to future emissions. Alternative approaches are needed to represent this uncertain factor.

A widely used approach to emissions uncertainties is scenario analysis, in which future concentrations are estimated for a range of different ‘storylines’ representing varying combinations of populations and economic development. There are four socio-economic storylines for which the IPCC have defined 40 emissions scenarios, and each scenario family – A1, A2, B1 and B2 – has an illustrative ‘marker’ scenario (Nakicenovic et al., 2000). Significant expertise goes into designing these storylines. For example, numerical modelling may be carried out to ensure self-consistency in assumptions (Sugiyama, 2005). Yet there has been some criticism of the manner in which they are designed. In particular, economic assumptions that the SRES scenarios make about GDP have come under scrutiny (Castles and Henderson, 2003). Emissions scenarios provide information about GHG concentrations for a range of plausible futures and cannot cover all eventualities. Outcomes are left unaccounted for even at this initial stage, introducing uncertainty to the overall projections. Since the future is not static, it is also possible that the actual outcome may be entirely unexpected, a scenario that had never been considered. It is conceivable that the very creation of particular emissions scenarios and the resulting research carried out alters the likelihood of scenarios coming to be, as humanity adopts

unforeseen new strategies to avoid a negative scenario becoming reality.

2 Climate sensitivity

Climate sensitivity is a measure of how responsive the climate system is to a change in forcing. Assume that the climate system undergoes a change in forcing ΔF_{2x} , brought about by a doubling of CO₂ concentration levels. When the climate system reaches its new equilibrium, ΔT_{2x} is the resultant surface temperature response, averaged globally. The sensitivity of the climate system to this forcing is therefore:

$$\lambda = \Delta T_{2x} / \Delta F_{2x}$$

In this way, the anthropogenic contribution to radiative forcing can be quantified as a figure of global temperature change. The magnitude and impacts of climate change are strongly dependent on climate sensitivity, so there is a real and immediate need to quantify uncertainty associated with sensitivity in climate projections. Andronova and Schlesinger (2001) state:

If ΔT_{2x} is less than the lower bound given by the Intergovernmental Panel on Climate Change (IPCC) then AICC (anthropogenic induced climate change) may not be a serious problem for humanity. If ΔT_{2x} is greater than the upper bound given by the IPCC, then AICC may be one of the most severe problems of the 21st century. (Andronova and Schlesinger, 2001: 22,605)

Climate sensitivity can be determined using a perturbed physics ensemble (eg, Piani et al., 2005) in which the same atmosphere-ocean global climate model (AOGCM) is run numerous times with slightly altered parameters, or using an ensemble of different AOGCMs (eg, Yokohata et al., 2008). In addition to inheriting the uncertainties of the emissions scenario, differences in the design of AOGCMs, such as the vertical and horizontal resolution of the atmosphere and ocean and the parameterization of various processes, and uncertainties regarding radiative

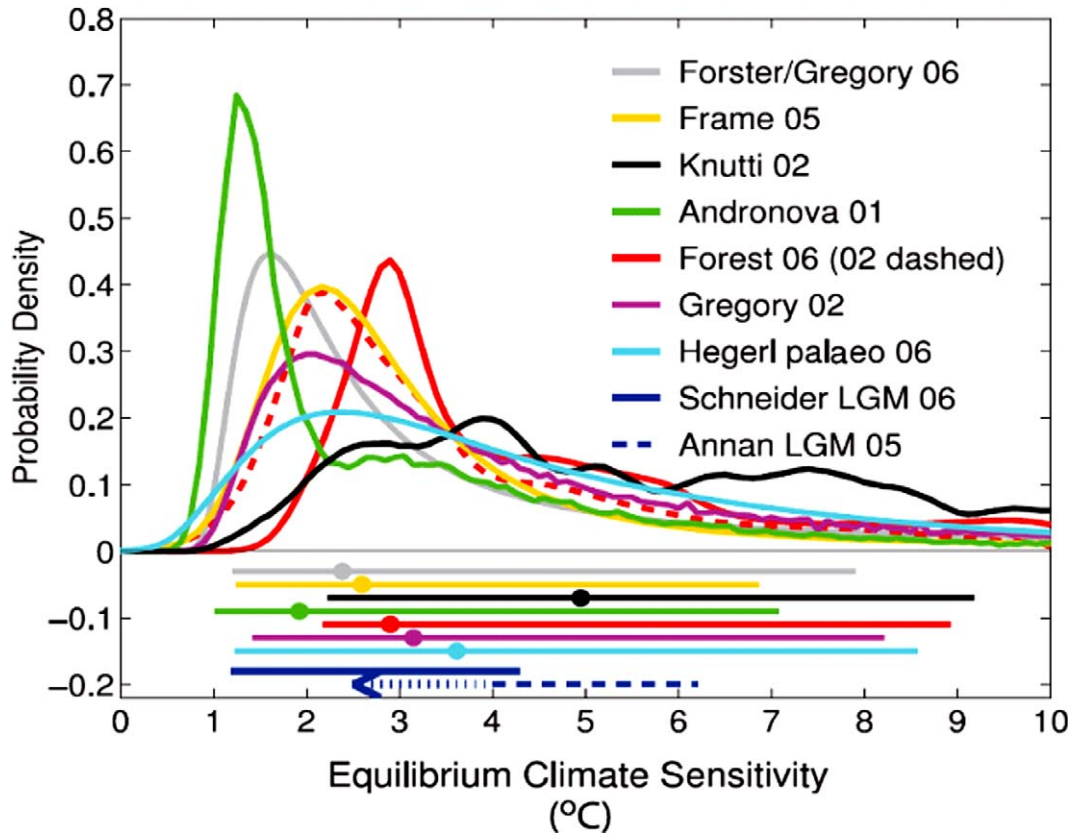


Figure 3. A summary of results from climate sensitivity experiments
 Source: IPCC (2007: Figure 9.20)

forcing (Tanaka et al., 2009) introduce further uncertainty into the calculation.

AOGCM experiments provide one measure of sensitivity. Much work has been carried out on ‘constraining’ estimates of climate sensitivity using twentieth-century observations (Andronova and Schlesinger, 2001; Knutti et al., 2002). Palaeoclimate data has also been used to determine sensitivity to past changes in forcing (Watson, 2008). Such research is now being used as a method of validating AOGCMs, the hypothesis being that if AOGCM climate sensitivity matches the climate sensitivity obtained from study of palaeodata, then greater confidence can be placed in the estimate (Edwards et al., 2007; Hoffert and Covey, 1992). Of course, as the anthropogenic forcing influencing climate at present is unprecedented, non-linear feedbacks

may not operate in the same manner in palaeoclimates as they will under doubled CO₂ forcing. Combining constraints from different palaeoclimates is likely to be more reliable than looking at single eras (Covey et al., 1996), but using different constraints or combinations thereof yields different values for climate sensitivity, adding an additional layer of uncertainty.

Ranges for climate sensitivity vary depending on the method employed (Figure 3). For the full range of emissions scenarios, the range of global climate sensitivity is 1.4–5.8°C (a normal distribution, with a 5–95% probability range of 2–4.5°C, and a most likely value of around 3°C) (IPCC, 2007). Wigley and Raper (2001) take account of other key uncertainties but maintain that all emissions scenarios are equally likely, to show that the probabilities of warming

are low on both tails of the distribution and, in the absence of climate mitigation, the 90% probability of warming is more likely to be in the range 1.7–4.9°C.

3 Natural variability

Even with some idea of how sensitive the climate system is to increased greenhouse gas forcing, there are barriers to understanding how the climate will ultimately respond. The climate system is a complex, non-linear, dynamical system, so understanding the behaviours of various components of the system does not imply understanding of the overall behaviour. As the system evolves it is influenced by natural variations, which are limited in their predictability. For example, the dominant influence on climate in western Europe, the Atlantic Ocean (Sutton and Hodson, 2005), is affected by modes of variability operating on a range of timescales from decadal (eg, El Niño/Southern Oscillation) to thousands of years (eg, thermohaline circulation). The predictability of these modes has been a topic of study for some time (eg, Davies et al., 1997; Graham, 1994; Marshal et al., 2001) and some modes have been shown to be quasi-predictable. For example, Griffies and Bryan (1997) found that the North Atlantic Oscillation may possess predictability in the order of a decade or longer, but not beyond that.

Such variability is naturally forced, as these oscillations of the climate system, which operate on a range of timescales, are present even in a stable climate not undergoing any anthropogenic forcing. The signals of anthropogenic climate change are then superimposed on this background of natural variability. However, estimates of natural climate variability are small relative to the warming observed over the twentieth century (IPCC, 2007).

4 Climate feedbacks and ‘surprises’

It is also possible that increased GHG emissions may interfere with natural climate modes and

processes. Climate feedback mechanisms exist which can amplify or diminish the effects of a change in forcing. One example is the effect of melting Arctic and Siberian permafrost (Anisimov, 2007). As permafrost melts, soil carbon and methane may be released, resulting in further warming. This may lead to further thawing, resulting in an amplification of the original signal known as a positive feedback. Kennedy et al. (2008) suggest that methane released from permafrost may have been a trigger for deglaciation at the end of the Marinoan ‘snowball’ ice age (~635M BP).

There is much debate about the presence of ‘tipping points’ in the climate system (Hansen, 2006). For example, there may be a critical threshold in the climate-carbon cycle system, where regional drying leads to the loss of large tracts of the Amazon Rainforest (Cox et al., 2004). The loss of such a large carbon sink would lead to further warming, and further forest loss. Similarly, global climate model (GCM) simulations show that strong surface freshening in the North Atlantic, which may be brought about by melting glaciers, could force a reduction in the strength of thermohaline circulation (THC). Such a reduction could occur on a timescale of decades (Hulme and Carter, 1999), or the onset could be even more rapid, taking place over just a few years (Alley et al., 1993). It has been shown that THC resembles a non-linear system in many ways, becoming increasingly sensitive to small perturbations as its critical threshold is neared, and thus less predictable (Knutti and Stocker, 2002). Palaeodata suggests that THC reduction, triggered by the sudden release of meltwater from Lake Agassiz (Carlson et al., 2007), may have caused the Younger Dryas cold event (11,500 BP).

Anthropogenic effects on natural climate variation could manifest in many ways, from a slow shift from a phase of low activity to one of high activity to a sudden jump from one state to another (Figure 4). There may even be a

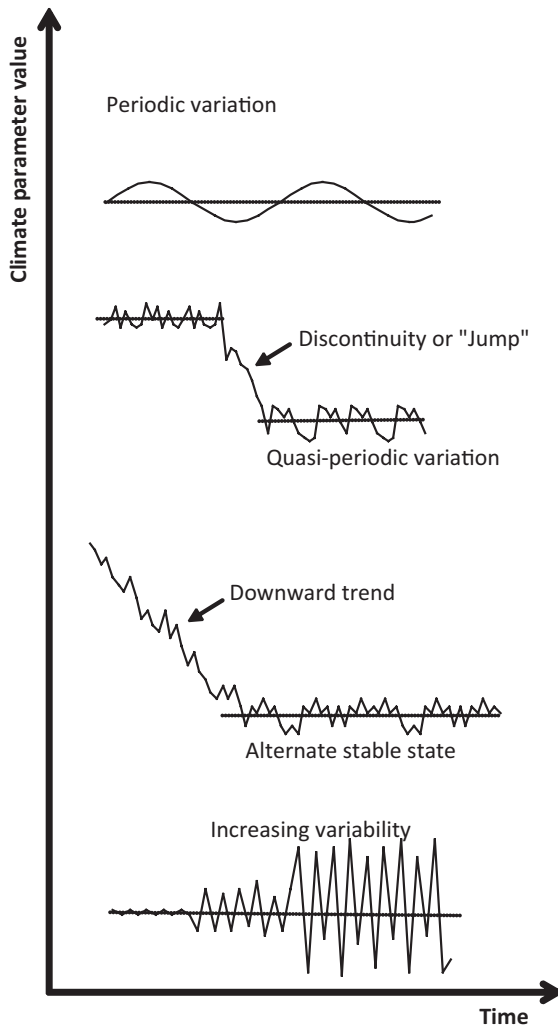


Figure 4. Types of climate variations
Source: Marcus and Brazel (1984)

number of states that the system changes between. Such jumps are also known as abrupt events or climate surprises and the Younger Dryas cold event would be an example of such an event. Palaeodata and modelling can give an indication of possible outcomes, making such uncertainties ontological as they are due to the non-deterministic nature of the system but are not entirely unknowable. The more model runs considered, the larger the range of potential outcomes that can be simulated. However,

models cannot be expected to reveal the full range of potential surprises as, even at their most complex, they represent a simplification of the actual system.

5 External forcing

Future external forcing may come from unexpected solar variability or volcanic eruptions, which can have a significant impact on the climate system. Major volcanic eruptions such as El Chichón in 1982 and Mount Pinatubo in 1991 resulted in temperature anomalies of -0.2°C and -0.4°C , respectively, in the year following the eruptions (McCormick et al., 1995). Simulations show that the impacts of 'super-eruptions' could be much greater, potentially reducing global temperatures by up to 10°C (Jones et al., 2005). While this initial effect may last only for a few months, it could take several decades for temperatures to return to normal. Such forcings are unlikely ever to be predictable in a deterministic sense and are thus classed as an unknowable uncertainty.

Yet some form of action is required to reduce the risk of crossing critical thresholds within the climate system, and information is needed to plan adaptation strategies. Past observations of the climate are no longer reliable indicators of future behaviour. Therefore, although climate models can never take account of every uncertainty, they remain a vital source of information about future climates.

IV Uncertainty in climate models

Emissions scenarios provide the primary input used to drive a GCM. Due to computational limitations, GCM resolution tends to be quite coarse, in the order of $1.2\text{--}4^{\circ}$ (Genton et al., 2009). Various methods can be used to bridge the gap between GCM output and regional response, but the focus of this review is regional climate modelling. RCMs have become an increasingly important source of information for environmental planners,

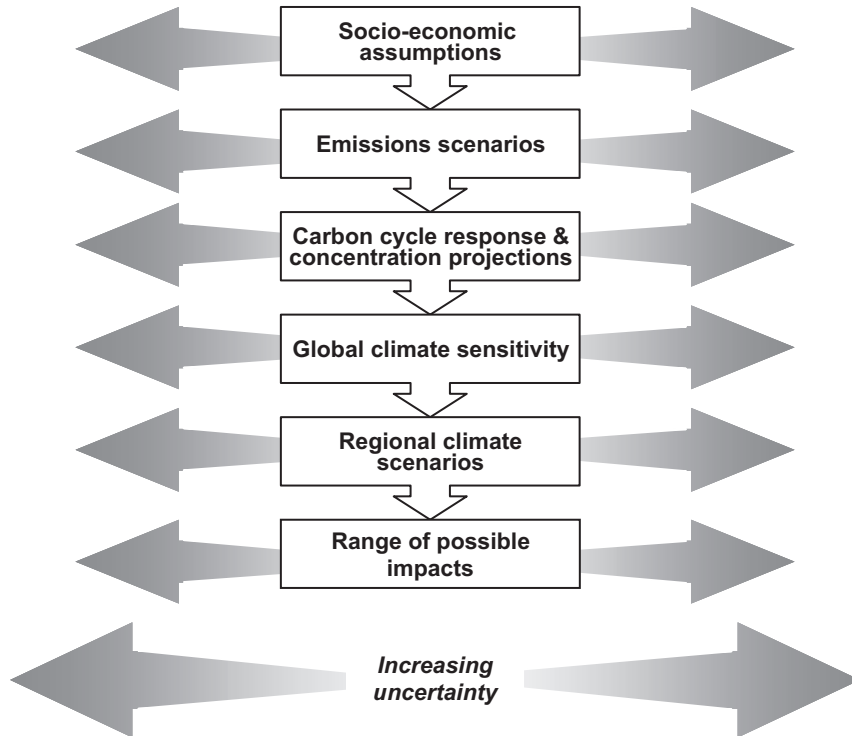


Figure 5. 'Uncertainty explosion' of major typical uncertainties
 Source: Jones (2000b)

providing the necessary, detailed information over a limited area. However, an RCM is but one part of the modelling process. It is part of a chain of procedures in which uncertainties and inferences at each level can impact outcomes at subsequent levels. This chain has been referred to as the 'cascade of uncertainty' (Mitchell and Hulme, 1999) or the 'uncertainty explosion' (Henderson-Sellers, 1993; Jones, 2000b) (Figure 5).

Both GCMs and RCMs are impacted by uncertainties which, if left unaccounted for, weaken confidence in end projections and limit the usefulness of those end projections in planning and policy decisions. Ultimately, choices must be made about which driving GCM and RCM to use, and for every choice there are combinations left unconsidered. Such uncertainties must be recognized as an unavoidable part of climate modelling.

Epistemological uncertainty in climate modelling

Epistemological uncertainties are influential in both GCMs and RCMs, and uncertainties associated with clouds are a prime example of this category of uncertainty. Clouds have a variety of effects on both the radiation budget and water balance, so it is highly important that models reproduce them accurately. According to Schwarz (2008: 439), 'a 10% error in treatment of clouds in the climate model would result in an error of some 4.8 W/m^2 '. The type and height of cloud determines the effect it will have. Thin, high clouds such as cirrus clouds produce a positive forcing by trapping outgoing longwave radiation. Low, thick clouds such as stratocumulus have a cooling effect as they reflect sunlight back into space (ie, the cloud albedo effect). An increase in cloud amounts is projected as a

consequence of anthropogenic warming, but specific cloud types and overall effects on surface temperatures are unknown. However, the sensitivity of clouds to warming can be assessed through the analysis of observations and also through the use of mesoscale models (Bony et al., 2004).

There are two main reasons for the knowledge gaps surrounding clouds. First, accurate satellite observation records are quite short, with most records commencing in the 1970s. The surface observation record is longer but subjective. Only clouds visible to the observer could be recorded, so higher-level clouds hidden by low-level clouds would not be noted (IPCC, 2007). Baker and Peter (2008) suggest new observational and laboratory programs are needed to fill cloud science knowledge gaps and thus reduce epistemological uncertainty through further research.

Second, the large-scale effects of clouds are actually the result of processes occurring on a much smaller scale, and further research is needed to characterize these processes. For example, increases in concentrations of anthropogenic aerosols such as sulphate and mineral dust have both direct and indirect effects on clouds by impacting on processes at this microphysical scale. New research (eg, Berg et al., 2008; Khain et al., 2005; Lohmann, 2008) and new data collection methods such as remotely piloted aircraft (Lu et al., 2008) are helping to close knowledge gaps and enable better modelling of clouds, which in turn enables better modelling of the climate system.

As knowledge of the system increases, a new problem emerges. AOGCMs require considerable computer resources, which are not limitless. Therefore, decisions must be made about how to focus computing power (Pope et al., 2007). To maximize one attribute of the model it is necessary to compensate in other areas. Presently, to produce long and highly complex output, a model would need to be run at a low resolution. If high-resolution output is required, it is sometimes necessary to leave out or empirically

approximate processes rather than physically resolve them. Leaving out a process can have an effect on the model's performance, as demonstrated by Senior (1999) who found the modelled response of large-scale circulation changes significantly when interactive radiative properties are excluded from the model. An alternative is to parameterize such processes. Instead of explicitly resolving the process in the model, a scheme is developed to describe the impact of the mechanism on the atmospheric system. The effect of the subgrid-scale processes is approximated in terms of resolved grid-scale variables.

A number of issues arise from the use of such schemes. First, parameterization schemes are not equally effective. Convective cloud formation is an example of a process that should not be excluded from models, as deep convection significantly affects the stability of the large-scale circulation (Emanuel et al., 1994). But the scale on which convective clouds form can be less than a kilometre. To model the processes occurring at this scale using the equations of fluid motion would require much finer grid resolution than is currently feasible. So a scheme is created which simulates the collective effects of convective clouds in each model grid cell. However, as noted by Randall et al. (2003), some of the assumptions the parameterization scheme makes to calculate these effects are difficult to verify, and additionally may not be valid in a warmer world. Different schemes vary in design and assumptions, and as a result they vary in skill also (eg, Wang and Seaman, 1997).

The second issue is that whether or not the effect of the subgrid-scale processes will be the same under different forcing conditions is impossible to say. Parameterizations are constructed based on our knowledge of the atmospheric system as it currently is, but the processes are not physically represented in the model. Under uncertain forcing conditions, different parameterizations could yield different outcomes and, in the absence of empirical data for comparison, they must all be treated as

plausible projections of future climate. This issue can be seen as a form of the problem of induction (Frame et al., 2007). In inductive reasoning, a series of observations are made and a claim inferred based on them. But the observations made in themselves do not establish the validity of inductive reasoning. The observation-based knowledge that climate models partially use relies on the uniformity of nature: the concept that the future will resemble the past. The problem is that the future will obviously not resemble the past in all respects, and *a priori* we cannot specify the respects in which the resemblance holds. Keeping in mind these considerations, the task of modelling future climate scenarios at all may at first seem quite fruitless. Fundamentally, however, models are based on established physical laws, and have proven skill at representing important features in both past and present climate, as demonstrated by the climate sensitivity experiments referred to earlier. There is good reason to be confident that models provide credible estimates of future climate, but also much scope to improve upon epistemological uncertainties through further research.

2 Ontological uncertainty in climate modelling

As the climate system has similarities with a non-linear, chaotic system, unpredictability arises in two distinct ways. If a chaotic system evolves n number of times from slightly different starting conditions, n different outcomes can be expected. Although the paths taken may at first be similar, over time errors in initial conditions amplify and make it impossible to forecast with certainty. For this reason, it is not possible to forecast individual weather events beyond the order of a week. This problem, sensitivity to initial conditions, is referred to as predictability of the first kind.

There is also predictability of the second kind, relating to boundary conditions. The RCM

domain has a certain boundary with the surrounding environment, and the model must consider processes in this boundary region also. These conditions can never be precisely specified as there is no unique solution to the mathematical problem posed by RCM boundary conditions (Rummukainen, 2010). Although it has been the focus of less research than the first kind of predictability, seemingly small perturbations to boundary conditions can also lead to significantly different future behaviour (Chu, 1999; Collins and Allen, 2002).

Weather prediction was identified as an initial and boundary problem early in the twentieth century. Bjerknes (1914) recognized that if one could make some simple assumptions, one could arrive at integrable systems of dynamic and thermodynamic equations to represent meteorological phenomena. He also appreciated the need for accurate, reliable information on the state of the system, to use in solving such systems of equations. Bjerknes (1919) believed that the most important advance in weather forecasting would be the development of a close-knit network of weather stations to provide high-quality data. Although forecasts at the time were of the order of hours, not even days, Bjerknes understood that forecasts would be far more reliable if the observations on which they were based were accurate. This data quality issue persists today on a different scale in climate science.

For control runs (simulations of present-day climate used to validate models) RCMs can take these conditions from gridded observational data. They typically include wind components, temperature, water vapour and cloud variables and surface pressure (Giorgi, 2006). For future projections, RCMs take initial and boundary conditions from a parent GCM, a technique known as nesting (eg, Antic et al., 2006; Ding et al., 2006; Ju et al., 2007). To further increase accuracy in driving conditions, a double-nesting approach uses global output to drive a second model, perhaps an atmosphere-only GCM, over an intermediate domain. The output from that

experiment is then used to drive the RCM (eg, Gao et al., 2006; Im et al., 2006). Two-way nesting is another variation, in which RCM information is allowed to feed back into the GCM (eg, Barth et al., 2005), to improve representation of the general circulation (Lorenz and Jacob, 2005). As the GCM has its own inherent flaws, boundary and initial conditions will always be imperfect. Although the imperfections themselves arise through epistemological uncertainties in the parent GCM, they are a source of ontological uncertainty for RCMs because they detract from the predictability of the system.

Additionally, the various fluxes of heat, water and momentum need to be in dynamic and thermodynamic equilibrium for initial conditions to be valid. It is not enough for the initial climate of the model to resemble the real climate; it also must be stable. Typically, models are given a 'spin-up' period during initialization, during which the faster adjustments (ie, 50-year timescale) take place and stabilize. But a slower adjustment also takes place, as the deep ocean adjusts to surface heat and water flux imbalances. During initialization, models are allowed to reach a stage where this adjustment, known as 'climate drift' (eg, Bryan, 1998; Dirmeyer, 2001), is so slow as not to interfere significantly with the interpretation of climate change signals. Computational demands make it unrealistic to initialize the model over a timescale so long that the deep ocean adjustments fully stabilize, therefore a flux adjustment may be required to minimize climate drift and prevent the model from sliding into unrealistic climate states. Due to improvements in the simulation of the large-scale heat balances, many of the most recent generation of models employed in the IPCC Fourth Assessment Report do not require a flux adjustment and instead maintain their own physical consistency. Further research into the behaviour of the climate system clearly has the potential to improve the realism of climate model simulations, though models will always be a simplification of the real system.

3 Intermodel variability

Model design at all levels is a subjective process. Choices must be made about what to include in a climate model, what to exclude, what to parameterize and how, and each decision introduces uncertainty. Intermodel variability, variation in projections due to choice of model, is an important issue. Figure 6 compares control output for Ireland from 19 simulations obtained through the EU PRUDENCE (Prediction of Regional scenarios and Uncertainties for Defining European Climate change risks and Effects) (Christensen et al., 2002) data archive to observations for 1961–1990 and illustrates this spread in outcomes due to the different GCM drivers and parameterizations employed by each model. Such differences can be quite significant; a bias of +2°C in one month is quite large when one considers that the observed range of temperature across the whole year is 1.8°C. Additionally, even when the same GCM driver is used, differences in RCM design can result in quite different outcomes (Figure 7).

The choice of which model or models to utilize is not arbitrary, as it can be based on assessments of model skill – eg, CMIP (Coupled Model Intercomparison Project) and PRUDENCE. But this can never be a truly objective choice. Blyth (1972) distinguishes between knowledge, defined as beliefs held by the entire scientific field, and subjective beliefs, the personal beliefs of individuals. A knowledge-guided decision may use a measure of model skill acknowledged by the modelling community, but there are many such measures and no designated index for intercomparison. So the choice must be partially subjective as the decision of how to assess skill is made by the individual and not commonly agreed by the scientific field.

Model performance can be interpreted in different ways and quantified using a variety of metrics, using the observed climatic records for comparison. Multiple statistics of climate must be considered to provide a full picture

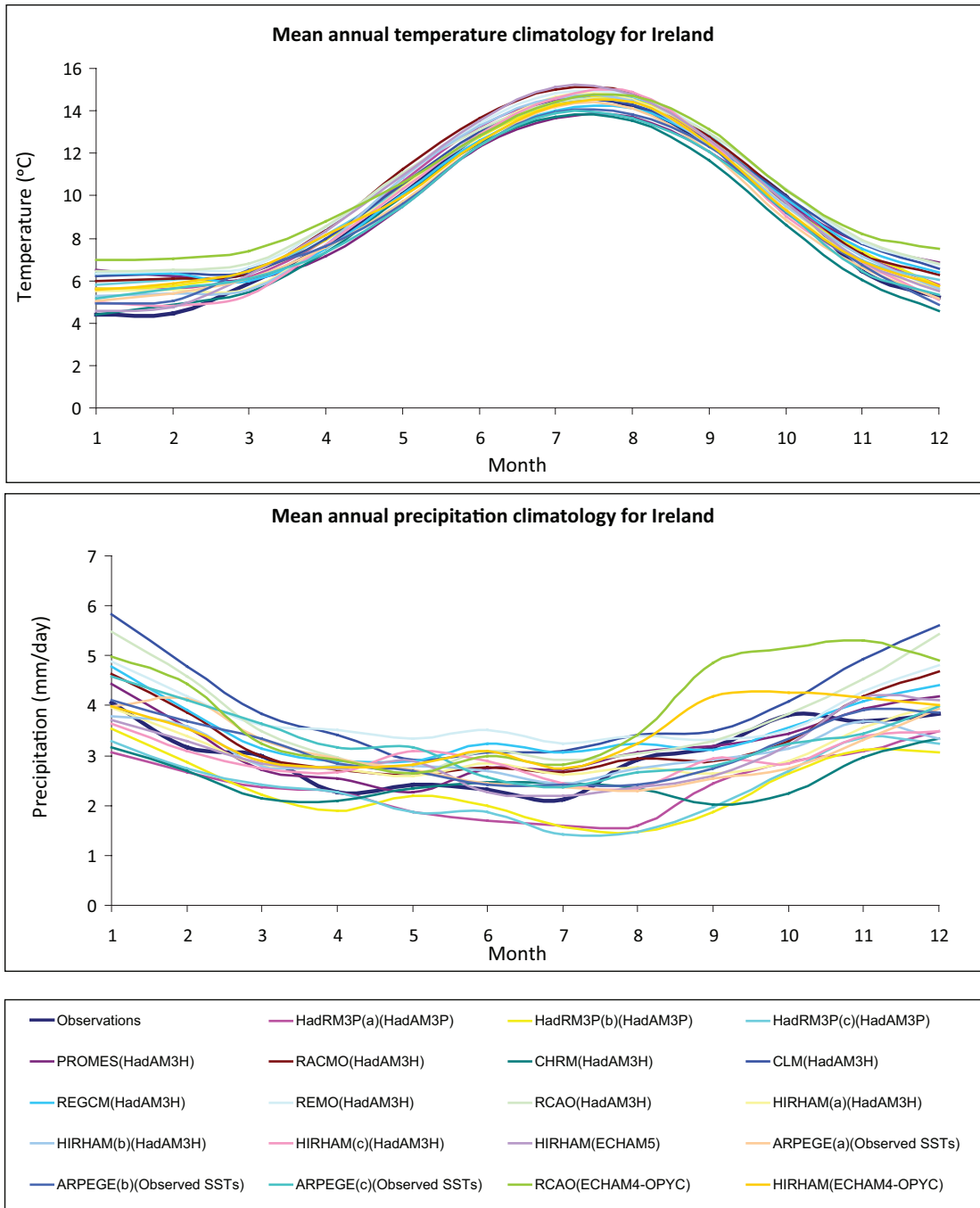


Figure 6. Control output for Ireland from 19 simulations obtained through the EU PRUDENCE Project for 1961–1990

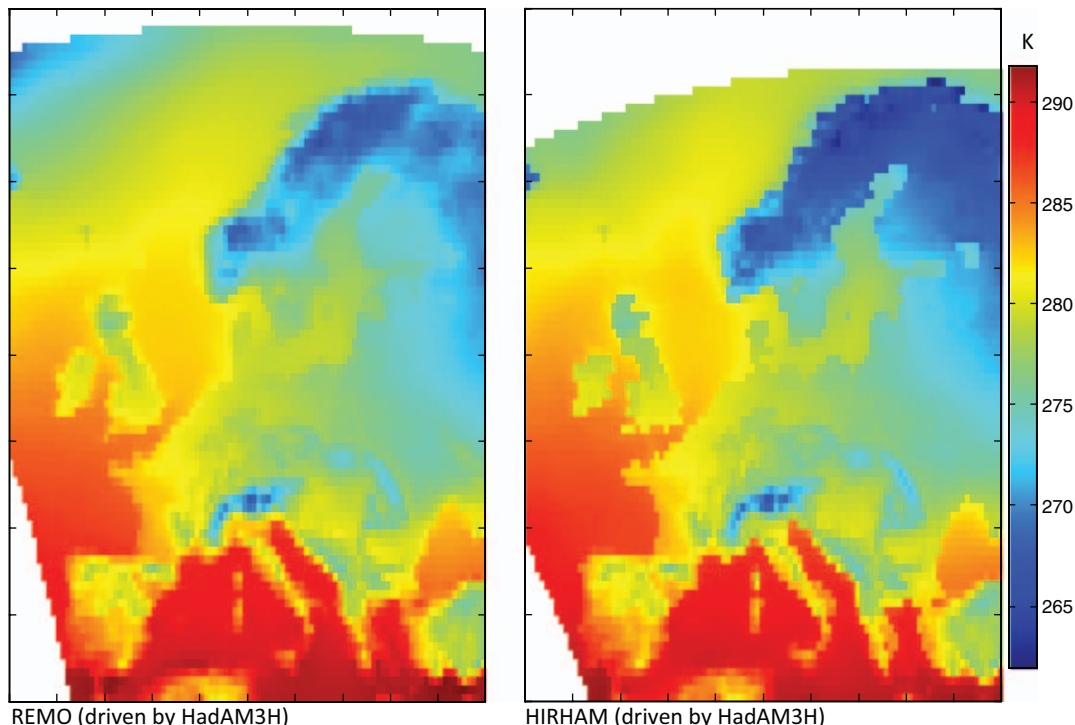


Figure 7. Projections of mean winter (DJF) temperature (K) for Europe for 2071–2100 by REMO (left) and HIRHAM (right), both driven by HadAM3H GCM under A2 emissions scenario ($273.15\text{K} = 0^{\circ}\text{C}$). Note differences in projections across Scandinavia. Data is obtained from the EU PRUDENCE data archive

of model skill. A change in the mean can have a disproportionate effect on the extremes of a distribution because other characteristics such as the variance are also altered by the mean change. Therefore, a model which predicts mean seasonal trends accurately may not possess similar skill at modelling extremes (eg, Hanson et al., 2007).

Aside from the subjectivity of methods that account for model differences, there are a number of philosophical arguments as to whether any of these methods are truly legitimate. The terms ‘validation’, ‘verification’ and confirmation’ are often encountered in climate modelling literature, and all are commonly used refer to the general process of comparing a climate model’s output over a control period to the observed climate record as a means of establishing

reliability, but in the philosophical sense each has a distinct meaning and it is possible for a model to be validated without essentially being verified. Validation means that a model has met specified performance standards and is therefore suitable for a particular use (Rykiel, 1996), while verification refers to the demonstration of the ‘truth’ of the model as a basis for reliability. However, there are fundamental barriers to the validation and verification of computer models of natural systems.

First, it is impossible to demonstrate the truth of any proposition except in a closed system (Oreskes et al., 1994). A natural system is not closed. It is not isolated from the environment, but can instead be influenced by events outside of the conceptual boundaries imposed on it for the purposes of study. It is also dynamical, with

components that change over time. For example, one cannot assume that errors in the future projections of a model will be of the same magnitude as those in the hindcast, as errors may not be constant in time and may change under different forcing conditions.

Second, it has been argued that techniques which use past observations to calibrate future model projections are misleading as the model is simulating a state of the system that has not been experienced before (Stainforth et al., 2007a). Therefore verification of a model's performance can only ever be partial. To expand on this definition of verification, one could consider other criteria such as ability to simulate changes in palaeoclimates. A model that simulates both the recent and distant past effectively is more likely to provide credible future scenarios than a model that has been tested only for the twentieth century.

Third, a deficiency in a model could arise for a number of reasons. A temperature bias, for example, could be due to an error in how the model handles cloud cover, or in how the topography is resolved. The error could even be the result of a summation of different errors. To definitively locate the source of the error, it would be necessary to run the model in question repeatedly, varying a particular parameterization each time while holding everything else constant. This is not viable for the many end-users who work with RCM output but not with the model itself.

Even if model biases and errors cannot be comprehensively accounted for, knowing they are present is valuable information in itself. The propensity for errors could serve as a qualitative measure of model reliability. However, agreement between model output and observed climate does not signify that the model is an accurate representation of the real system, and this must be acknowledged. But the model should reflect the behaviour of the real system if it is to be suitable for contributing to scenario development

V Working with uncertainty: ensembles and probabilities

A model can have skill at modelling one aspect of the climate and lack skill at modelling another. The model that simulates average seasonal trends accurately may not give a true picture of future changes in extreme events, which due to their sudden nature can cause much greater damage over a short space of time compared to a gradual change. Results that vary depending on choice of model are not very reliable, and decisions need to be based on robust findings. For one particular variable or location, a single best model may perform well, but when considering all aspects of climate and uncertainty, a combination of several different models, known as an ensemble, can provide better overall skill and reliability (Tebaldi and Knutti, 2007). Ensemble techniques are in widespread use in the climate modelling community and have been used to characterize the spread of climate responses for a range of variables, impacts and regions.

I Multimodel ensembles

One approach, suggested in Mitchell and Hulme (1999), is to combine multiple predictions from different models to form a multimodel ensemble. Ideally, individual ensemble members should possess high skill by themselves and be independent of one another. However, such ensembles are also known as 'ensembles of opportunity' (Stone et al., 2007) as members are sometimes chosen more for availability than demonstrated skill, an approach which has the potential to generate misleading output (Allen and Stainforth, 2002). Multimodel ensembles allow a range of different models to contribute to the overall projection so that intermodel variability is represented in the spread of the projections. It also helps to account for intramodel variability, as a more complete range of possible future climate scenarios is sampled.

The precise reason why an ensemble so often performs better than the individual ‘best’ model is debatable. Doblas-Reyes et al. (2005) attribute the improvement to the use of different models and increased ensemble size, while Hagedorn et al. (2005) states that a large part of the ensemble’s superiority is due to error cancellation, and argues that if a model existed that performed poorly in every measure, it could only add skill in this way. Conversely, Weigel et al. (2008) argued that even a poor model can add skill, if the model’s poor performance is due to overconfidence and not low potential predictability. It seems that both studies arrive at a similar conclusion: there is nothing to be gained by including models that are fundamentally flawed in their performance. If a poor model is taken to mean an overconfident one, then this model can be compensated for using ensembles; but if we take poor to mean a model that struggles to represent the climate system properly, then only revisiting the mechanics of the model and looking for ways to improve its parameterizations can truly enhance such a model.

2 Perturbed physics ensembles

An ensemble may also consist of different runs of the same model (Barnett et al., 2006), each with perturbed versions of the original model physics. In theory, by varying the physics parameters of the model uncertainties due to parameterization choice are represented in the spread of the output. The key advantage is that the sampling of uncertainty is more systematic than in a multimodel ensemble, whose members are chosen on an opportunistic basis (Murphy et al., 2007). One can choose a single skilful model and run many iterations rather than using many models of varying skill. Of course, this requires a subjective decision to be made about which single model to use, and the most skilful model in the present may not remain skilful under future forcing conditions.

While a perturbed physics approach is highly useful for quantifying variability within the model, it cannot characterize intermodel variability like a multimodel ensemble. The optimal approach would be to use a multimodel perturbed-physics ensemble. The traditional multimodel ensemble is formed by combining output from single iterations of many different models to construct a distribution of climate parameters. Combining perturbed physics distributions from individual models rather than single outputs would give a fuller sample of uncertainties, an approach like that of Christensen et al. (2001), which used two eight-member ensembles from different RCMs. A larger ensemble will naturally capture a greater proportion of uncertainty.

The distributed computing project *climateprediction.net* has been used to create multithousand member GCM ensembles (eg, Piani et al., 2005; Sanderson et al., 2008; Stainforth et al., 2007b) but, to date, RCM perturbed physics ensembles have been much smaller in size. Examples include Lynn et al. (2009), Lucas-Picher et al. (2008) and Yang and Arritt (2002), which featured ensembles of 8, 10 and 25 members, respectively. Due to the time and computer resource constraints associated with regional modelling and the limitations of current computing standards, it is just not feasible to produce RCM ensembles of similar size to the current crop of GCM ensembles. Hawkins and Sutton (2009) note the importance of targeting investments in climate science on the areas with the greatest potential for reducing uncertainty and indeed it may be worth focusing on the problem of computer power. Better resources would enable more complex models to be run, as well as larger ensembles.

3 Ensemble methodologies

For ensemble scenarios to be reliable, it is important that the performance of individual members is assessed. It is also essential that the

methods used to generate ensembles are valid (Leung et al., 2003) There is a level of subjectivity in ensemble construction, and to formulate robust climate scenarios, assumptions need to be justified.

A key question is whether to use information about a model's performance in the present to constrain the influence of its future output on the overall ensemble. One can consider all outcomes as equally likely or assign weights to models based on a performance criterion. Reliability Ensemble Averaging (REA) (Giorgi and Mearns, 2003) is one such quantitative approach, which assigns a weighting function to each model based on their performance at simulating the present climate, and their convergence. As bias or distance from the simulated ensemble mean grows, the model is deemed less reliable. Yet skill in the present does not necessarily equate to skill in the future. It is impossible to state with certainty how a model will perform under unprecedented forcing conditions. However, it is hard to see how a model lacking skill at representing the current climate would have better skill at modelling a future climate. Therefore, while there is an argument to be made for constraining poorly performing models based on present-day skill, one must not mistake present-day skill for a guarantee of future skill.

Model convergence is the second criterion used in the REA method: the further a model's result is from the ensemble mean, the less reliable it is taken to be. But convergence may not be a robust reliability criterion, as there may be underlying similarities that lead a group of models to converge. Similarities could include sharing the same GCM driver or dynamical core, or having a key parameterization scheme in common. Alternatively, the absence or inclusion of certain parameterizations may be key. Rockel and Woth (2007) studied changes in wind speed over Europe using an ensemble of RCMs, and discovered that the absence of a gust parameterization leads to much poorer simulation of high wind speeds or 'storm peaks'. Additionally, as

model skill can vary with location (Haylock et al., 2006; Hellstrom et al., 2001; Jacob et al., 2007), a model can be an outlier in one region but not in another. The reliability of the model convergence criterion depends on the independence of the models in the ensemble, which is often difficult to establish. Therefore it would be unwise to discount a model only because other models disagree with it.

As our understanding of the climate system, and the climate models we design based on this understanding are incomplete, we must assume that all well-specified models provide plausible future scenarios even though they differ in their design and outcomes, unless a clear and justifiable reason to omit a particular model is found. It is better to exercise caution and work with a large range that the 'true' outcome is likely to lie within than to be overconfident and work with a smaller range that may not contain it at all. The range of outcomes supplied by climate models becomes part of a chain of inferences; regional effects are inferred from global effects which are in turn used to infer and prioritize adaptive decisions. In the words of Frame et al. (2007: 1986), we 'run the risk of building inferential edifices on unstable foundations', a situation best avoided where investment decisions must be made.

4 Ensembles with probability

Approaches like the REA technique are quantitative but not probabilistic. An advantage of such a technique is that one avoids making assumptions about distributions of factors, which is required for a probabilistic approach. But probabilities are very useful in climate science. Patt and Dessai (2005) investigated how people link descriptive phrases with probability ranges and found that they use intuitive heuristics rather than formal definitions. Given the same descriptive terms to describe a high-magnitude event and a low-magnitude event, people interpret the language to mean the high-

magnitude event is less likely, leading them to actually underestimate the damage that could be expected and under-respond to the threat of the high-magnitude event. The potential for biased interpretation can be lessened by utilizing both numerical probability ranges and probabilistic language. A similar approach is used in the UK Climate Projections project to quantitatively assess the probability attached to a variety of climate risks (Willows and Connell, 2003).

Probabilistic methodologies have a history of use within short- and medium-range weather forecasting, so their application to climate projections is a logical step. Räisänen and Palmer (2001) demonstrate how a GCM ensemble can be treated as a probabilistic forecast, with inter-model uncertainty characterized by the ensemble dispersion. Furthering this methodology, one can utilize probability distribution functions (PDFs) or cumulative distribution functions (CDFs) as a technique for quantifying uncertainties in RCM output as well as GCM (Ghosh and Mujumdar, 2009).

The probabilities used by climate change researchers are not classical frequentist probabilities. They would be better defined as Bayesian probabilities (Dessai and Hulme, 2004; Smith et al., 2009). Bayesian probability is very applicable to climate change simulations as it assigns probability to propositions that are uncertain. This methodology interprets probability as a measure of a state of knowledge. But the 'state of knowledge' can be subjective. For example, Bayesian statistics could be used to make a quantitative determination of climate change impacts, but it would be based on a prior assessment of the probability of climate change. This assessment would have to be subjective, and the use of different yet equally plausible priors would yield different outcomes (Barnett et al., 1999). However, as Berliner et al. (2000) assert, Bayesian statistics acknowledges that it is imperfect by stating the assumptions and quantifying them so that the sensitivity of the results can also be assessed.

Objective Bayesian probability also exists (Berger et al., 2001), which utilizes a non-informative, non-subjective prior distribution. But this can lead to paradoxes as outlined by Kriegler (2005), who notes that if one assumes complete ignorance regarding future atmospheric CO₂ concentration, one cannot also make this assumption for the associated radiative forcing as it is logarithmically dependent. Taking a strictly objective view can also lead to the exclusion of qualitative information which has the potential to be very valuable.

Different researchers have adopted variations of the methodology, some more objective and some more subjective. An objective approach was used by Jones (2000a), which relied on properties of classic probability distributions. If the uncertainties associated with various sources are taken to be uniform and independent, then when multiplied together they will yield a peaked probability distribution for key climatic variables. In practice, it is common to assume a uniform distribution over the appropriate range of values for the prior distribution.

Tebaldi et al. (2005) proposed a Bayesian analysis approach which would formalize the performance and convergence criterion that the REA method first quantified. Uniform, uninformative prior distributions are adopted, to avoid making assumptions about the prior distributions that could be construed as subjective. Tebaldi et al. (2004) proposed a variant of the methodology in which convergence could be weighted differently relative to performance.

Both objective and subjective methodologies have their merits. If the avoidance of assumptions is paramount, then objective methods would be more appropriate. For some researchers, this is extremely important as it is perceived that subjective choice introduces further uncertainty to the problem. Conversely, there is an argument that by treating model outcomes as equally likely, even when the evidence from control runs suggests differences in skill, an

important opportunity for quantifying uncertainty has been neglected. Inevitably, the choice between objective and subjective probabilities introduces an additional layer to the cascade of uncertainty.

VI Conclusions

In the words of Collins (2007: 1958), ‘the very fact that a team of people can produce a simulation that bears a passing resemblance to the world we live in is, in retrospect, a significant feat’. Yet a simulation can never capture the complexities of the real system. Any numerical model is limited by the knowledge the scientist has about the real system, and the computing resources available to run it. As a result, uncertainty is unavoidable in regional climate scenarios and indeed in any geographical discipline which utilizes numerical modelling.

As adaptation strategies may require costly infrastructure it may at first seem unwise to use RCM output to inform such decisions. Strategic decisions may be flawed if decision-makers assume risks are well characterized when they are not. However, the cost of inaction is likely to be far greater than the cost of early, adaptive measures (Stern, 2006). If climate sensitivity is at the upper end of the range specified by the IPCC, steps towards adaptation must be taken to reduce the risks to people, infrastructure and the natural environment.

The uncertainties in regional climate model output must be identified and acknowledged for the information to be put to best use using approaches appropriate to the deep uncertainty of the situation (Lempert et al., 2004). By working with a range of models, decision-makers can build strategies that cater for a range of plausible futures. Rather than looking for an optimum strategy which depends upon precise projections, decision-makers can build robust strategies that are open to critique and revision (Baer and Risbey, 2009) and will be beneficial under a range of different conditions (Popper et al., 2005).

Uncertainty in regional climate model output cannot be eliminated. What is more, the growing and present concern of climate change means that we cannot wait until the tools are perfected before making decisions about adaptation. Fortunately, uncertainty in RCMs can be minimized, quantified and communicated effectively, and, in spite of their uncertainties, regional climate models can provide valuable information for the robust decision-making process.

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