5 Projections from the ensemble of regional climate models

This chapter describes data from an ensemble of eleven variants of the Met Office Regional Climate Model (HadRM3), run from 1950–2099 and used to dynamically downscale global climate model (GCM) results as part of the UKCP09 methodology. The daily RCM time series are not included as a UKCP09 product, and are therefore not accessible via the User Interface. However, RCM daily data may have advantages over that from the UKCP09 Weather Generator for some impacts studies, and is the only 25 km resolution data available over the seas around the UK, so has therefore been made available via the Climate Impacts LINK project. We describe here the RCM data, the advantages it may have for some users, and also its limitations — the main one being that it does not cover such a wide range of uncertainty as the UKCP09 probabilistic projections.

5.1 Regional climate models

A regional climate model contains the same representations of atmospheric dynamical and physical processes as in a global model. It is run at a higher horizontal resolution (in our case 25 km) but over a sub-global domain (typically 5000 km square), and is driven at the boundary of the domain by time series of variables (such as temperature and winds) saved from a GCM projection. Sea surface temperatures and sea-ice extents are also prescribed from the GCM, since HadRM3 (like most RCMs) does not include an interactive ocean component. The purpose of RCMs is to provide a high resolution climate projection consistent with its driving GCM projection at spatial scales skilfully resolved by the latter, but adding realistic detail at finer scales. This is the *downscaling* process referred to above. The advantages of projections from RCMs over those from GCMs are:

- RCMs simulate spatial contrasts in time-averaged climate at a scale much smaller than that of the driving GCM, in particular where there are significant regional influences arising from surface features such as mountains and coastlines (see Figure 5.1).

- The higher resolution of RCMs also allows improved representation of climate variability, particularly aspects associated with small scale meteorological processes. As a result, they can provide skilful (though not perfect) projections of regional climate extremes, such as localised intense precipitation events, which cannot be captured in GCMs.

- The higher resolution of RCMs allows small islands to be explicitly represented in the model.

- While RCM projections are designed to be consistent with their driving GCM projections at large scales, some types of climate impact, such as changes in river flow, are likely to be so strongly dependent on the fine scale detail that the use of downscaling, either based on RCM data or a statistical method, is essential for the generation of a credible assessment of future changes.

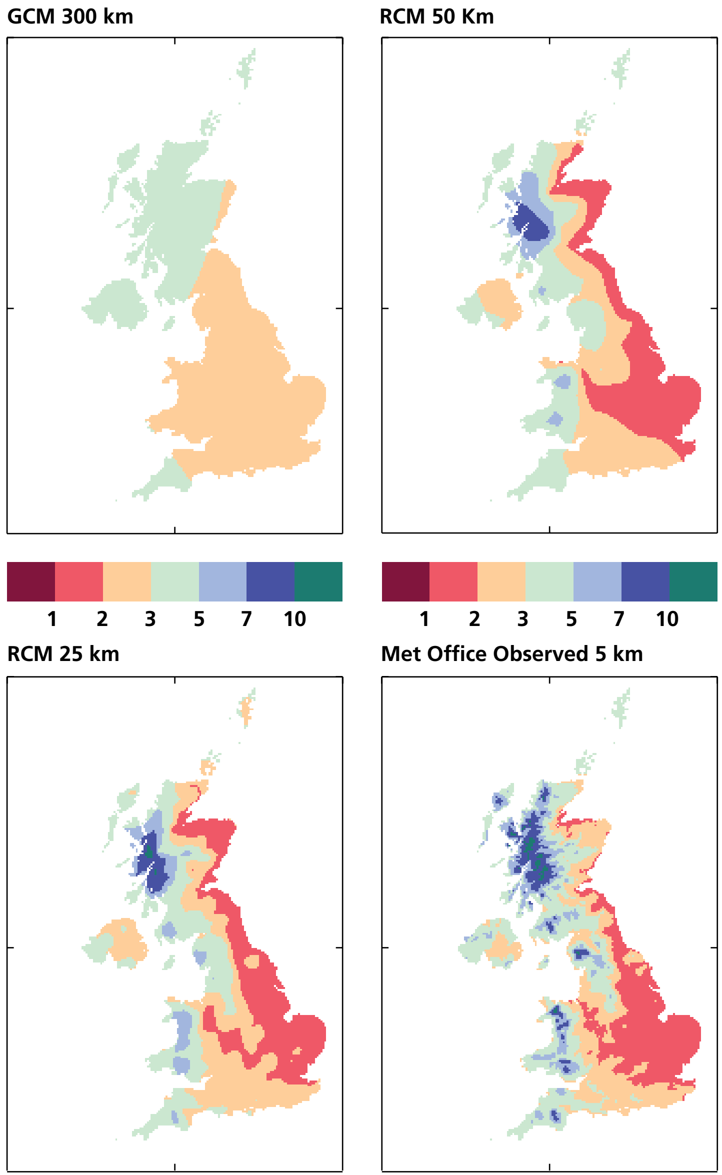


Figure 5.1: The distribution of winter precipitation over Britain (bottom right map) for 1961–2000, compared to simulations for the same period from a GCM (top left), and from two versions of the corresponding RCM at 50 and 25 km resolution, both driven with boundary conditions derived from analyses of observations. The GCM (inevitably) fails to resolve the observed spatial detail, whereas the RCM simulations show better agreement with increasing resolution.

General guidelines for applying RCM data can be seen in a report from the IPCC Task Group on Climate Impacts Assessments (Mearns *et al*. 2003). A key caveat is that while RCMs are now well established as skilful and sophisticated downscaling tools, they inevitably inherit all the uncertainties in large scale aspects of climate change present in their driving GCM simulations (see Annex 2), so the enhanced detail in their projections should not be taken to imply higher accuracy (see also Annexes 3 and 6). The same caveat applies to fine scale projections derived from the UKCP09 Weather Generator (see further discussion below).

5.2 RCM experiments

As mentioned above, and described in more detail in Chapter 3, transient (that is, continuous from 1950 to 2099) projections from GCM experiments were used as boundary conditions to drive transient regional climate model experiments. Only the Medium emissions scenario was used. Each RCM variant used parameter settings selected to be consistent with those used in the relevant driving GCM variant. In 11 RCM ensemble members this experimental design produced physically plausible simulations of detailed climate variability and change over the UK. In the case of an additional six ensemble members, however, the RCM simulations were found to be deficient in their simulations of storms and precipitation, because one of the parameter perturbations employed in the RCM failed to produce an impact consistent with that found in the driving GCM projections (details in Section 3.2.11). These members were therefore not used in the downscaling procedure for UKCP09, which was based on the remaining 11 RCM variants.

Daily data from 1950 to 2099 has been archived from each of these 11 variants, for a large number of variables (at the surface and at levels in the atmosphere) for 25 km grid squares over the domain shown in Chapter 3, Figure 3.8. Following interest from the user community, it was agreed to make this data available. This will be done via the Climate Impacts LINK project (http://badc.nerc.ac.uk/data/link), a Defra-funded activity operated by the British Atmospheric Data Centre, which allows access for research to a range of data from model experiments undertaken at the Met Office. Data accessed via LINK is not accompanied by extensive guidance.

Data from the RCM ensemble is also available as monthly and seasonal means. The RCM data can be used to create projections of climate change, by differencing averages for a future period from a reference period. This operation cannot be performed using the LINK website, but can be done offline once the data has been downloaded. Information on the use of this data is available in the UKCP09 User Guidance.

5.3 Advantages and disadvantages of data from the RCM ensemble

As described in the companion UKCP09 report *Projections of future daily climate for the UK from the Weather Generator*, daily data for future decades is also available from the Weather Generator, which is part of the UKCP09 projections. Why, then, should there be interest in using RCM data? Some reasons are:

1. The daily data from the 25 km model squares is coherent both spatially and temporally, in the sense that it arises from a model which produces dynamically and physically consistent simulations of the passage over the UK of a sequence of atmospheric weather systems. This means, for example,

that daily data from any number of squares (contiguous or otherwise) can simply be spatially aggregated by the user to form a physically plausible area average over any desired region. This could be, for example, a river basin or administrative region — although such averages are not provided as products. This is not the case for the output from the UKCP09 Weather Generator, which is designed to produce daily time series which are temporally consistent at individual locations, but not to produce daily time series which are physically coherent over a larger region.

2. It follows from point (1) that temporal sequences of, for example, daily temperature and precipitation over any set of 25 km squares can be used to study the impacts of the evolution of these variables when spatial consistency is required, for example when modelling flow in large river catchments.

3. Changes in long term averages of key variables are fed into the Weather Generator, which then generates characteristics of daily sequences, using a set of statistical relationships derived from present day observations and assumed not to change in the future. The influence of climate change feedback processes (see Chapter 2, Box 2.1) on characteristics of daily time series (for example runs of consecutive hot or dry days) therefore enters only through their effects on the input long term averages. Each of the RCM projections also accounts for effects of feedbacks on aspects of daily variability *not* explained directly by changes in the long-term average, subject of course to the uncertainties associated with climate model projections.

4. Each of the RCMs give a continuous time series of day-to-day data from January 1950 to December 2099 (see, for example, Figure 5.3). The UKCP09 probabilistic projections, however, give changes in *long term averages* of climate for particular 30-yr periods. This means that daily time series from the Weather Generator, fed by inputs from the probabilistic projections, will be typical of the average climate throughout the relevant period, but will not show any trend in climate change within that period.

5. There are a large number of variables available from the RCM ensemble, at many model levels over both land and sea (for details see the LINK website); the Weather Generator outputs a more restricted number of variables at the land surface only — although these are the ones most commonly used in impacts research.

The UKCP09 report *Projections of future daily climate for the UK from the Weather Generator* discusses the limitations of the Weather Generator in more detail.

On the other hand, the main disadvantages of RCM ensemble data are:

1. The 11 model variants do not sample the full range of changes in time-averaged climate expressed in the UKCP09 probabilistic projections. This is because the latter account for a wider range of process uncertainties, by sampling the full parameter space of the HadCM3 atmosphere model, while also catering for additional uncertainties arising from structural errors in atmospheric processes using alternative climate models, plus those arising from carbon cycle, sulphur cycle and ocean transport processes (see Chapter 3). The Weather Generator, however, can be run by selecting from a very large sample of possible changes in time-averaged climate covering the full range implied by the probabilistic projections.

2. It follows from (1) above that users of RCM data should check projections of time-averaged climate change for variables of interest, to see where in the UKCP09 probability distributions they lie. An example is shown in Figure 5.2; this is for a specific variable and different variables and time periods will show different distributions of the 11 RCM variants within the probability distributions. Such an exercise can provide an assessment of the relative likelihood of the time-averaged changes in any given RCM projection, just as it can for any set of time-averaged changes selected to drive the Weather Generator. Note, however, that it would be unwise to assume that the corresponding daily time series possess the same relative likelihood. This is because limitations in current climate modelling capability, or in the statistical assumptions used in the Weather Generator, imply that projections of future changes in detailed regional variability cannot be assumed to carry the same level of credibility as corresponding projections averaged over long periods. In the case of the Weather Generator, the statistics of changes in variability (for a given set of time-averaged changes) can be sampled more robustly than in the case of the RCM, by running multiple realisations with different initial conditions. However the results are still conditional on the assumptions indicated above.

3. The RCM data are projections of simulated climate of the future, rather than ready-made projections of climate change. If the latter are required, then the user will need to difference data sets data for the two periods between which the change is required, for example 2060–2099 and 1990–1999. This does give the user the flexibility of using any number of different future time periods, and indeed baseline periods, of any length, rather than the 30-yr time periods and 1961–1990 baseline period used in UKCP09. As with all model data, that from the RCM will contain biases, due to systematic errors of various sorts — note that these biases will also affect projections from the weather generator. Creating projections of climate change by taking RCM differences as described above will remove the effect of historical model biases. This does not, of course, imply that the future values will then be error free, due to the uncertainty in modelling future changes themselves.

4. When using RCM data to drive models of climate impacts, the issue of model bias again needs to be considered. For example, in some cases the impacts model can be driven with daily data for both a future time period and a reference time period. The difference can then be taken as a plausible realisation of the impact of climate change. However, in other cases, the bias in the RCM may produce implausible results for the present climate from the impacts model, in which case a bias adjustment to the impacts by subtracting present from future may be inappropriate.

Table 5.1 shows some of the differences between the two types of daily data sets; that available from the UKCP09 weather generator, and that from the RCM ensemble.

Table 5.1 (opposite): Some characteristics of the data from the RCM ensemble and from the Weather Generator.

Characteristic	RCM ensemble	Weather Generator
Geographic coverage?	Land and marine areas (see Chapter 3, Figure 3.8).	Land only. UK plus Isle of Man, but not Channel Islands.
Spatial Resolution?	25 km	5 km, but with no additional climate change information above projections at 25 km resolution.
Temporal resolution?	Daily	Synthetic daily data. No climate change information additional to that at monthly resolution in the probabilistic projections. Daily data is also disaggregated to hourly.
Continuous?	Yes, from 1950 to 2099.	7 standard UKCP09 30-yr time periods, plus 1961–1990.
Can users average daily time series from different grid squares to obtain time series for larger regions?	Yes, any number of grid squares can be averaged by users.	No, but users can configure the WG to produce time series for a single region of any size, up to a maximum area of 1000 km^2.
Temporal averaging?	Yes, can be done by users.	Yes
Consistency between variables?	Yes	Yes
Spatial coherence between grid squares?	Yes	No
Can a relative probability be attached to the projected daily time series?	No. Daily time series from particular RCM variants should be interpreted as plausible realisations, but are subject to additional modelling caveats which preclude the assumption that we can assign some level of probability to them, based on the corresponding changes in time-averaged climate.	No. Weather Generator time series are also subject to additional caveats, associated with their internal statistical assumptions. Again, they should be regarded as plausible realisations consistent with current knowledge, but should not be treated as results to which some level of probability can be attached.
Samples the UKCP09 probabilistic projections?	Partially. Designed to sample a range of possible responses, but not the full range expressed in UKCP09, for reasons explained above.	Yes: can be driven by prescribed climate changes sampled from the full range of possibilities captured in the UKCP09 probability distributions.
Projections of climate or climate change?	Daily climate, but with model biases in the historical simulations. Such biases can be empirically removed by expressing the future projections as changes relative to the model baseline climate, and then adding them onto an observed baseline. This does not guarantee that the projected changes are free from error.	Daily synthetic climate. Historical baseline simulations are generated using statistics based on observations, which should (by construction) reduce biases in their characteristics, though the extent to which this is achieved depends on the characteristics in question. Future simulations are obtained by prescribing change factors obtained from the UKCP09 probability distributions, giving future time series whose characteristics can be differenced relative to the historical simulations to obtain projected changes.
Variables?	Many, at several levels.	Nine surface variables.
Threshold analysis of daily data?	No tool provided, but can be done by users offline.	Yes, using UKCP09 User Interface Threshold Detector.
Visualisation of results?	None provided, but can be done by users offline.	Yes, using extensive capability in UKCP09 User Interface.
Emission scenarios?	Medium	Low, Medium, High

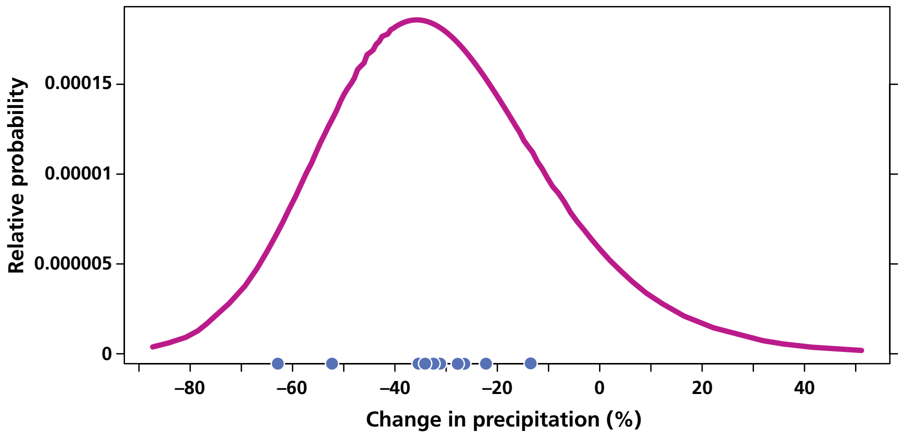


Figure 5.2: A UKCP09 probability distribution function, of change in mean summer precipitation at a 25 km square near Portsmouth, by the 2080s under the Medium emissions scenario. The added blue dots show the same change as projected by each of the 11 members of the RCM ensemble. Of course the PDF may well be quite different from the spread of RCM results, as the former includes information from other climate models and the effect of carbon cycle feedback, for example.

5.4 Examples of data from the RCM ensemble

Figures 5.3–5.5 show some results from the RCM ensemble; these are purely to illustrate the sort of data which can be accessed by the user, rather than to draw any conclusions about climate change. However, note that the LINK access does not provide any graphics capability, so these types of figures cannot be created online.

Figure 5.3 compares the simulated time series of summer (JJA) seasonal-mean daily maximum temperature from 1951 to 2099, from a 25 km grid square over Berkshire of each of the 11 RCM variants under the Medium emissions scenario. Figure 5.4 shows a similar set of time series of summer-mean precipitation for a grid square near Inverness; the large amount of *noise* due to natural variability is immediately apparent, showing that, despite a gradual reduction in summer precipitation through the 21st century, natural year-to-year changes remain larger than the projected climate change, even at the end of this period. Figure 5.5 shows maps of summer-average rainfall simulated by one RCM variant for two 30-yr periods, 1961–1990 and 2070–2099.

5.5 Some applications of RCM ensemble data

The RCM data has been used at the Centre for Ecology and Hydrology, Wallingford, to investigate changes in river flows over the course of the century. This is used as a worked example in the UKCP09 User Guidance to demonstrate the sort of application for which the RCM data might be appropriate. The data has also been used to drive the POL CSX model to estimate changes in the height of extreme water heights (storm surges); results from this are given in the companion UKCP09 science report *Marine and coastal projections*.

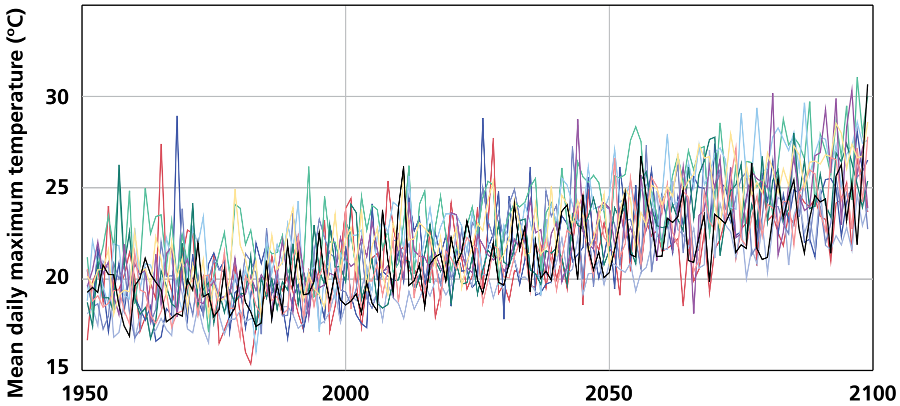


Figure 5.3: Simulated summer (JJA) seasonal-mean daily maximum temperature for a 25 km grid point in Berkshire, 1950–2099, under the Medium emissions scenario, from each of the 11 RCMs.

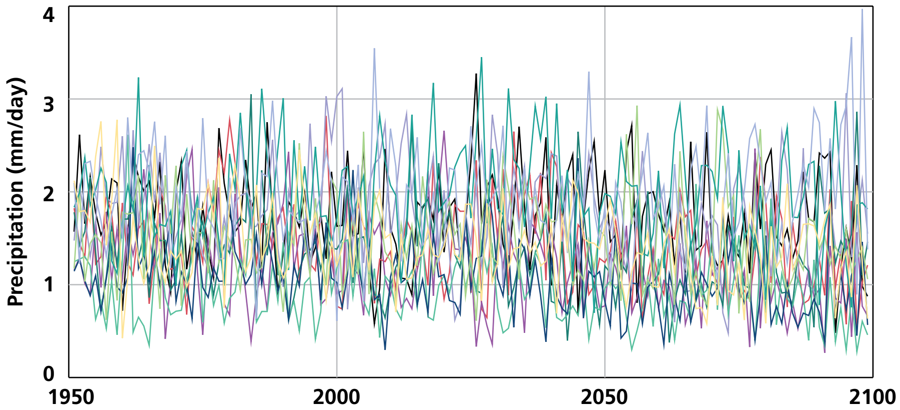


Figure 5.4: Simulated summer (JJA) seasonal-mean daily precipitation for the 25 km grid point near Inverness, 1950–2099, under the Medium emissions scenario, from each of the 11 RCMs.

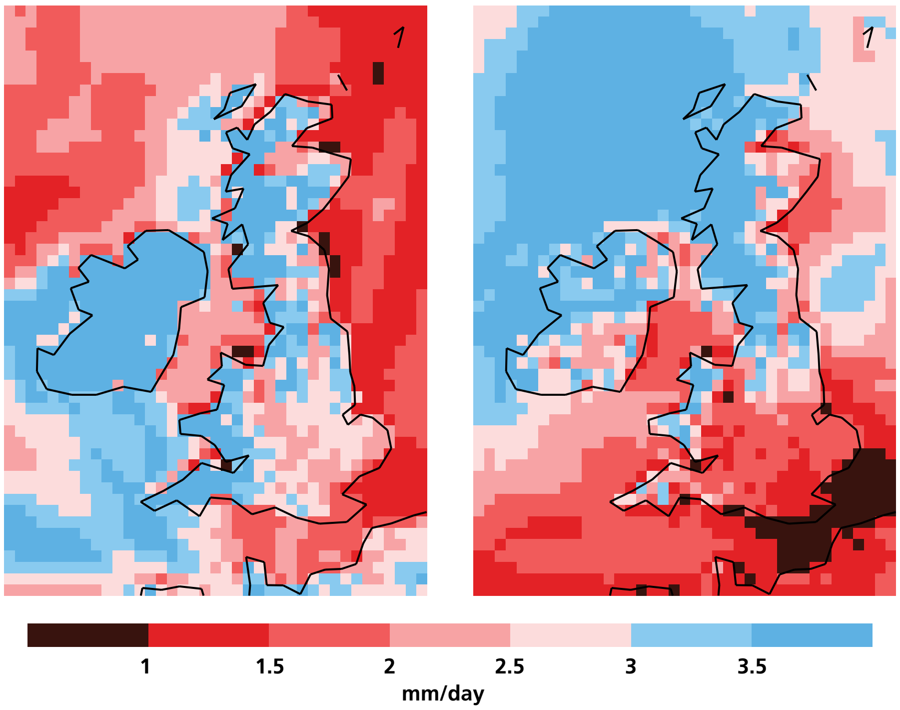


Figure 5.5: A map of summer (JJA) average precipitation (mm/day) from one member of the 11-member RCM ensemble, averaged over the period 1961–1990 (left) and over the period 2070–2099 under the Medium emissions scenario (right).

5.6 Reference

Mearns, L. O., Giorgi, F., Whetton, P., Pabon, P., Hulme, M. & Lal, M. (2003). Guidance on use of climate scenarios developed from regional climate model experiments. DDC of IPCC TGCIA. Available at: http://ipcc-ddc.cru.uea.ac.uk/guidelines/guidelines_rcm.html.

Annex 1: Emissions scenarios used in UKCP09

Rachel Warren, Tyndall Centre for Climate Change Research, UEA.

Each of the SRES emissions scenarios used in UKCP09 suggests a different pathway of economic and social change over the course of the 21st Century. Changes in population, economic growth, technologies, energy intensity, and land use are considered in the emissions scenarios. They do not assume any planned mitigation measures and cannot currently be assigned probabilities.

A1.1 Background

We need to make some assumptions about future emissions of greenhouse gases (and other pollutants) from human activities in order to make projections of UK climate change over the next century. Because we cannot know how emissions will change, we use instead a number of possible scenarios of these, selected from the IPCC Special Report on Emissions Scenarios (SRES) (Nakićenović and Swart, 2000). These correspond to a set of comprehensive global narratives, or storylines, that define local, regional and global socio-economic driving forces of change such as economy, population, technology, energy and agriculture — key determinants of the future emissions pathway. The scenarios are alternative conceptual futures to which no probabilities can be attached.

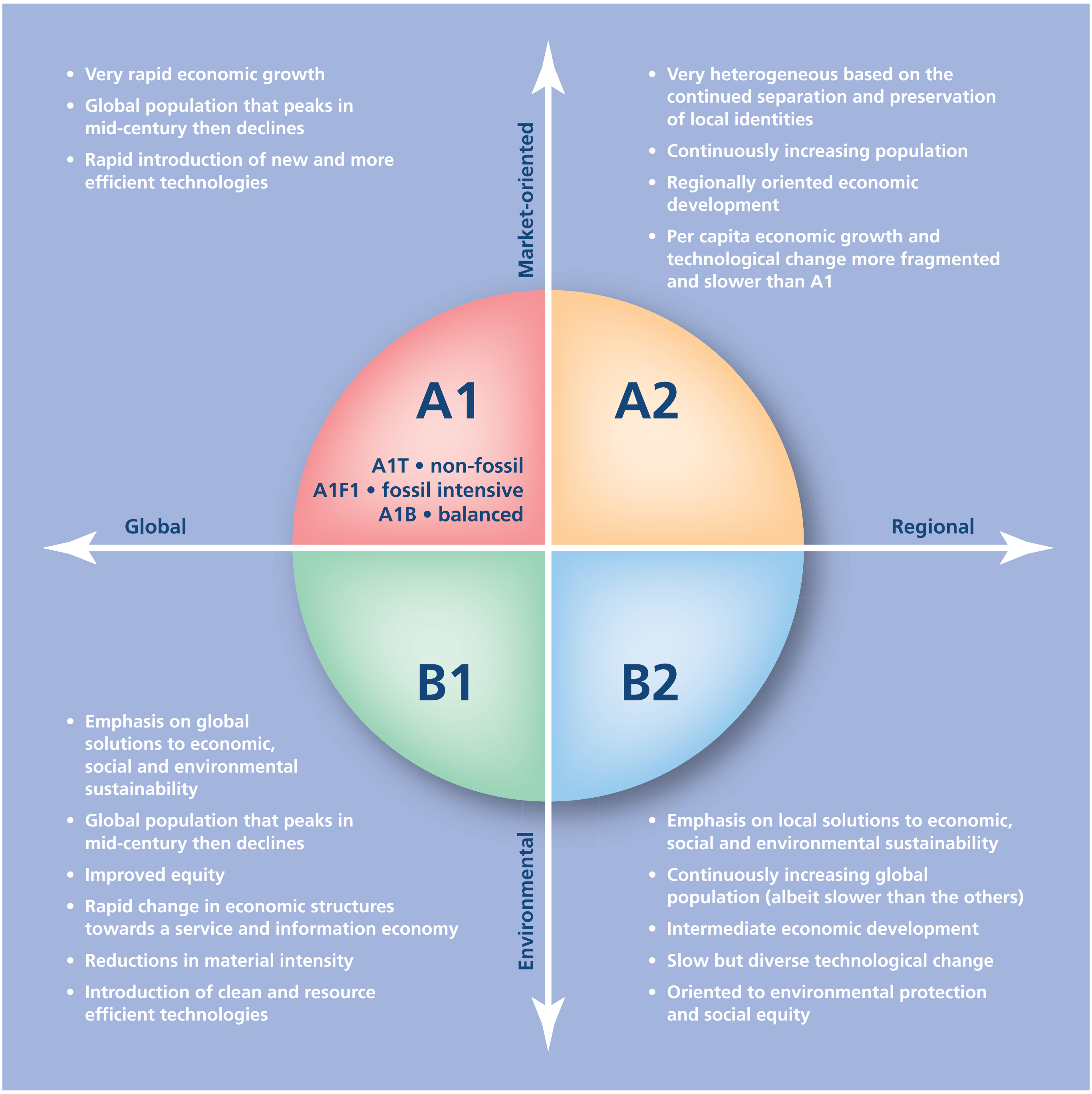
SRES emissions scenarios are structured in four major *families* labelled A1, A2, B1 and B2, each of which represents a different storyline. They are commonly shown as in Figure A1.1, in which the vertical axis represents the degree to which society is economically or environmentally oriented in the future, whilst the horizontal axis refers to the degree of globalisation. All scenarios are *non-interventionist*, that is, they assume that emissions will not be changed in response to concerns over climate change.

The A1 storyline describes a future world of very rapid economic growth, and a population that increases from 5.3 billion in 1990 to peak in 2050 at 8.7 billion and then declines to 7.1 billion in 2100. Rapid introduction of new and efficient technologies is assumed, as is convergence among regions, including large reductions in regional differences in Gross Domestic Product (GDP). Within the A1 family are three subgroups, referring to high use of fossil fuels (A1F1), high use of non-fossil energy sources (A1T) or an intermediate case (A1B).

The B1 storyline also describes a convergent, more equitable world, and has the same population scenario as the A1 storyline: however, rapid changes in economic structures towards a service and information economy are assumed, with reductions in material intensity, and the introduction of clean and resource-efficient technologies. Global solutions are found to economic, social and environmental sustainability.

The *High*, *Medium*, and *Low* emission scenarios in the UKCP09 report correspond to the A1F1, A1B and B1 SRES scenarios. The High and Low emission scenarios are the same as those of the same name used in UKCIP02. They span almost the full range of SRES scenarios, with cumulative (2000–2100) CO_2 emissions of 2189 GtC and 983 GtC respectively. SRES A2 and B2 storylines, with higher, continuously increasing population scenarios (to 15.1 and 10.4 billion in 2100 respectively), are

Figure A1.1: The SRES storylines/emissions families.



not used in UKCP09, as the population assumed in the A2 storyline is significantly higher than the high end of current projections.

Extreme high or low emissions scenarios, for example very high rates of fossil fuel combustion or strong mitigation in response to concerns over climate change, are also not considered in the projections available from UKCP09. The UKCP09 Low emissions scenario (SRES B1) does, according to some models, result in approximate stabilisation of CO_2 concentrations between about 500 and 600 ppm. However, when the full (ocean and land) climate–carbon cycle feedback is included, as is done in UKCP09, then the CO_2 concentrations will vary over a wide range.

A1.2 Relevant work since the publication of SRES

The IPCC AR4 (2007) assessment, Working Group 1 Chapter 10 and Working Group 3 Chapter 3, reviewed the new data on demographics, economic trends and energy use and concluded that the emission ranges from scenarios that do not include climate policy that were reported before and after the SRES study in 2000 have not changed appreciably: hence they are still used as the basis for the 2007 IPCC assessment and for the UKCP09 projections. However, population scenarios produced by some major institutions (van Vurren and O'Neill, 2006) are now lower than they were in 2000, specifically for Asia, Africa, Latin America and the Middle East, which more than compensates for the slightly higher population projections for OECD countries. As a result, the population projections that are considered within the emission scenarios assumed as the basis of the UKCP09 projections, with a population of 7.1 billion in 2100, are some 1.3–1.9 billion below the current central estimates of 8.4–9.0 billion (Lutz *et al*. 2004; UN, 2004; Fisher *et al.* 2006). However, van Vurren and O'Neill (2006) also note that the projection of global GDP growth for the A1 family is higher (3.1% per yr) than the ranges (1.2–2.5%/yr) of current projections (USDoE, 2003; IEA, 2004).

The full SRES range of emission projections is actually still considered to be representative of the range of likely outcomes, because in studies which have incorporated the revised lower population estimates, emissions have not decreased because the reduction has been partly compensated for by changes in other drivers such as energy intensity (which has declined slower than anticipated) and the rate of technological change (which has also been slower than expected). These is turn are due to less rapid turn-over of capital stock in the energy sector, and slow penetration of new and advanced technologies due to lack of investments (Grubler *et al.* 2004). Other studies have not yet been revised to take account of these lower projections.

In the SRES scenarios used here, as well as in subsequent studies of future emission pathways, baseline land-related greenhouse gas emissions remain important throughout the 21st century. They include continued, although slowing, land use change (e.g. deforestation) and also increased use of high-emitting agricultural intensification practices due to the anticipated rising global food demand and shifts in dietary preferences towards meat consumption. More recent scenarios (e.g. Soares-Filho *et al.* 2006) suggest significantly more rapid rates of deforestation than those in the SRES scenarios, which would act to enhance the climate forcing and potentially make climate change more rapid.

There has been a debate on the form of exchange rates, market exchange rates or purchasing power parities, used in the SRES (2000) simulations. However, evidence from the limited number of new studies indicates that the choice of metric for

GDP does not appreciably affect the projected emissions, when metrics are used consistently, with the differences being small compared to other uncertainties such as rates of technological change. This is because when the exchange rate type is changed, the emission intensities change in a compensating manner when the GDP numbers change (van Vurren and O'Neill, 2006; Fisher *et al*. 2007).

Raupach *et al.* (2007) have compared recent global carbon dioxide emissions, estimated by two US government groups, EIA (Energy Information Administration) and CDIAC (Carbon Dioxide Information Analysis Center), with those assumed in the SRES scenarios. They find that CO_2 emissions increased by more than 3%/yr between 2000 and 2004, compared to 1.1%/yr for 1990–1999. This rate of 3%/yr is faster than that in any of the SRES scenarios, and it might be inferred from this that the latter underestimate future emissions, and this would mean that the UKCP09 projections are also an underestimate. However, there are obvious dangers in using comparisons over such a short period to draw conclusions about emissions over the next decades and century.

Some guidance on using the uncertainty associated with the three UKCP09 emissions scenarios is provided in the UKCP09 User Guidance.

A1.3 References

Fisher, B. S., Jakeman, G., Pant, H. M., Schwoon, M. & Tol, R. S. J. (2006). CHIMP: A simple population model for use in integrated assessment of global environmental change. *The Integrated Assessment Journal,* **6**(3), 1–33.

Fisher, B., Nakićenović, N., *et al.* (2007). Issues related to mitigation in the long term context. In: *Climate change 2007: Mitigation Of Climate Change. Contribution Of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel of Climate Change (IPCC)*. Metz, B. *et al.* (Eds) Cambridge University Press, Cambridge, UK, 169–250.

Grübler, A., Nakićenović, N., Alcamo, J., Davis, G., Fenhann, J., Hare, B., Mori, S., Pepper, B., Pitcher, H., Riahi, K., Rogner, H. H., La Rovere, E. L., Sankovski, A., Schlesinger, M., Shukla, R. P., Swart, R., Victor, N. & Jung, T. Y. (2004). Emissions scenarios: a final response. *Energy and Environment*, **15**(1), 11–24.

IEA (2004). *World Energy Outlook 2004*. International Energy Agency, Paris.

Lutz, W., Sanderson, W. C. & Scherbov, S. (2004). The end of world population growth. In: *The End of World Population Growth in the 21St Century: New Challenges for Human Capital Formation and Sustainable Development*. Lutz, W. & Sandersen, W. (Eds) Earthscan Publications, London, 17–83.

Nakićenović, N. & Swart, R. (Eds) (2000). Special Report on Emissions Scenarios. A Special Report of Working Group III of the Intergovernmental Panel on Climate Change. Cambridge University Press: Cambridge, UK and New York. 570 pp. http://www.ipcc.ch/ipccreports/sres/emission/index.htm.

Raupach, M. R., Marland, G., Ciais, P., Le Quere, C., Canadell, J. G., Klepper, G. & Field, C. B. (2007). Global and regional drivers of accelerating CO_2 emissions. *Proceedings of the National Academy of Sciences*, **104**, 10288–10293 (doi/10.1073/pnas.0700609104).

Soares-Filho, B. S., Nepstad, D. C., Curran, L. M., Cerqueira, C. G., Garcia, R. A., Ramos, C. A., Voll, E., McDonald, A., Lefebvre, P. & Schlesinger, P. (2006). Modelling conservation in the Amazon basin. *Nature*, **440**, 520-523. (doi:10.1038/nature04389).

UN (2004). World population to 2300. Dept of Economic and Social Affairs, Population Division, UN, New York pp 254. http://www.un.org/esa/population/publications/longrange2/WorldPop2300final.pdf

USDoE (2003). International Energy Outlook US Department of Energy — Energy Information Administration, Washington DC.

Van Vuuren, D. & O'Neill, B. (2006). The consistency of IPCC's SRES scenarios to recent literature and recent projections. *Climatic Change,* **75**, 9–46 (doi:10.1007/s10584-005-9031-0).

World Bank (2004). *World Economic Prospects 2004*. World Bank, Washington DC.

Annex 2: Sensitivity of UKCP09 projections to key assumptions

David Sexton and James Murphy, Met Office Hadley Centre

The UKCP09 probabilistic projections inevitably depend upon a number of assumptions in the methodology used to produce them. Sensitivity tests can be performed on elements of the methodology to assess the robustness of the projections to reasonable variations in key assumptions. It should be noted that not all variables and assumptions can be tested at this time, but further work is planned.

A2.1 Introduction

This Annex supplements the description of our methodology for probabilistic climate projection, given in Chapter 3. Here, we describe a number of sensitivity tests designed to assess the robustness of the projections to reasonable variations in some of our main assumptions. We also give examples showing how the spread of outcomes implied by our probabilistic projections arises from different components of the method. The material described in this Annex necessarily assumes a similar level of scientific and technical understanding to Chapter 3; however, we summarise key conclusions in Section 4, omitting technical detail.

The key point is that while the UKCP09 probabilistic projections provide estimates of uncertainties in future climate change, it is also inevitable that the probabilities are themselves uncertain. If the uncertainties in the probabilities are sufficiently small compared with the uncertainties quantified by the probabilities, then the UKCP09 results are likely to be sufficiently reliable to be used in support of assessments of impacts, vulnerability or adaptation. This Annex provides examples of the type of information which will help users judge the robustness of the projections in the context of their specific applications. It should not be assumed that the precise levels of robustness shown in this Annex apply to all UKCP09 variables, time periods and spatial locations. Further examples of our sensitivity tests will therefore be made available on the UKCP09 website (see http://ukclimateprojections.defra.gov.uk). Note that user assessments of the reliability of the UKCP09 projections will also depend on the degree of precision required on a case-by-case basis, compared with other uncertainties that users would have to contend with (for example in greenhouse gas emissions, impacts models, adaptation costs, government policy, local planning decisions, etc.).

Therefore, while we can assess the robustness of the probabilistic projections based on tests of the underlying scientific methodology, decisions on their utility in user applications depend on additional factors beyond the scope of climate science.

Chapter 3 describes how our probabilistic projections are derived. Essentially, we produce a large number of projections of historical and future climate using perturbed variants of a number of configurations of the HadCM3 climate model, designed to sample major known uncertainties in relevant climate system processes. Different projections are weighted according to how well their historical components fit a set of observations, and we then integrate over the weighted projections to produce probabilities for alternative realisations of 21st century climate. The probabilities are therefore Bayesian in their nature, representing the relative credibility of different future outcomes, conditioned on a mixture of expert judgements, model and observational data and their associated uncertainties (the statistical framework used to produce them is described in Chapter 3). However, probabilistic climate projections inevitably depend not only on the data, but also on the statistical method used and the choices required by that method (see Chapter 3). Plausible variations in those choices will alter the projections to some extent, and this gives rise to uncertainties in the specified probabilities, as pointed out above. Henceforth, for clarity, we use the term *sensitivity* to refer to variations in the UKCP09 probability values in responses to the exploration of alternative methodological assumptions, and *uncertainty* to refer to the spread of outcomes quantified by the UKCP09 probabilities themselves.

A2.2 Sensitivity studies

Methodological choices generating sensitivities in the probabilistic projections fall into several categories:

i. Some assumptions are currently untestable (see discussion in Section 3.3). This is an inevitable consequence of any probabilistic projection method, due to limitations in scientific understanding, modelling capability, or computational resource. For example, we neglect the possibility of non-linear interactions between uncertainties in regional climate feedbacks arising from atmospheric, carbon cycle, sulphur cycle and ocean processes, because it is not yet feasible to run large ensembles of climate model simulations in which all of these processes are simultaneously perturbed.

ii. Some choices are based on a mixture of scientific reasoning and feasibility. For instance, we aim to use historical observations of a wide range of different climate variables to constrain our projections, because this reduces the risk that a model variant could be given a high weight by achieving a good historical simulation of a limited set of variables through a chance compensation of errors in its detailed representations of physical processes. We achieve this by using many thousands of pieces of observational information (consisting mainly of multiyear averages of global fields of several different variables in different seasons of the year), while noting limitations imposed by compromises in our experimental design, and by lack of availability of data from other climate models. In principle, we could test the impact of withholding some of the observational variables used in our analysis. However each of the observables (Section 3.2.9) was chosen to provide information about a different aspect of historical climate, and as such provides information with a significant degree of independence from that provided by the other variables. Removing one or more of these would therefore significantly degrade our ability to provide an observational constraint which effectively discriminates between physically plausible and implausible model variants, so the results of such a sensitivity test would be less credible than the UKCP09 results. We therefore do not investigate such a test here.

iii. Other choices are subjective. These can be divided into three groups, explained in this paragraph, and in (iv) and (v) below. First, there are a number of choices in our procedures which require expert judgement, but can be supported by diagnostic checks. These include, for example, choices between alternative statistical regression models in the emulation, timescaling and downscaling techniques described in Chapter 3. Another example relates to the use of observational data. While we wish to use as many observational variables as possible (as explained above), in practice we have to reduce the information to a limited set of global spatial patterns (multivariate eigenvectors), in order to make our statistical calculations tractable. These eigenvectors explain the main variations in simulated values of the observable variables found in a large ensemble of perturbed climate model variants (see Section 3.2.9). We use six eigenvectors, based on diagnostic tests indicating that this choice strikes a reasonable balance between the need to include enough information to calculate weights which are effective in capturing variations in simulation quality between different model variants, and the risks of trying to include too much information. Use of too many eigenvectors could result in (a) the inclusion of noisy patterns which do not capture physically meaningful variations in behaviour across our ensemble of alternative model variants, and (b) the risk that too few model variants would receive a non-negligible weight, in which case it would not be possible to obtain statistically robust projections when approximating an integration over all possible model variants (i.e. over all points in the model parameter space) using a finite sampling strategy (see Section 3.2.12). However, we test the sensitivity to this choice by recalculating selected results assuming retention of five eigenvectors (see following discussion of Figure A2.1).

iv. Some choices are subjective in principle, but are also limited by what information is available. An important example is the set of alternative climate model results available for use in our calculation of the effects of structural model errors (*discrepancy*, see Section 3.2.8). We recognise that if a larger sample had been available we might have obtained different results; however, we show below that reducing the set of climate models used has a limited impact on our probabilistic projections for surface temperature and precipitation, compared with the total uncertainty expressed through the spread in the UKCP09 probability distributions.

v. The third category of subjective choices encompasses those which are based on expert judgement, and are essentially unconstrained by objective checks or practical issues such as availability of resources. In our case, the most obvious example consists of the expert distributions for uncertain climate model parameters controlling surface and atmospheric processes, which form a fundamental prior input to our Bayesian method of climate projection (see Section 3.1). In our integration over model parameter space, we assume that these parameters are equally likely within the middle 75% of the range estimated by experts, and that the probability drops linearly to zero at the minimum and maximum values. However, alternative choices could also be justified, so the sensitivity of the results to these needs to be tested (see below). This is feasible, because our method includes a statistical emulator of climate model output which can estimate results likely to be obtained for any given combination of parameter settings.

A2.2.1 Sensitivity of results to plausible variations in the UKCP09 methodology

In this section we demonstrate the sensitivity of our results to a number of choices falling into categories (iv) and (v) above. We focus on changes in 30-yr averages of temperature and precipitation over Wales in winter and summer, as examples of two of the most important variables contained in the projections. Note, however, that the sensitivities are liable to be different for different variables.

The black curves in Figure A2.1 quantify the total uncertainty in the UKCP09 projections (omitting the downscaling component, as this example considers a global climate model grid box). The contribution of structural modelling errors to the total uncertainty, represented by the discrepancy term of our Bayesian

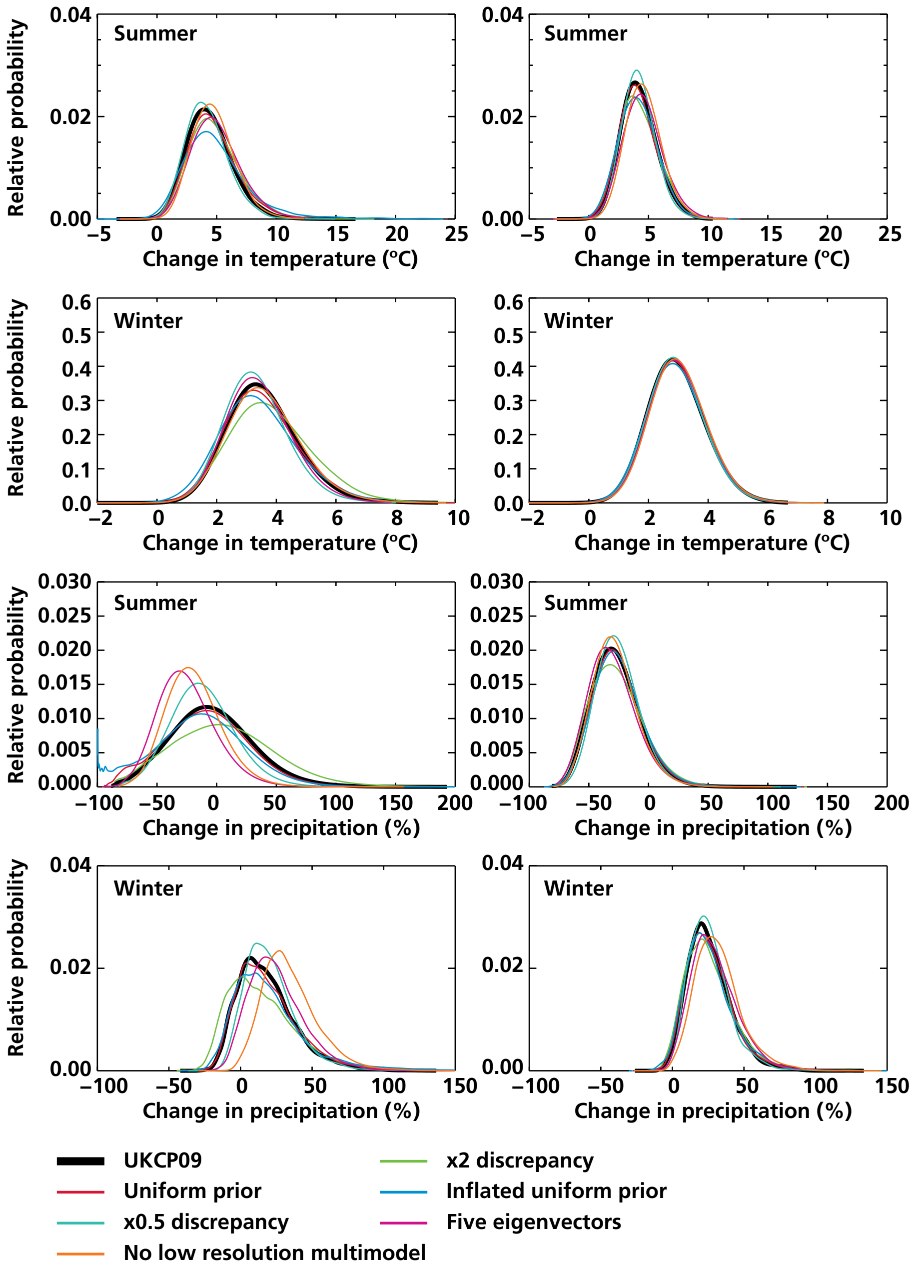


Figure A2.1: Probability distributions from six sensitivity tests (coloured) compared to UKCP09 results (black). The tests were done for summer and winter, for absolute changes in mean temperature (°C), and percentage changes in mean precipitation, for 2070–2099 relative to 1961–1990. Results are presented for a global climate model grid box corresponding approximately to Wales, and are based on application of the full methodology of Chapter 3, apart from the downscaling step of Section 3.2.11. *Uniform prior* and *Inflated uniform prior* refer to changes to the expert-specified distributions for surface and atmospheric climate model parameters; *x2 discrepancy*, *x0.5 discrepancy* and *No low resolution multimodel* denote variations to our method of estimating the effects of structural model error, and *Five eigenvectors* tests the effect of reducing the number of multi-variate spatial patterns used to weight different model variants according to their fit to historical observations of recent climate. Plots on the left-hand side show prior probabilistic projections, that is ones obtained after sampling the uncertainties accounted for in UKCP09, but without constraining the projections with observations. Plots on the right hand side show posterior probabilities after applying the observational constraints. Further details in text.

framework and derived from alternative climate models, is recognised as an element of the methodology which is important, yet difficult to quantify (see Section 3.2.8 and above). We test the sensitivity to the discrepancy in two ways. First, we double the variance of the discrepancy associated with future projections of climate variables. This is done on the basis that our method could underestimate discrepancy, given the relatively small sample of results available from alternative climate models; we also try halving the variance, in order to clarify the effects of varying the discrepancy spread in both directions. Diagnostic tests show that our estimates of the discrepancy associated with historical simulations of climate (Section 3.2.8) may actually be larger than the systematic component of model error found in verification against observations in practice (at least for the observables used in our calculations). While it does not necessarily follow that our estimates of future discrepancy are also likely to be too small, this result does underline the possibility that we could have overestimated discrepancy, particularly by assuming that all the alternative climate models included in our calculation are equally credible (Section 3.2.8). In addition to halving the discrepancy variance, we also test the possible consequences of this by removing two models with relatively low spatial resolution from the multimodel ensemble (noting that low resolution is only one of a number of possible causes of model error). This test can potentially alter the mean value of the contribution of structural model error, as well as the spread about the mean value, whereas the variance perturbation tests only alter the spread. Neither of these tests addresses the possibility that there could be a common bias in future projections from all current climate models. This is another example of an untestable assumption, since there is no obvious basis on which to estimate how large such a bias could be.

We also test the expert prior choices for the distributions of uncertain climate model parameters controlling surface and atmospheric processes, this being a fundamental input to our methodology (see Sections 3.2.3 and 3.2.7). For any given parameter, we assume its distribution to be uniform (i.e. to show an equal probability for alternative settings) for values within the middle 75% of the range of possible values given by experts, and then to drop to zero at the extreme low and high values. However, such prior distributions are recognised as being themselves uncertain (e.g. Frame *et al.* 2005; Rougier and Sexton, 2007), so we investigate two other choices: assuming uniform probability across the full expert range, and assuming uniform probabilities across a full range of values 15% larger than that specified by experts. The latter, in particular, is a conservative specification which assumes both that the experts systematically underestimated the extremes of their ranges, and that the extreme values can be assumed no less likely than values near the middle of the range. For some parameters, this test involves pushing their values close to absolute extremes: for example the mixing coefficient for convective entrainment (which has the largest impact on global climate sensitivity of any of the parameters considered (Murphy *et al.* 2004; Stainforth *et al.* 2005) cannot fall below zero by definition, yet the inflated uniform prior has the effect of considering values close to zero at one of its bounds. In order to pursue the second test, we have to assume that our emulator (used to predict climate model output at any desired combination of parameter settings — Section 3.2.3) gives realistic results when applied to parameter values outside the range on which it was trained.

Figure A2.1 shows in its left-hand column the effects of the applied sensitivity tests on the prior probabilistic projections (that is prior to the weighting of different regions of parameter space according to the fit to our set of historical observations), and in its right-hand column the effects on the posterior projections (after the observational constraints have been applied). The sensitivity tests

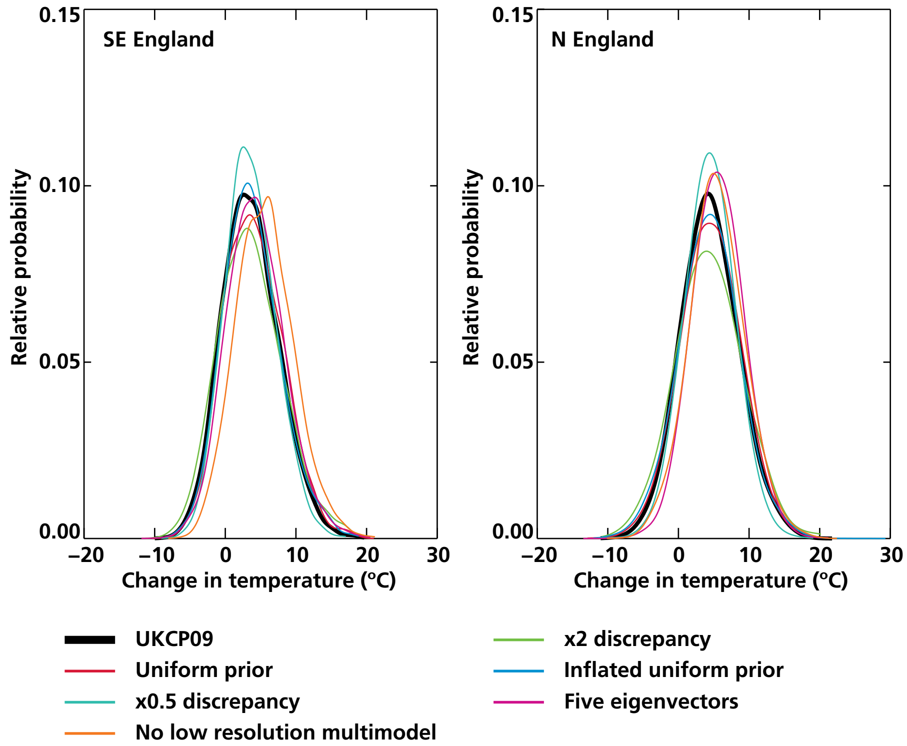


Figure A2.2: Posterior probabilistic projections from six sensitivity tests (coloured) compared to UKCP09 results (black), for summer changes in a typical warmest day of summer (°C), defined as the 99th percentile of daily maximum temperatures during June to August. Changes are shown for the global climate model grid boxes corresponding to SE England (left) and NE England (right), for 2070–2099 relative to 1961–1990. Sensitivity tests are as described in Figure A2.1.

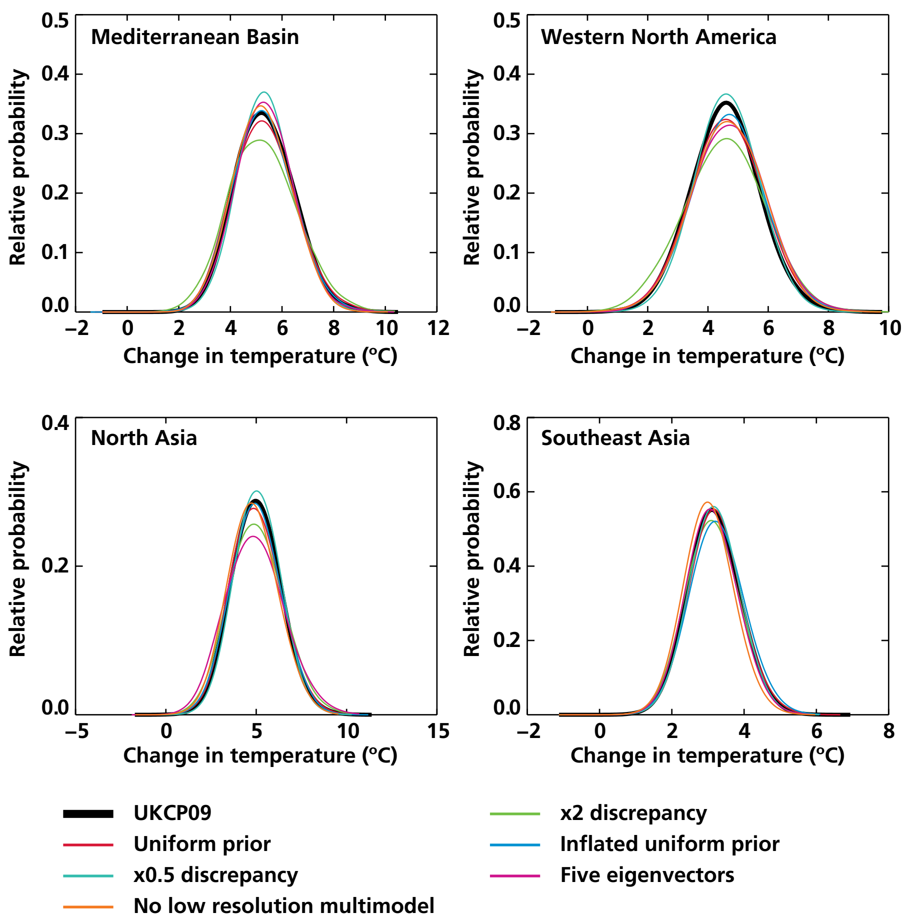


Figure A2.3: Posterior probabilistic projections from six sensitivity tests (coloured) compared to UKCP09 results (black), for summer changes in average temperature (°C) for 2070–2099 relative to 1961–1990, over a number of regions defined by Giorgi and Francisco (2000). Sensitivity tests are as described in Figure A2.1.

are found to have a significant impact on the prior projections, especially for precipitation. This shows that the tests represent significant perturbations to our methodology, potentially capable of exerting an important influence on the results. However the impacts on the posterior projections are more modest, and the induced differences in probability are also relatively small compared with the uncertainties indicated by the UKCP09 distributions (black curves). This shows that the observational constraints play a key role in discriminating between the degrees of credibility of projections obtained from different parts of the model parameter space, and hence in rendering the method reasonably robust to significant variations in the set of key choices investigated, at least for the variables considered in Figure A2.1. This is underlined by Table A2, which shows how the sensitivity tests affect values for the 10, 50 and 90% probability levels of the projected changes. The variations from the UKCP09 results do not exceed 0.5°C for surface temperature, or 7% for changes in precipitation. These sensitivities, while relatively modest, are larger for the more extreme probability levels, and users will need to assess their consequences when set against other uncertainties associated with specific decision problems, as well as against the backdrop of climate projection uncertainties discussed in this Annex.

Figure A2.2 shows the impact of the same sensitivity tests on changes in the intensity of a typical warmest day of summer, characterised as changes in the value of the 99th percentile of daily maximum temperatures from June to August. Again the effects of the sensitivity tests, on the posterior probabilistic projections are fairly modest, while the impacts on the prior probabilistic projections (not shown) are considerably larger. Similar results are found for projections of mean temperature and precipitation in other regions of the world. As an example, Figure A2.3 shows temperature projections for June to August over several different regions. Again the variations in the posterior projections are modest, while the variations in the prior projections (not shown) are larger.

A2.3 Comparison of UKCP09 methodology against alternative approaches

The above tests consider variations in specific aspects of our methodology, however it is also important to consider how different the results could have been had we chosen an entirely different approach. Here, the first point is that while a number of methods for probabilistic climate projection have been published in the research literature, we are not aware of any that have been designed to sample uncertainties as comprehensively as is done in UKCP09 (for example, there are several methods which sample uncertainties in physical climate system processes, but none which combines these with uncertainties in both carbon cycle processes and downscaling). This is because it is acceptable in academic studies to explore methodologies which are conditional upon the omission of

Table A2: Sensitivity to a number of key assumptions (see text) of three probability levels values for changes in surface temperature (°C) and precipitation (%) for Wales, as an example GCM grid box. Summer and winter changes are for the period 2070–2099 relative to 1961–1990. Each triplet consists of the UKCP09 value (in bold), accompanied by the lowest and highest values obtained from the six sensitivity tests of Figure A2.1.

	10% Probability level	50% Probability level	90% Probability level
Summer temperature	2.1, **2.4**, 2.7	4.1, **4.2**, 4.6	6.1, **6.3**, 6.8
Winter temperature	1.7, **1.8**, 1.9	2.9, **2.9**, 3.0	4.2, **4.2**, 4.3
Summer %precipitation	–54.5, **–51.2**, –48.0	–31.7, **–28.1**, –26.6	–3.2, **0.2**, 3.6
Winter %precipitation	6.4, **8.4**, 13.3	23.9, **24.4**, 30.6	44.5, **46.9**, 54.0

important known sources of uncertainty, however this would not be acceptable in a project like UKCP09, since our aim is to produce information suitable to support user decisions in the real world. So we cannot compare UKCP09 against some competing approach designed to produce probabilities with the same level of decision-relevance.

However, by omitting some elements of the UKCP09 approach we can compare it against alternative methodologies conditional on sampling similar subsets of the uncertainties in climate projection. For example, a number of approaches have been suggested in which probabilistic projections are derived purely from results from a multi-model ensemble of global coupled ocean–atmosphere models of typically 10–20 members (Tebaldi and Knutti (2007) review several of these), rather than our approach of using larger ensembles of model variants specifically designed to sample uncertainties, with multi-model ensemble results playing a significant but more subsidiary role. Some of the multi-model approaches are nevertheless similar to ours in their basic character, in that they seek to construct a range of alternative projections which express the effects of uncertainties arising from modelling errors, and then adjust these according to some set of observational constraints. Another class of approaches seeks to project future changes explicitly designed to be consistent with uncertainties in some set of observations of recent climate, using climate model results to provide the necessary relationships between historical observations and future changes (e.g. Piani *et al.* 2005; Knutti *et al.* 2006; Sanderson *et al.* 2008). Closely related to these are approaches which seek to project future changes by assuming a linear relationship between errors in past and future changes, constraining future changes according to the range of past errors consistent with observations (Allen *et al.* 2000; Stott and Kettleborough 2002; Stott *et al.* 2006a).

We compare our projections for annual mean temperature with those made by a method of the latter type, based on Stott *et al.* (2006a). Their method uses model simulations and historical observations of changes in surface temperature during the 20th century to derive a distribution of alternative scaling factors which can be applied to the simulated changes to fit the observed changes to a level consistent with uncertainties in the latter. The distribution of scaling factors is then applied to the future model response to produce a probabilistic climate projection. Stott *et al.* (2006a) produced two versions of this technique. The first version projected future regional changes according to past changes in

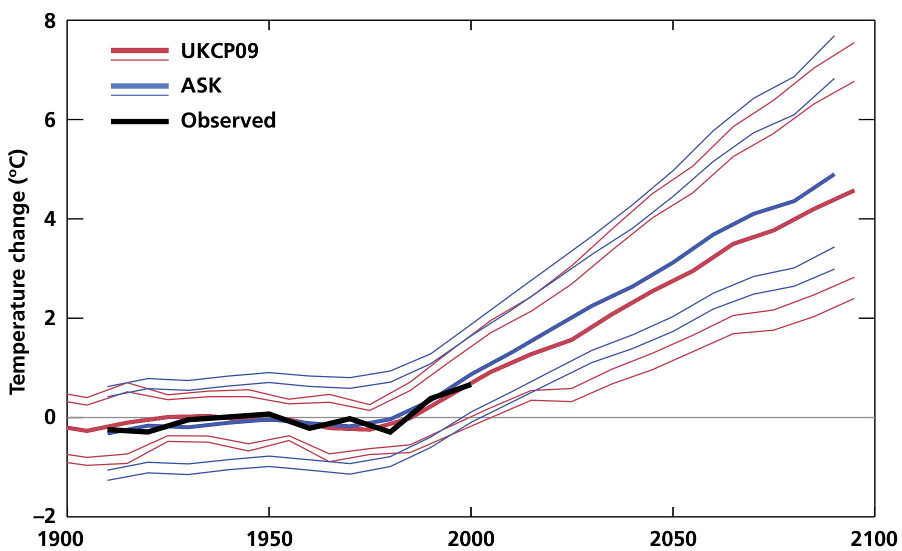


Figure A2.4: Comparison of probabilistic climate projections for changes in 10-yr annual mean 1.5 m temperature (°C) in response to SRES A1B (i.e. UKCP09 medium) emissions. Changes shown are for Northern Europe, relative to 1906–2005, from two methods: UKCP09 (red) and an updated version of Stott *et al.* (2006a) (blue). The probability levels are 2.5, 10, 50 (thick), 90, and 97.5% as used in Stott *et al.* (2006a). The observations are also shown as the black line.

the same region (thus obtaining relatively conservative estimates of uncertainty by neglecting possible constraints from aspects of past change remote to the region of interest); the second version scaled future regional changes according to errors in past spatial and temporal patterns of change over the whole globe (thus obtaining narrower estimates of uncertainty, although this does not take account of possible errors in the regional pattern of response, since it scales the model's pattern of response over the whole globe by the same factor, with uncertainties, for each region). We use an updated version which accounts for past changes in global patterns of surface temperature, thus removing the contrasting limitations of the two earlier techniques. The Stott *et al.* method provides projections for large regions (no downscaling method is included), and does not account for uncertainties in future changes in radiative forcing arising from carbon cycle processes. Therefore, we consider a like-for-like comparison of projections of spatially averaged temperature for the whole of northern Europe, applying the UKCP09 methodology without downscaling, and with no sampling of the effects of future uncertainties in climate feedbacks involving the carbon cycle (by holding these feedbacks fixed at values diagnosed from the standard published variants of the relevant configurations of HadCM3). Both methods assume that there is a negligible effect from other possible sources of uncertainty in either historical forcing (e.g. black carbon) or future changes (e.g. methane cycle) — see Box 2.1, Chapter 2.

We applied the Stott *et al.* method to each of the 17 members of our PPE_A1B ensemble of perturbed variants of HadCM3 (Section 3.2.4 and Figure 3.2), obtaining projections with associated uncertainties from each ensemble member, and combining these to form probabilistic projections shown by the blue curves in Figure A2.4. The results show that the median projection of future changes is slightly smaller in the UKCP09 method. The UKCP09 method also produces a slightly wider spread from 2010 onwards, but a somewhat narrower spread during the historical period. Uncertainties from UKCP09 broaden by including a more complete sampling of the possible uncertainties arising from parameter choices in models and structural model errors common to model projections, and narrow by including a wider range of observational constraints, whereas the Stott *et al.* uncertainties rely on linear scaling of available model simulations based on a more limited range of observational constraints. Such differences could serve to broaden or narrow the UKCP09 uncertainty ranges relative to the Stott *et al.* uncertainty ranges, dependent on their competing influences. A detailed examination of these differences is beyond the scope of this report.

The Stott *et al.* method is set up to provide projections which are relatively conservative (in the sense that only one relatively well understood observational constraint is used), and which minimise their dependence on the set of climate model simulations used to produce them (Stott *et al.* 2006b). Projections derived from this technique will be determined by the scaling factors, and associated uncertainties, found by matching simulated and observed realisations of the past climate warming attributable to human activity. On the other hand, the UKCP09 approach is based on a different philosophy which seeks to place more weight on detailed aspects of climate system physics, both by sampling possible variations in these more widely, and then seeking to constrain them with a wider range of observations. It is therefore reassuring that two methods based on different principles and assumptions should give relatively similar projections in practice. This further supports the results of Figure A2.1 in indicating that the UKCP09 projections are likely to be reasonably robust to the key assumptions involved in their generation.

A2.4 Contributions to uncertainty in the UKCP09 projections

In Chapter 2, we identify three basic sources of uncertainty in projected climate change, associated with emissions of greenhouse gases, aerosols and their precursors, internal climate variability arising from natural unforced variations in the atmospheric and oceanic circulation, and uncertainty in modelling the forced response to emissions. For a given emissions scenario (in this case SRES A1B, the UKCP09 medium scenario), we consider the relative contributions of internal variability and modelling uncertainty to the total uncertainty expressed in the UKCP09 projections. We consider first an example involving the same variables analysed in Figure A2.1 (i.e. changes to summer and winter temperature and precipitation over the global climate model grid box representing Wales), thus omitting uncertainty arising from the downscaling step of Section 3.2.11, which is considered later. We partition modelling uncertainty into a few components representing key elements of our methodology. These consist of:

- **Parameter uncertainty**, arising from uncertainties in the values of climate model input parameters that control key physical processes. UKCP09 is based on a comprehensive strategy for sampling parameter uncertainties in the atmospheric component of the HadCM3 climate model, by combining a large ensemble of model simulations with emulation of the outputs of possible model variants for which we do not possess an actual simulation (Section 3.2.3). In addition, we sample parameter uncertainties in ocean and sulphur cycle processes using a more limited strategy based on 17 member ensembles of alternative model variants. We define parameter uncertainty to include all of these sources of uncertainty (including uncertainty arising from emulator error in the case of atmospheric parameters), but note that atmospheric parameters provide the dominant contribution. Our method for the quantification of uncertainties in carbon cycle processes, which we consider under a separate heading below), also contains a substantial contribution from parameter uncertainties associated with terrestrial ecosystem processes in HadCM3C (the configuration of HadCM3 including an interactive carbon cycle).

- **Structural uncertainty**, which measures the additional uncertainty due to modelling errors which cannot be resolved by varying uncertain parameters in HadCM3 (Section 3.2.8). As a proxy for this, we use information from alternative contemporary climate models, assuming that errors in our ability to predict their historical and future simulations of climate form reasonable estimates of structural errors in the ability of HadCM3 to simulate the real climate system. Note that our strategy estimates the impacts of structural errors in atmospheric processes, but not in ocean transport or sulphur cycle processes.

- **Timescaling uncertainty** is the uncertainty that arises from the need to predict time-dependent climate responses from the simulations of the equilibrium response to doubled levels of carbon dioxide which form the basis of our strategy for sampling uncertain atmospheric model parameters (see Sections 3.2.4 and 3.2.6). The uncertainties associated with timescaling include the effects of internal variability. We remove these in the analysis below, in order to isolate uncertainties arising from methodological assumptions in our procedure, for example that time-dependent climate changes can be assumed to be linearly related to changes in globally averaged temperature.

- **Carbon cycle uncertainty**. This is assessed in a separate category because carbon cycle feedbacks (e.g. Friedlingstein *et al.* 2006) are recognised to give rise to a level of uncertainty in global temperature projections comparable to that due to atmospheric processes. These are sampled by combining 15 perturbed variants of HadCM3C with simulations from an alternative multi-model ensemble of nine coupled climate–carbon cycle models (see Sections 3.2.4 and 3.2.6).

Uncertainty due to internal variability is estimated from long *control* simulations of members of the PPE_A1B ensemble carried out with no changes to the applied external forcing. We quantify timescaling uncertainty by executing our methodology with parameter and carbon cycle uncertainties removed (by fixing values for all model parameters in all Earth System components to those used in the standard published variants of the relevant HadCM3 configuration), and with the future component of the structural uncertainty set to zero. The component of timescaling uncertainty due to internal variability is then subtracted, in order to isolate the aspects that could potentially be removed by improvements to the methodology in future (see Section 4).

The contributions from parameter, carbon cycle and structural uncertainty are calculated by repeating the probabilistic projections, each time removing one or more of these components (either by fixing relevant parameters to their standard values, or by setting future structural uncertainty to zero), and then comparing the spread of the projected changes for 2070–2099 relative to 1961–1990. For instance, to estimate the increase in spread due to carbon cycle uncertainty we run the projection twice, the first time sampling the carbon cycle parameters as described in Section 3.2.6, and the second time fixing the carbon cycle parameters to their standard values. A limitation of this approach is that the change in spread due to addition of carbon cycle uncertainty depends on which other sources of uncertainty have previously been sampled, as the uncertainties combine in nonlinear ways. For instance, carbon cycle feedbacks (and their associated uncertainties) are larger when temperature changes are high, and only when the other sources of uncertainty are sampled do the temperature changes become large enough for a large carbon cycle feedback. So we run all eight permutations of fixing/sampling parameter, carbon cycle and structural uncertainty (with internal variability and timescaling uncertainties always included). From this set of eight, we have four pairs of runs which can each be used to look at the increase in spread that arises from allowing each of the three types of uncertainty to be sampled rather than kept fixed. Then we take the root-mean-square change in spread, and plot the relative size of the contributions in a pie chart in Figure A2.5. Spread is measured as the distance between the 10 and 90% probability levels of relevant probability distributions.

For the four examples shown in Figure A2.5, parameter uncertainty provides the largest contribution (22–31%). This occurs despite the fact that formal observational constraints have been applied to limit the impact of parameter uncertainties (particularly the dominant contribution from atmospheric model parameters), whereas this is not the case for the other components of uncertainty in Figure A2.5. In fact each of the other components typically adds a significant contribution of its own (in the range 12–27%), and no single source of uncertainty dominates. For winter precipitation no contribution from (the methodological aspects of) timescaling is shown, as the total timescaling uncertainty (i.e. including internal variability) is found to be the same as our

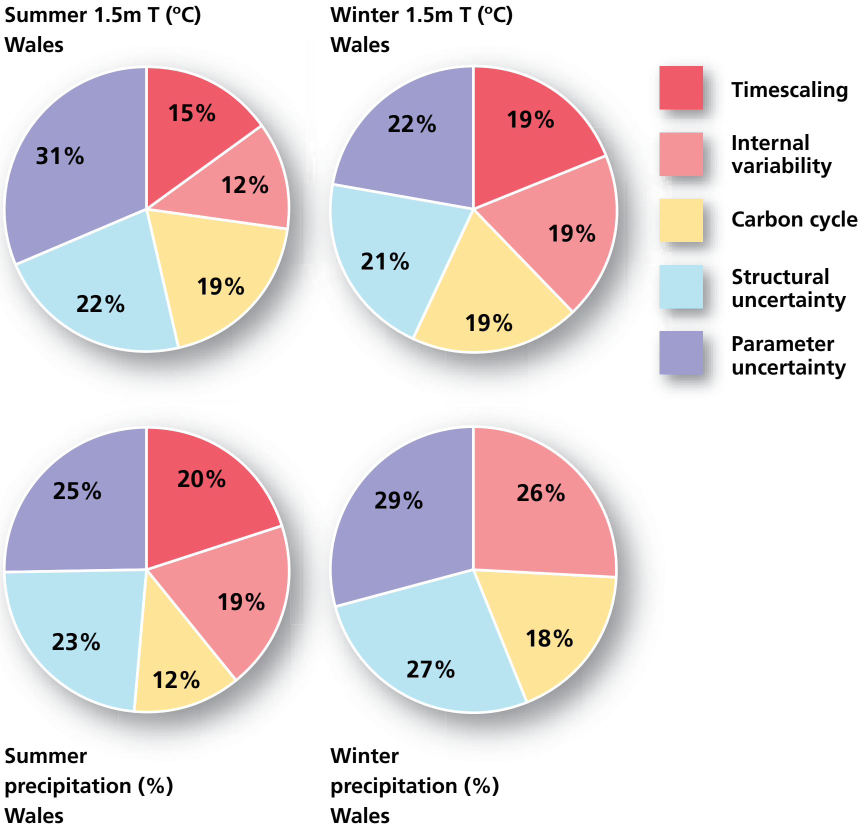


Figure A2.5: The relative contributions of different components of uncertainty to the overall spread in UKCP09 projections. These are calculated for summer and winter and for changes in temperature and percentage changes in precipitation for the Wales global climate model grid box, considering projected changes for 2070–2099 relative to 1961–1990. Spread is measured as the distance between the 10th and 90th probability levels of relevant probability distributions (this being a standard metric of spread in non-Gaussian distributions), expressing the spread obtained from each component of uncertainty relative to that obtained when all components are included.

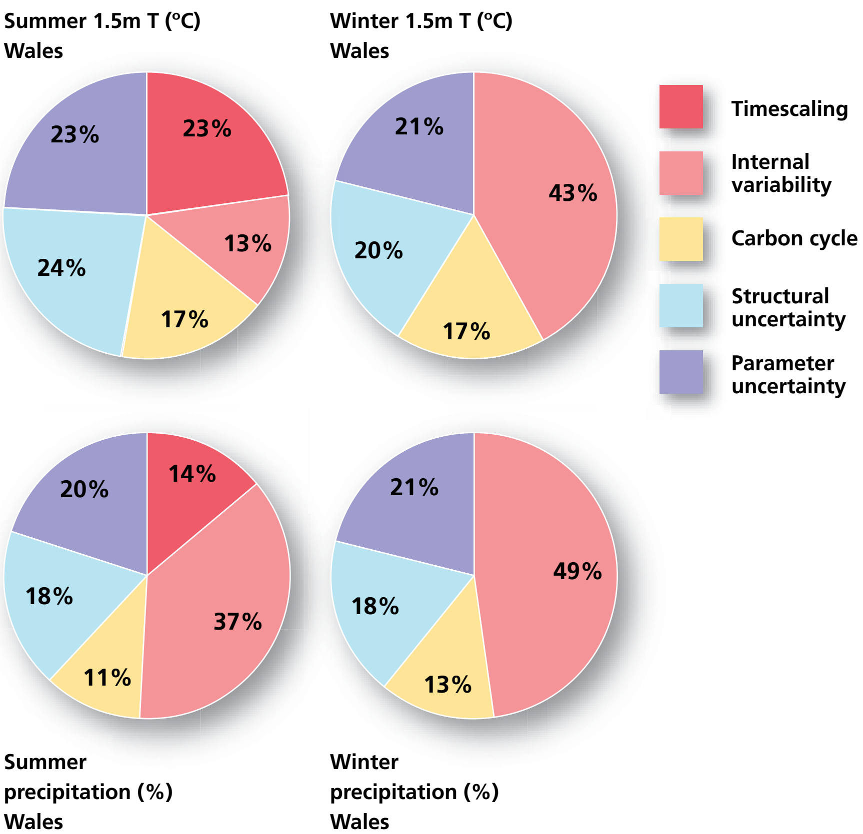


Figure A2.6: As Figure A2.5 but for 2010–2039.

independent estimate of internal variability in isolation (derived from model control simulations as described above). While we focus here on contributions to the spread of our probabilistic projections, we stress that each of the elements of the methodology considered in Figure A2.5 (apart from internal variability) can also shift the distributions, thus affecting aspects such as the mean, median or mode. For example adding carbon cycle feedbacks increases the mean projected warming (as well as adding uncertainty), while the mean reduction in summer precipitation projected over much of the UK is ameliorated somewhat by the inclusion of the uncertainty associated with structural model errors, since our projections of the changes simulated by other climate models tend to be too dry.

Figure A2.6 repeats the analysis of Figure A2.5 for an earlier projection period, 2010–2039. This demonstrates the changing role of different contributions to uncertainty at different lead times. In particular, internal variability increases in significance, becoming the largest contribution in three of the four cases. The other components are generally smaller than at 2070–2099, though parameter un-certainty still contributes at least 20% in all cases.

Downscaling uncertainties

The effect of downscaling, and its accompanying uncertainty, varies greatly with climate variable, meaning period and location (e.g. Figure 3.11 in Section 3.2.11), so cannot be characterised using a single *typical* example. We therefore show several examples of how uncertainties break down when downscaling is included. In UKCP09, uncertainties in downscaling are characterised by the variance of the residual errors found when regressing changes in the local target variable in our regional climate model simulations against changes in the same variable at a nearby grid point in the driving global model simulations (see Figures 3.9 and 3.10 and associated discussion). These residuals arise from uncertainty in the relationships between future changes simulated by the global and regional models, which in general can arise both from the systematic effects of variations in model physics, and also from internal variability at fine scales generated within the regional model domain. We do not attempt to diagnose the relative magnitudes of these two contributions here, as we do not possess the long unforced control simulations of the regional model that would be needed.

The contribution of downscaling to the total uncertainty is shown in Figure A2.7, using examples derived from changes in winter precipitation for 2070–2099 relative to 1961–1990 at several 25 km grid squares. This contribution is quantified by comparing the spread found in downscaled probabilistic projections when the residual variance is either included or excluded. The other uncertainty contributions are obtained as described in the discussion of Figures A2.5 and A2.6 above. At three of the featured locations the contribution of downscaling uncertainty is relatively small (less than 10%). In three further cases a larger but still secondary contribution is made to the total spread in the projections (in the range 12–19%). Downscaling uncertainties are modest where there is a strong relationship between the global and regional model changes, indicating that most of the total uncertainty arises from larger scale climate processes resolved in the global climate model simulations. However, downscaling uncertainty makes a large contribution at one of the featured locations (48%, over the Cairngorm mountains). This is a region where the relationship between changes in the regional and global models is weaker (Figure A2.7 cf. Figure 3.9), indicating that the localised precipitation anomalies are influenced strongly by fine scale variability generated within the regional model, and not so strongly (compared to other locations) by changes driven by larger scale processes resolved by the global model. A detailed examination of the mechanisms of downscaling uncertainty

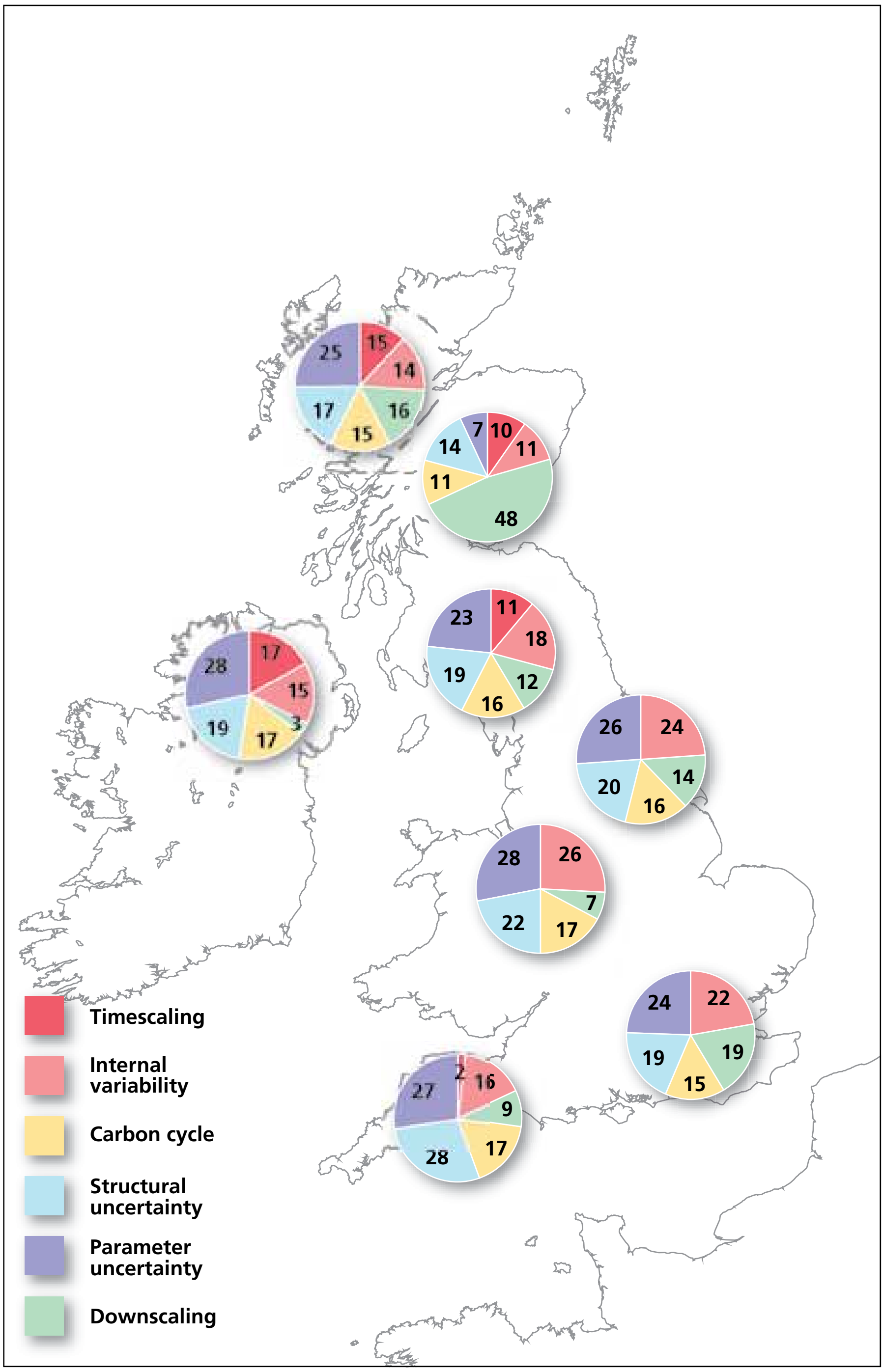


Figure A2.7: Contributions to the uncertainty in winter precipitation changes for 2070–2099 relative to 1961–1990, at selected 25 km grid squares. Contributions are calculated as in Figures A2.5 and A2.6, and also include that due to downscaling from global climate model grid squares to regional climate model grid squares (see text for details).

is left to future work; however, a good example would be local enhancements or reductions in precipitation caused by the effects of mountains or coastlines. These local modifications vary substantially between the different members of our regional model ensemble in some regions, due partly to differences in the projected changes in the regional atmospheric circulation. The results of Figure A2.7 demonstrate that the contribution of downscaling uncertainty can vary significantly from region to region. The contribution also varies with future period, tending to be larger for relatively near-term projections (e.g. for 2010–2039) compared with projections for the end of the coming century (not shown). This is because our metric of downscaling uncertainty does not (typically) increase proportionately as the forced response increases in the global model (see Figures 3.9 and 3.10, noting the scatter of the changes about the regression lines), suggesting that much of it may arise from locally generated internal variability. Further examples will be given on the UKCP09 website (see http://ukclimateprojections.defra.gov.uk). Finally, we note that our analysis relates specifically to uncertainties quantified by the downscaling strategy chosen for UKCP09, and does not consider potential additional uncertainties associated with the structural assumptions made in the approach (see Section 3.2.11).

A2.5 Summary

The UKCP09 probabilistic projections provide expressions of the relative likelihood of different future outcomes for 21st century climate, obtained by sampling uncertainties in physical and biogeochemical processes as represented in the current generation of climate models, and combining these with a set of observational constraints and expert judgements in order to provide estimates of the credibility of different outcomes conditioned on present knowledge. In this sense the resulting probabilities are effectively summary statements of the information from climate modelling and observations. However, they are also conditional on the choice of method and its associated assumptions. In this Annex we have explored the sensitivity of the results to reasonable variations in a few of our most important assumptions, and have shown that the projections are robust to them for several examples. These involved changes in 30-yr averages of surface temperature and precipitation in several regions of the world, and changes in a typical warmest day of summer over South East England (see Figures A2.1–A2.3).

We also provided examples of how the total uncertainty expressed in the UKCP09 projections is broken down into a number of distinct components arising from different aspects of the methodology. The component termed *parameter uncertainty* (dominated by uncertainties in atmospheric processes sampled in our perturbed physics ensemble simulations) generally provides the largest contribution. However, the other components (carbon cycle processes, internal variability, structural model uncertainties, timescaling and downscaling) all provide significant contributions as well, hence no single component dominates the total uncertainty. This important result reduces the extent to which an individual assumption (relevant to one specific component of uncertainty) is likely to affect the overall spread of outcomes found in the projections, thus helping to explain why they are found to be robust in the reported sensitivity tests. Despite this, it remains imperative that efforts should be made to reduce uncertainties in all of the categories considered here. In this context, we comment below on prospects for achieving this through future work (see also the discussion in Section 3.3).

- Internal variability in climate projections is inevitable, and to some extent represents an irreducible component of uncertainty. However, recent results suggest there is potential to predict some aspects of internal variability out to a decade or more ahead, by initialising climate model projections using estimates of current observed climate anomalies in the ocean (Smith *et al.* 2007; Keenlyside *et al.* 2008), rather than the current practice of using random initial states typical of pre-industrial conditions.

- Timescaling uncertainty could in principle be removed. This would require future versions of our methodology to be based upon very large ensembles of projections of time-varying climate change carried out using the model configuration in which the atmosphere is coupled to a dynamical threedimensional ocean module. This would remove the necessity to estimate the results of such an ensemble from simulations of the equilibrium response to doubled carbon dioxide carried out using a simple mixed layer representation of the ocean. In practice, prospects for achieving this will depend on the level of available computing resources relative to the cost of running future climate models.

- Parameter uncertainty can be reduced by developing better climate models. This is a long term, ongoing task, to which significant resources are being devoted in the Met Office Hadley Centre. An additional route is through the development of improved observational constraints. This could be achieved by developing metrics which test the ability of climate models to simulate relevant physical processes in a more detailed manner (e.g. Williams *et al.* 2005). More effective ensemble designs could also help, by reducing errors associated with emulation of climate model results for parameter combinations at which we lack a climate model simulation.

- Structural uncertainty could be reduced by a worldwide improvement in the quality of climate models, assuming that such developments lead to a narrowing of the spread of systematic biases found in different models. It is also possible, however, that improvements in models could lead to a broadening of structural uncertainty. This could happen, for example, if developments in spatial resolution or in the parameterisation of physical processes were to lead to the discovery that climate change feedbacks are more uncertain than currently thought, because current models underestimate the potential role of certain processes (see Annex 3).

- Carbon cycle uncertainty is a major source of uncertainty in projections of globally averaged temperature, and hence on the UKCP09 projections, through their links with global temperature. Improved understanding and modelling of terrestrial and oceanic ecosystem processes would help to reduce this component of uncertainty. In UKCP09 there is no formal or comprehensive use of observations to constrain carbon cycle feedbacks (though a simple metric based on historical global carbon cycle budgets is used to rule out a small subset of the available model projections). Development of a more sophisticated and comprehensive approach (such as the approach taken in UKCP09 to constrain projections according to their representations of physical climate system processes) could therefore also help to reduce uncertainties associated with carbon cycle processes.

- Downscaling uncertainty consists of: (i) a combination of internal variability generated at fine scales in regional climate model simulations (independent of the larger scale information supplied by the driving global model simulations); plus (ii) uncertainty in the component of the fine scale response controlled by the global model inputs. In principle the need for a specific downscaling strategy could be removed, by basing future projections entirely on global climate model simulations run at the spatial resolution for which users require projections. This would remove the component of uncertainty arising from type (ii), and would subsume type (i) into the global model simulations. In practice, however, this will not be feasible for the foreseeable future, so we anticipate a continuing need for downscaling methods. Downscaling uncertainties of type (ii) could potentially be reduced by investigating more sophisticated regression techniques which allow the regional model changes to be inferred more accurately from global model variables. Note also that the UKCP09 method does not support the use of observations of fine-scale aspects of climate to constrain the detail added to the projections through downscaling (which could reduce the uncertainty if included), and also omits any consideration of structural errors associated with downscaling (which could increase the uncertainty). Addressing these limitations would require larger ensembles of regional climate model simulations, including some made using regional models from other modelling centres (e.g. Christensen *et al.* 2007), and hence containing different structural assumptions from those employed in the perturbed physics ensemble of Met Office model variants.

In Section 2 of this Annex we describe the nature of the assumptions involved in the UKCP09 methodology, recognising that some of these (as in any probabilistic climate projection method) cannot be tested, due to limitations of current knowledge or resources. It is important to note that the UKCP09 probabilistic projections are conditional upon these assumptions; however, there is scope for future work to address some of them. For instance, with extra computational resource the design of our ensembles of model projections can be improved to sample interactions at a regional level between uncertain processes in different modules of the Earth System. With this in mind, an ensemble of projections is currently being developed in which parameters controlling uncertain atmospheric, terrestrial ecosystem, sulphur cycle and ocean transport processes are perturbed simultaneously, in order to assess the extent to which neglect of interactions between (say) regional atmospheric and carbon cycle feedbacks could affect the projected changes.

A2.5 References

Allen, M. R., Stott, P. A., Mitchell, J. F. B., Schnur, R. & Delworth, T. L. (2000). Quantifying the uncertainty in forecasts of anthropogenic climate change. *Nature*, **407**, 617–620.

Christensen, J. H., Carter, T. R., Rummukainen, M. & Amanatidis, G. (2007). Evaluating the performance and utility of regional climate models: the PRUDENCE project. *Climatic Change*, **81**, 1–6.

Frame, D.J. *et al.* (2005). Constraining climate forecasts: The role of prior assumptions. *Geophysical Research Letters*, **32**, L09702, doi:10.1029/2004GL022241.

Friedlingstein, P. *et al.* (2006). Climate–carbon cycle feedback analysis: Results from the C4MIP model intercomparison. *Journal of Climate*, **19**, 3337–3353.

Keenlyside, N. S., Latif, M., Jungclaus, J., Kornblueh, L. & Roeckner, E. (2008). Advancing decadal-scale climate prediction in the North Atlantic sector. *Nature*, **453**, 84–88.

Knutti, R., Meehl, G. A., Allen, M. R. & Stainforth, D. A. (2006). Constraining climate sensitivity from the seasonal cycle in surface temperature. *Journal of Climate*, **19**, 4224–4233.

Murphy, J. M., Sexton, D. M. H., Barnett, D. N., Jones, G. S., Webb, M. J., Collins, M. & Stainforth, D. A. (2004). Quantification of modelling uncertainties in a large ensemble of climate change simulations. *Nature*, **429**, 768–772.

Piani, C., Frame, D.J., Stainforth, D. A. & Allen, M. R. (2005). Constraints on climate change from a multi-thousand member ensemble of simulations. *Geophysical Research Letters*, **32**, L23825.

Rougier, J. C. & Sexton, D. M. H. (2007). Inference in ensemble experiments. *Philosophical Transactions of the Royal Society A,* **365**, 2133–2144.

Sanderson, B. M., Piani, C., Ingram, W. J., Stone, D. A. & Allen, M. R. (2008). Towards constraining climate sensitivity by linear analysis of feedback patterns in thousands of perturbed-physics GCM simulations. *Climate Dynamics*, **30**, 175–190.

Smith, D. M., Cusack, S., Colman, A. W., Folland, C. K., Harris, G. R. & Murphy, J. M. (2007). Improved surface temperature prediction for the coming decade from a global climate model. *Science*, **317**, 796–799.

Stainforth, D. A. *et al*. (2005). Uncertainty in predictions of the climate response to rising levels of greenhouse gases. *Nature*, **433**, 403–406.

Stott, P. A. & Kettleborough, J. A. (2002). Origins and estimates of uncertainty in predictions of twenty-first century temperature rise. *Nature*, **416**, 723–726.

Stott, P. A., Kettleborough, J. A. & Allen, M. R. (2006a). Uncertainty in continental-scale temperature predictions. *Geophysical Research Letters*, **33**, L02708.

Stott, P. A., Mitchell, J. F. B., Allen, M. R., Delworth, T. L., Gregory, J. M., Meehl, G. A. & Santer, B. D. (2006b). Observational constraints on past attributable warming and predictions of future global warming. *Journal of Climate*, **19**, 3055–3069.

Tebaldi, C. & Knutti, R. (2007). The use of the multi-model ensemble in probabilistic climate projections. *Philosophical Transactions of the Royal Society A*, **365**, 2053–2076.

Williams, K. D. *et al.* (2005). Evaluation of a component of the cloud response to climate change in an intercomparison of climate models. *Climate Dynamics*, **26**, 145–165.

UK CLIMATE PROJECTIONS

Annex 3: Strengths and weaknesses of climate models

Mat Collins, Simon Brown, Tim Hinton, and Tom Howard, Met Office Hadley Centre

In this annex we discuss some generic aspects of climate modelling, including strengths and weaknesses of climate models. These are illustrated by discussion of some of the recent *hot topics* in modelling, such as the ability of models to simulate modes of climate variability and phenomena such as atmospheric blocking (periods when high pressure dominates the weather and how they might impact the signal of climate change). While in no way comprehensive, it should give a flavour of the type of research which is ongoing in improving our ability to model, understand and predict climate change.

A3.1 What are climate models?

We can describe the climate system using mathematical equations derived from well established physical laws that capture the evolution of winds, temperatures, ocean currents, etc. Computers are used to solve the equations in order to resolve all the complex interactions between components and processes and produce predictions of future climate change (see Chapter 2, Box 2.1 for more information). The core computer code for the atmosphere component of the Met Office climate models is the same as that used to make daily predictions of weather.

The equations of climate are, in the case of the Met Office model, solved by dividing the world up on a grid which follows lines of longitude and latitude and extends above the surface of the Earth and below the oceans (see Figure 2.4). Physical properties such as temperature, rainfall and winds evolve in time on this grid, and these short time scale variations are averaged together to produce climate averages (monthly means, for example). Because the time-variation of atmospheric and oceanic motions is chaotic, it is not possible to reproduce the exact time variation of the real-world weather and climate (it is chaotic behaviour which limits weather forecast accuracy to about a week). Rather the model is representative of one possible trajectory the system may take. This "uncertainty due to natural variability", is one aspect of the uncertainty captured in the PDFs presented in this report.