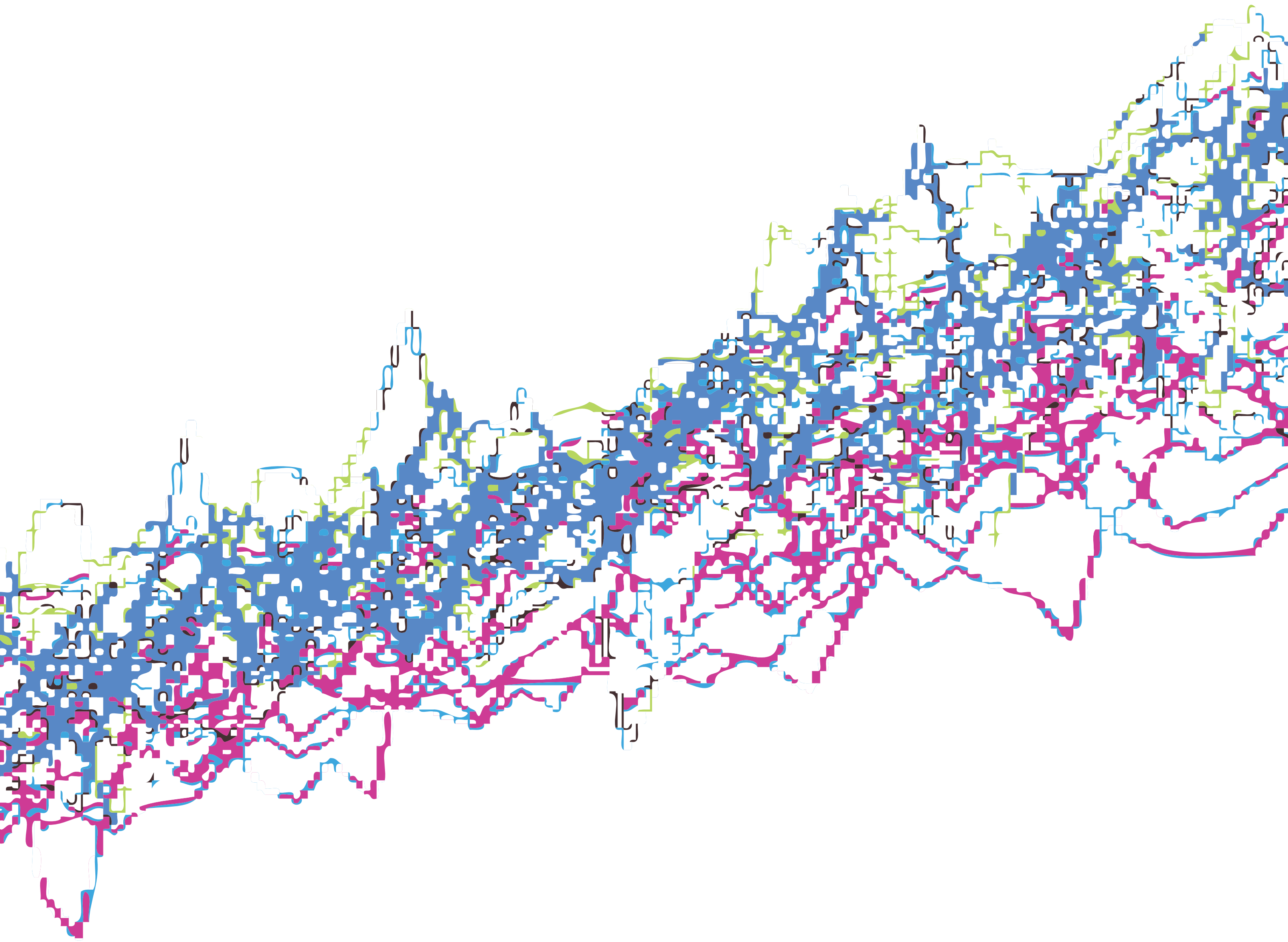
UK CLIMATE PROJECTIONS

Climate change projections



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UK Climate Projections science report: Climate change projections

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The authors would like to acknowledge the original suggestion from Professor Alan Thorpe (when Director of the Met Office Hadley Centre) for a project to quantify uncertainty using large climate model ensembles, without which the UKCP09 probabilistic projections would not have been possible.

Discussions with Prof. Jonathan Rougier, University of Bristol, have encouraged us to adopt the methodology for the UKCP09 Probabilistic Projections.

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Summary

The UK Climate Projections (UKCP09) provide projections of climate change for the UK, giving greater spatial and temporal detail, and more information on uncertainty, than previous UK climate scenarios.

This report is designed for those who wish to find out more about the purpose and design of the UKCP09 methodology for producing the probabilistic projections of climate change, and is drafted to suit a range of levels of expertise. It shows some examples of projections; the full set of results is available through the User Interface and the pre-prepared maps and graphs, with key findings presented in the Briefing Report.

Purpose and design of UKCP09

- Over land, UKCP09 gives projections of changes for a number of climate variables, averaged over seven overlapping 30-yr time periods, at 25 km resolution and for administrative regions and river basins. Similar projections are given for a smaller number of variables averaged over marine regions around the UK (Chapter 1).

- UKCP09 is the first set of UKCIP projections to attach probabilities to different levels of future climate change. The probabilities given in UKCP09 represent the relative degree to which each climate outcome is supported by the evidence currently available, taking into account our understanding of climate science and observations, and using expert judgement (Chapter 1).

- The Met Office Hadley Centre has designed a methodology to provide probabilistic projections for UKCP09, based on ensembles of climate model projections consisting of multiple variants of the Met Office climate model, as well as climate models from other centres. These ensembles sample major known uncertainties in relevant climate system processes (Chapters 2 and 3).

- UKCP09 gives projections for each of three of the IPCC's Special Report on Emissions Scenarios (SRES) scenarios (A1FI (called High in UKCP09), A1B (Medium) and B1 (Low)) to show how different emissions pathways affect future climate (Chapter 2 and Annex 1). Each of the emissions scenarios suggests a different pathway of economic and social change over the course of the 21st Century; it is not possible to assign probabilities to each scenario. They do not include planned mitigation measures directly.

- For a given emissions scenario, the UKCP09 probabilistic projections account for uncertainties arising from the representation of climate processes, and the effects of natural internal variability of the climate system (Chapter 2).

- Changes to external factors such as solar activity and volcanic eruptions cannot be predicted, and are not considered (Chapter 2).

- UKCP09 projections explicitly include the climate carbon cycle feedback for the first time, and uncertainties in the feedback from the land carbon cycle. They also include the direct and first indirect effects of sulphate aerosol and uncertainties in these. Some feedbacks, such as those from the methane cycle, are not well enough understood to be included (Chapter 2).

- The UKCP09 methodology uses the Met Office regional climate model (RCM) to downscale global climate projections to a 25 km scale; uncertainties in this downscaling are also included in the probabilistic projections (Chapter 3).

- Continuous daily time series from 1950 to 2099 for 11 variants of the Met Office RCM are available via a separate project called LINK. These time series are spatially coherent between grid squares and are available over land and sea. However, being based only on Met Office models, they do not take as much uncertainty into account (Chapter 5)

- It has not been possible to produce probabilistic projections of changes in snowfall rate, and users are recommended to take these from the 11-member RCM ensemble (Chapter 4)

- The current observed strength of the Urban Heat Island effect is included in the projections of future climate, but possible changes in the strength of the Urban Heat Island in the future cannot yet be included (Annex 7).

- It is unlikely that an abrupt change in the Atlantic Ocean Circulation will occur this century. The effects of a gradual weakening of the circulation over time are included in the UKCP09 climate projections (Annex 5).

- Models will never be able to exactly reproduce the real climate system; nevertheless there is enough similarity between current climate models and the real world to give us confidence that they provide plausible projections of future changes in climate (Annex 3).

- There is a cascade of confidence in climate projections, with moderate confidence in those at continental scale; those at 25 km resolution are indicative to the extent that they reflect large-scale changes modified by local conditions such as mountains and coasts. The level of confidence is different for different variables.

- Errors in global climate model projections cannot be compensated by statistical procedures no matter how complex, and will be reflected in uncertainties at all scales.

Some examples of projected seasonal and annual changes

We summarise in the box below some changes by the 2080s with Medium emissions, but stress that projections can be very different for other time periods and other emissions scenarios. Users should look at the time period appropriate for their decisions, and examine projections for all three emissions scenarios, to gain a full appreciation of changes to which they might have to adapt.

Summer, winter and annual mean changes by the 2080s (relative to a 1961–1990 baseline) under the Medium emissions scenario. Central estimates of change (those at the 50% probability level) followed, in brackets, by changes which are very likely to be exceeded, and very likely not to be exceeded (10 and 90% probability levels, respectively).

- All areas of the UK warm, more so in summer than in winter. Changes in summer **mean temperatures** are greatest in parts of southern England (up to 4.2ºC (2.2 to 6.8ºC)) and least in the Scottish islands (just over 2.5ºC (1.2 to 4.1ºC)).

- **Mean daily maximum temperatures** increase everywhere. Increases in the summer average are up to 5.4ºC (2.2 to 9.5ºC) in parts of southern England and 2.8ºC (1 to 5ºC) in parts of northern Britain. Increases in winter are 1.5ºC (0.7 to 2.7ºC) to 2.5ºC (1.3 to 4.4ºC) across the country.

- Changes in the **warmest day of summer** range from +2.4ºC (–2.4 to +6.8ºC) to +4.8ºC (+0.2 to +12.3ºC), depending on location, but with no simple geographical pattern.

- **Mean daily minimum temperature** increases on average in winter by about 2.1ºC (0.6 to 3.7ºC) to 3.5ºC (1.5 to 5.9ºC) depending on location. In summer it increases by 2.7ºC (1.3 to 4.5ºC) to 4.1ºC (2.0 to 7.1ºC), with the biggest increases in southern Britain and the smallest in northern Scotland.

- Central estimates of **annual precipitation** amounts show very little change everywhere at the 50% probability level. Changes range from –16% in some places at the 10% probability level, to +14% in some places at the 90% probability level, with no simple pattern.

- The biggest changes in **precipitation in winter**, increases up to +33% (+9 to +70%), are seen along the western side of the UK. Decreases of a few percent (–11 to +7%) are seen over parts of the Scottish highlands.

- The biggest changes in **precipitation in summer**, down to about –40% (–65 to –6%), are seen in parts of the far south of England. Changes close to zero (–8 to +10%) are seen over parts of northern Scotland.

- Changes in the **wettest day of the winter** range from zero (–12 to +13%) in parts of Scotland to +25% (+7 to +56%) in parts of England.

- Changes in the **wettest day of the summer** range from –12% (–38 to +9%) in parts of southern England to +12% (–1 to +51%) in parts of Scotland.

- **Relative humidity** decreases by around –9% (–20 to 0%) in summer in parts of southern England — by less elsewhere. In winter changes are a few percent or less everywhere.

- **Summer-mean cloud amount** decreases, by up to –18% (–33 to –2%) in parts of southern England (giving up to an extra +20 Wm^{-2} (–1% to +45 Wm^{-2}) of downward shortwave radiation) but increase by up to +5% (zero to +11%) in parts of northern Scotland. Changes in cloud amount are small (–10 to +10%) in winter.

  - Projected changes in **storms** are very different in different climate models. Future changes in anticyclonic weather are equally unclear (Annex 6).

  - We have been unable to provide probabilistic projections of changes in **snow**. The Met Office Hadley Centre regional climate model projects changes in winter mean snowfall of typically –65% to –80% over mountain areas and –80% to –95% elsewhere.

  - We make no assessment of how the **Urban Heat Island** effect may change (Annex 7).

  - It is very unlikely that an abrupt change to the Atlantic Ocean Circulation (**Gulf Stream**) will occur this century (Annex 5).

- UKCP09 provides a state-of-the-art basis for assessing the risk of different outcomes consistent with current climate modelling capability and understanding. As our understanding, and our modelling and statistical capabilities, improve in future, the projections are very likely to change (Chapter 3 and Annex 2).

- UKCP09 projections are appropriate for decisions on adapting to long-term climate change which need to be taken on the basis of current knowledge (Chapter 2).

1 Introduction and overview

This report provides background information on, and key findings from, the new projections of UK climate change in the 21st century, known as UKCP09. It is designed for anyone who wants to know about the projections themselves, ranging from general awareness to their application in impacts and adaptation assessments. In particular, the projections have been designed as input to the difficult choices that decision makers will need to make, in sectors such as transport, healthcare, water resources and coastal defences, to ensure the UK is adapting well to the changes in climate that have already begun and are likely to grow in future.

This report has a rather different purpose to its predecessor in UKCIP02; it is not designed to give a comprehensive description, in graphics or text, of the changes that are projected. Many of these can be seen on the UKCP09 website, and custom products can be generated from the User Interface. Because the UKCP09 projections are more informative, but also more complex, than previous UKCIP scenarios, the report discusses at some length why and how they have been developed, and how they are presented, so that users can get the most out of them.

This report has been reviewed, firstly by the project Steering Group and User Panel, and secondly by a smaller international panel of experts, who also reviewed the methodology used to generate the probabilistic projections. Reviewers' comments have been taken into account in improving the reports.

Chapter 1 discusses briefly why the UKCP09 projections are needed, what information they provide, the uncertainties that they have been designed to treat and how this is done. Chapter 2 discusses causes of uncertainty in climate change projections, and gives a simplified description of the method used to derive the UKCP09 projections, with Chapter 3 going into much more detail on the methodology. Chapter 4 summarises the key findings based on the monthly and seasonal projections for regions of the UK, and displays maps and graphs of changes for some temperature and precipitation variables. Chapter 5 deals with daily time series of recent and future climate from the Met Office Hadley Centre (Met Office) regional climate model. Finally, there are a number of annexes which allow the user to go into greater depth; in particular Annex 2 identifies some of the uncertainties in the UKCP09 projections themselves.

The components of UKCP09 are shown diagrammatically in Figure 1.1; they are supported by a number of publications, both hard copy and on line.

1.1 Why are climate change projections needed? Why new ones?

That global climate is changing is unequivocal. Although the extent to which human activities are contributing is still a matter of research, compelling evidence allowed the fourth science assessment* (AR4) from the Intergovernmental Panel on Climate Change in 2007 to say that "Most of the observed increase in global average temperatures since the mid-20th century is very likely (>90% probability) due to the observed increase in anthropogenic greenhouse gas concentrations". Even since the publication of the 2007 IPCC report, new research attributing changes in precipitation and water vapour to human activity strengthen our confidence in this statement.

Although there are many uncertainties about how climate will change in the future, changes projected by climate models are likely to result in significant impacts on business, infrastructure and the natural environment in the UK. Furthermore, we know that the combined effect of the long effective lifetime of the most influential man-made greenhouse gas, carbon dioxide, and the large thermal inertia of the oceans, causes any change in climate to lag behind the man-made greenhouse gas emissions that drive them. By the same token, current emissions, and those over the past few decades, have already built into

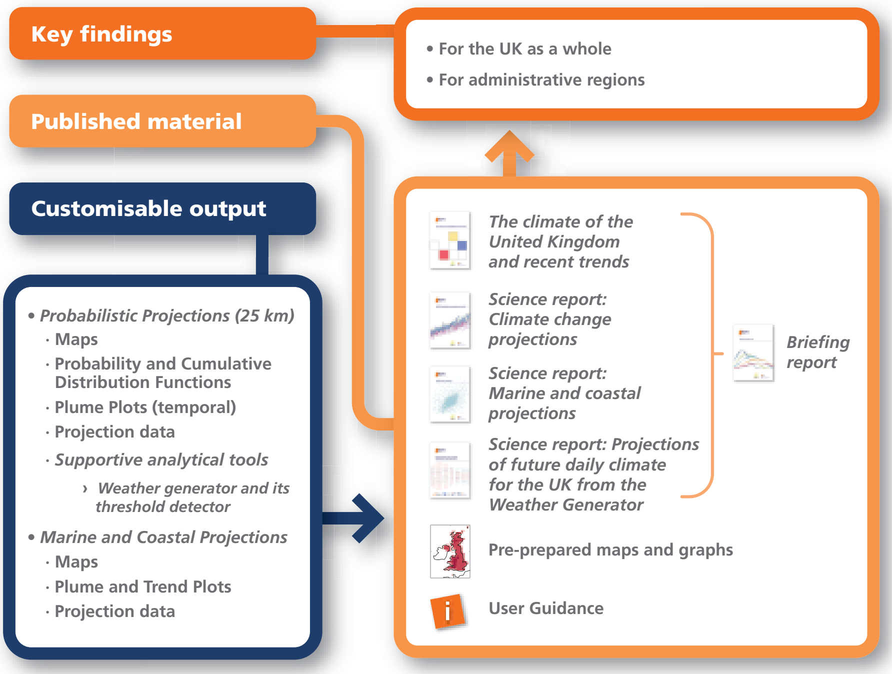


Figure 1.1: Information and publications supporting the UKCP09 projections.

* http://www.ipcc.ch/pdf/assessment-report/ar4/wg1/ar4-wg1-spm.pdf

the climate system a commitment to future climate change which cannot now, in any practical sense, be avoided. If there were to be reductions, even quite stringent ones, in global man-made greenhouse gas emissions, then this would be followed by a corresponding reduction in the rate of climate change, but the full effect would take decades or even centuries.

These three factors: the high likelihood that mankind has already begun to change the earth's climate, the projections of significant impacts in the future, and the commitment to further change over the next few decades irrespective of any emissions reductions in the short term, argue very strongly for a strategy of adaptation to minimise the consequences, and maximise the opportunities, of climate change. To adapt effectively, planners and decision-makers need as much information as possible on how climate will evolve, and this has been the purpose of the successive publications of climate change scenarios for the UK, firstly by the UK Climate Change Impacts Review Group in 1991 and 1996, and then by the UK Climate Impacts Programme (UKCIP) in 1998 and in 2002. Research has shown that most recent trends in observed climate fall broadly within the range of projections shown in these scenarios.

Why are new projections needed at this time? Continuing improvements in our understanding of the climate system and in modelling allows us to periodically update projections, which also helps to meet increasingly sophisticated user requirements. One example of the former is the growing recognition of how significant changes in the carbon cycle can act to exacerbate climate change; this factor is explicitly included for the first time in the UKCP09 projections. A more complex example concerns uncertainties; reports accompanying previous projections have mentioned the lack of a credible approach for handling these. The development of new techniques, together with increased computing power enabling them to be exploited, has allowed us to quantify the spread of future projections consistent with major known sources of uncertainty, by presenting projections which are probabilistic in nature. This sort of presentation is more complicated than the single projections (for each emission scenario) in UKCIP02, but more comprehensively reflects the state of the science; this is why probabilistic projections were adopted by IPCC for the first time in AR4. The UKCP09 projections respond to demands from a wide range of users for this level of detail.

1.1.1 What do we mean by probability in UKCP09?

It is important to point out early in this report that a probability given in UKCP09 (or indeed IPCC) is not the same as the probability of a given number arising in a game of chance, such as rolling a dice. It can be seen as the relative degree to which each possible climate outcome is supported by the evidence available, taking into account our current understanding of climate science and observations, as generated by the UKCP09 methodology. If the evidence changes in future, so will the probabilities. It is hoped that the constant quest to improve models, and make better use of observations to constrain their projections, will allow uncertainties to be reduced in the future. However, this cannot be guaranteed as the introduction of processes not yet included (for example, feedbacks from the methane cycle), or as yet unknown, could have the opposite effect. However, using a methodology developed by Met Office, UKCP09 provides state-of-the-art projections consistent with what we know now, together with an assessment of their limitations.

Box 1.1: Climate and climate change projections; some definitions

It is useful at this stage to define some of the terms that we will be using extensively in this report, using definitions broadly in line with those given in IPCC AR4, but adapted to be relevant to UKCP09. The term **climate** is usually defined as the statistical description in terms of the mean and variability of relevant weather variables over a period of time, which in this report is taken as 30 yr (the period adopted by the World Meteorological Organisation).

A **climate change projection** is a projection of the response of the climate system to a given emissions or atmospheric concentration scenario, expressed as a change relative to a baseline climate (taken as 1961–1990 in UKCP09). Both the projection and baseline climate are simulations by a climate model.

A **climate projection** is a projection of the response of the climate system to a given emissions or atmospheric concentration scenario. In UKCP09 climate projections are generated from model climate change projections added to a baseline observational climate.

Climate models are often used to make a single projection of climate change, for a given emissions scenario, which reveals nothing about uncertainty. Using an **ensemble** of a large number of model projections, **probabilistic projections** can be generated, allowing the uncertainty in projections to be quantified by giving the relative probability of different climate change outcomes.

A **variable** is a climate-related quantity such as mean temperature or precipitation.

A **time period** is a 30-yr period over which changes in variables are averaged.

Changes are **spatially averaged** over four areas: a 25 km grid square, an administrative region, a river basin or a marine region. Changes are **temporally averaged** over a month, a season or a year. So, as an example, projections of change in mean daily maximum temperature for the summer season (temporal average) might also be averaged over Wales (spatial average) and for the 2080s (time period).

An **emission scenario** is a plausible future pathway of emissions of greenhouse gases and other pollutants which can affect climate.

In this report we emphasise the assumptions in the UKCP09 methodology, and test the sensitivity of our results to reasonable variations in these, where possible. This is done for reasons of scientific integrity, but the need for such assumptions is an inevitable consequence of the nature of the climate projection problem, and is not unique to the particular approach adopted in UKCP09. Highlighting these assumptions could lead the reader to question the value of the projections, but it is important to put this in the context of their use in adaptation. Planners and decision makers use projections of change in many factors; not just climate itself but also demography, economics, technologies, etc. All of these are uncertain, and subject to assumptions and limitations of their own. We believe that our probabilistic climate projections, despite their limitations, are likely to provide information on climate change and its uncertainty which is at least as robust as the quality of information available for other planning factors.

1.2 What information do the UKCP09 projections provide? A summary

The UKCP09 projections cover changes in a number of atmospheric variables, with different temporal and spatial averaging, by several future time periods, under three future emissions scenarios. Box 1.1 defines these terms. Changes over land areas of the UK include more variables, and at a higher resolution, than those over marine regions.

1.2.1 Climate change over land areas

Variables. The variables for which changes are given over land areas are shown in Table 1.1 (overleaf), broadly similar to those in UKCIP02. Some additional information is given in Box 1.2 (overleaf).

Temporal averaging. For most variables changes are given as averages over three periods: month, season and year, except as shown in the last column of Table 1.1 (overleaf).

Spatial averaging. The resolution of the projections is 25 km over the land area of the UK, including islands large enough to be seen at this resolution (Figure 1.2(a)). Due to the probabilistic nature of the projections, it is not possible for probabilities of change over several individual grid squares to be simply averaged by the user in order to obtain probabilities of change over the total area of the grid squares. For this reason, we also provide probabilities of change for two different sets of aggregated areas over land, each decided upon following consultation.

The first of these aggregated areas (Figure 1.2(b)) encompasses the 16 regions made up of:

- the nine administrative regions of England
- Wales
- Northern Ireland
- Scotland, subdivided into its three climatological regions
- the Isle of Man
- the Channel Islands (represented by a single 25 km grid square)

For simplicity, these are all referred to as *administrative regions*.

Box 1.2: Some additional information on climate variables

Temperatures

Mean daily temperature (often referred to as simply *mean temperature*) is the average of the daily maximum and daily minimum temperatures.

Mean daily maximum temperature (sometime shortened in this report to just *maximum temperature*) is the average of the daily maximum temperatures over the temporal averaging period (for example, a season).

Mean daily minimum temperature (sometime shortened in this report to just *minimum temperature*) is the average of the daily maximum temperatures over the temporal averaging period.

Precipitation

Precipitation is given as a rate, in millimetres per day; however, when discussing monthly, seasonal or annual average changes to this we refer to it for convenience as simply *precipitation*. Note also that it is a total of precipitation of all types — rain, snow and hail.

Relative humidity (RH) and cloud

Just as a change in precipitation from 50 to 60 mm/day would represent a proportional increase of 20%, so a change of RH from 50% in the baseline climate to 60% in the future climate represents a proportional increase of 20% (rather than 10%). The same comment applies to changes in total cloud.

Extremes of temperatures and precipitation

These refer to changes in the 1st and 99th percentiles of the daily distribution of that particular variable during a season, over the complete 30-yr period (that is, about 2700 days). However, because a season has roughly 100 days, changes in the 1st and 99th percentiles of the distribution can be thought of as roughly equivalent to changes in the extreme value of the season, giving a more user-friendly name. Thus the change in the 99th percentile of the daily maximum temperature of the summer season can be thought of as the change in temperature of the *warmest day of the summer* and will be referred to as such in this report. The change in the 1st percentile of daily maximum temperature will be referred to as that of the *coolest day of the season*. The change in the 99th percentile of minimum temperature will be referred to as that of the *warmest night of the season*, that in the 1st percentile as that of the *coldest night of the season* — whilst recognising that the daily minimum temperature does not always occur at night. The change in the 99th percentile of daily precipitation will be referred to as the change in the *wettest day of the season*.

Variable	Unit	Change	Temporal averaging
Mean daily temperature	°C	°C	Month, season, year
Mean daily maximum temperature	°C	°C	Month, season, year
Mean daily minimum temperature	°C	°C	Month, season, year
99th percentile of daily maximum temperature	°C	°C	Season
1st percentile of daily maximum temperature	°C	°C	Season
99th percentile of daily minimum temperature	°C	°C	Season
1st percentile of daily minimum temperature	°C	°C	Season
Precipitation rate	mm/day	%	Month, season, year
99th percentile of daily precipitation rate	mm/day	%	Season
Specific humidity	g/kg	%	Month, season, year
Relative humidity	%	% (of %)	Month, season, year
Total cloud	fraction	%	Month, season, year
Net surface long wave flux	Wm^{-2}	Wm^{-2}	Month, season, year
Net surface short wave flux	Wm^{-2}	Wm^{-2}	Month, season, year
Total downward short wave flux	Wm^{-2}	Wm^{-2}	Month, season, year
Mean sea level pressure	hPa	hPa	Month, season, year

Table 1.1: The climate variables available over land as probabilistic projections of change in UKCP.

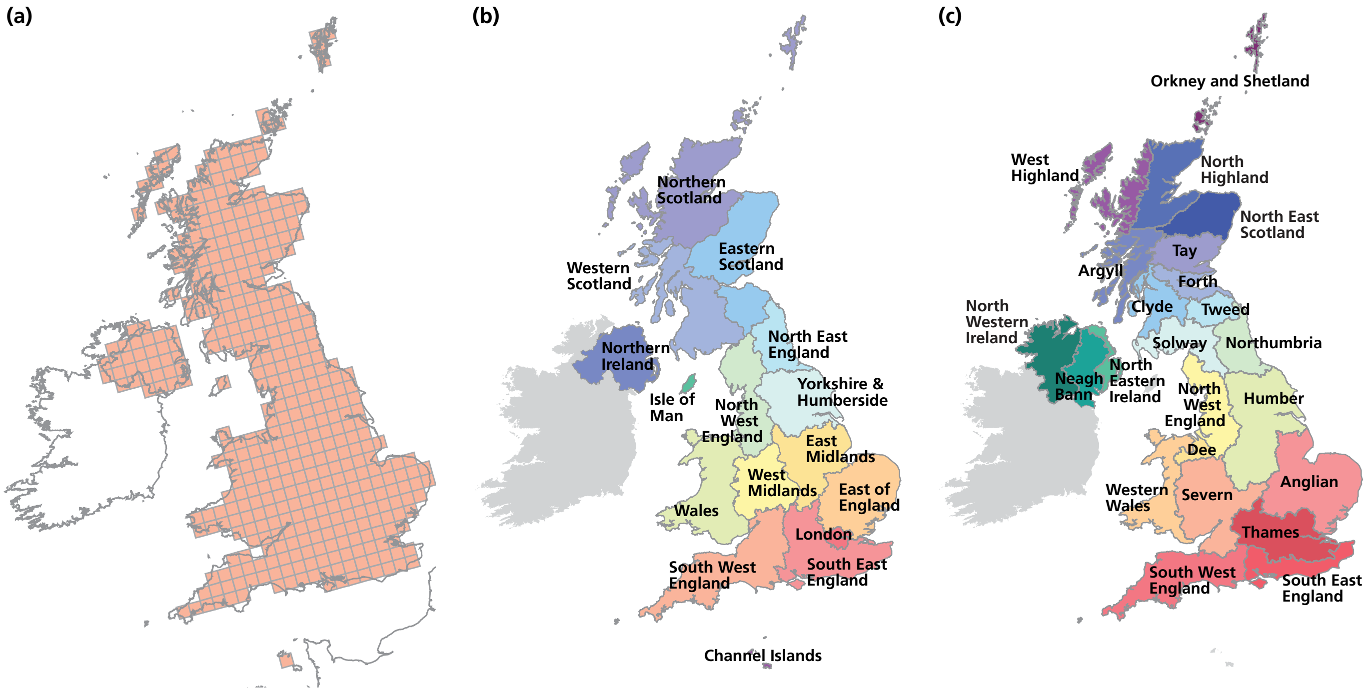


Figure 1.2: (a) Areas over which probabilistic projections are available: (a) the 25 km grid, (b) the 16 administrative regions and (c) 23 river-basin regions.

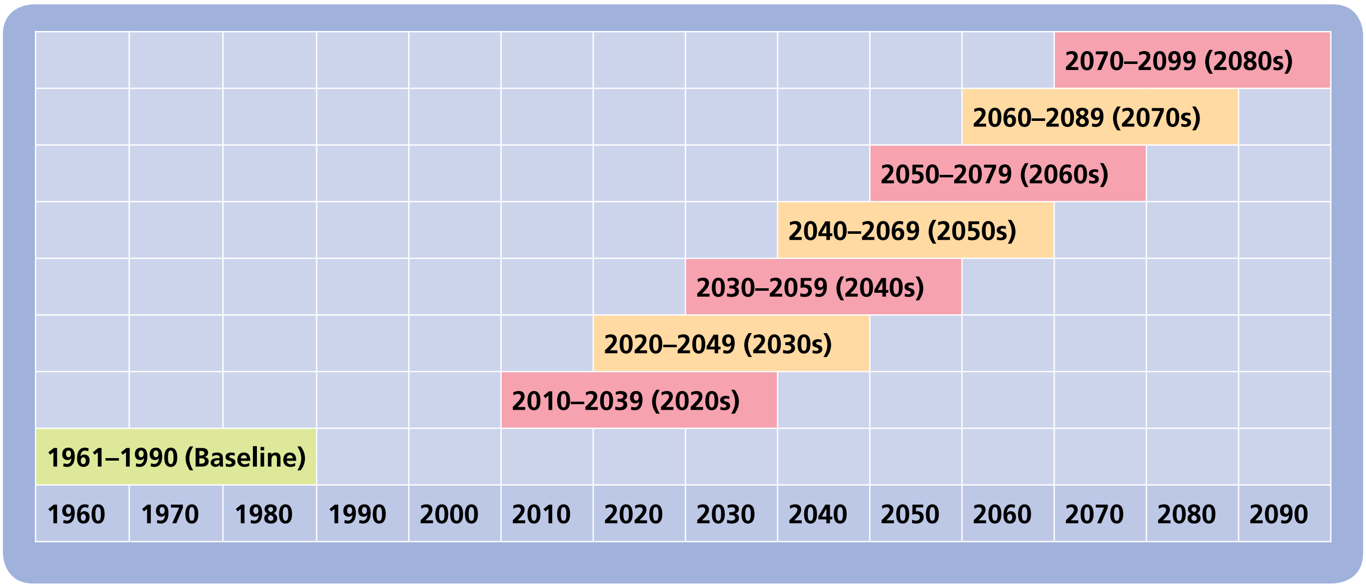


Figure 1.3: The seven 30-yr future time periods over which projections are averaged, relative to the baseline period.

Variable	Unit	Change	Temporal averaging
Mean daily air temperature	°C	°C	Month, season, year
Precipitation rate	mm/day	%	Month, season, year
Mean sea level pressure	hPa	hPa	Month, season, year
Total cloud	fraction	%	Month, season, year

Table 1.2: The climate variables available as probabilistic projections of change over marine regions in UKCP09. Note that the first variable is termed *air temperature* to avoid possible confusion with sea-surface temperature, projections of which are given in the UKCP09 Marine and coastal projections report.

The second set of aggregated areas are river basins, shown in Figure 1.2(c). These are based on the 13 Water Framework Directive River Basin Districts in England, Wales and Northern Ireland. In Scotland, these are based on the 10 Advisory Group Boundaries.

Time periods. Changes are given averaged over each of seven future overlapping 30-yr time periods, stepped forward by a decade, starting with 2010–2039 (specifically 1 December 2009 to 30 November 2039). These future time periods are referred to for simplicity by their middle decade, starting from the 2020s (2010–2039) and ending with the 2080s (2070–2099).

User surveys showed overwhelming support for retaining the same baseline period as used in UKCIP02, and hence all changes are expressed relative to a modelled baseline 30-yr period of 1961–1990 (specifically 1 December 1960 to 30 November 1990). The future time periods are illustrated in Figure 1.3.

Emission scenarios. Changes are given corresponding to three future emissions scenarios — Low, Medium and High.

In the case of mean sea-level pressure, precipitation, relative humidity, temperature (mean, maximum and minimum) and cloud amount, UKCP09 also makes available probabilistic projections over land of future climate in addition to those of the change in climate. This is done by combining probabilistic projections of climate change with the corresponding baseline (1961–1990) climate taken from observations. This is preferable to directly taking the climate model output for future years as it reduces the effect of biases in the model's simulation of the baseline climate, but obviously cannot account for any errors in the projected climate change response.

1.2.2 Climate change over marine regions

The four variables for which changes are given over marine regions are shown in Table 1.2. Changes are given as temporal averages over three periods: month, season and year, and as spatial averages over nine marine regions shown in Figure 1.4; the latter were selected by user consultation and are based on the UK *Charting Progress* areas, with extended natural boundaries where possible.

As with projections over land, changes are given averaged over each of seven future overlapping 30-yr time periods, stepped forward by a decade, from 2010–2039 (*2020s*) to 2070–2099 (*2080s*), and changes are expressed relative to a modelled baseline period of 1961–1990. Changes are given corresponding to three future emissions scenarios — Low, Medium and High.

Marine projections are provided only as changes. Projections of absolute future values are not given.

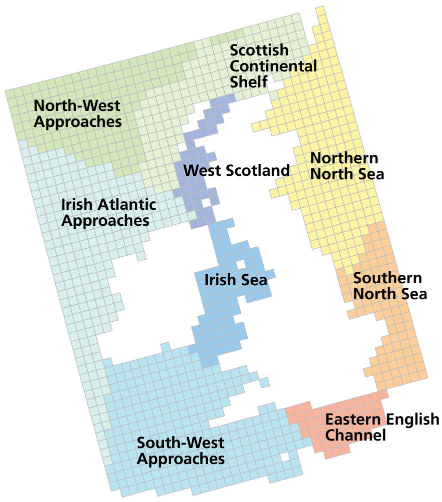


Figure 1.4 (above): The nine marine regions over which changes in climate variables have been projected. The names for these regions have been chosen specifically for the convenience of this report and hence may not be geographically or politically correct.

1.3 Uncertainty

Uncertainty in climate change projections is a major problem for those planning to adapt to a changing climate. Adapting to a smaller change than that which actually occurs (or one of the wrong sign) could result in costly impacts and endanger lives, yet adapting to too large a change (or, again, one of the wrong sign), could waste money. In addition there is the risk of maladaptation – adapting to climate change in a way that prevents or inhibits future adaptation. The 2008 projections are the first from UKCIP to be designed to treat uncertainties explicitly, by generating projections of change that are given, where justified, as estimated probabilities of different outcomes (see Box 1.3 for interpretation of probabilities in UKCP09) rather than giving a single realisation of possible changes from one model or a small sample of possible changes from several models. This means that probabilities are attached to different climate change outcomes, giving more information to planners and decision makers.

Uncertainty in projections of future climate change arises from three principal causes:

- natural climate variability, both internal and external;
- incomplete understanding of Earth System processes and their imperfect representation in climate models (which we term *modelling uncertainty*); and
- uncertainty in future emissions.

The effect of modelling uncertainty manifests itself in the different projections from different climate models, both globally and, to an even greater extent, at local or regional scales where information is critically needed. For the first time in UKCIP, we are able to estimate the size of this uncertainty by providing the user with *probabilistic projections* of climate change for certain key climate variables, where the estimated probabilities can be shown to be robust to the main assumptions in our methodology. This provides information on the estimated relative likelihood of different future outcomes, in the form of a *probability density function* or PDF (see Box 1.3). The PDF takes into account both the modelling uncertainty and that due to natural internal variability, but is not able to include the uncertainty due to future emissions, which is why separate PDFs are given for each of three emissions scenarios.

The reason why different climate models give different projections is because they use different, but plausible, representations of climate processes. Hence, we generate probability distributions using projections from a very large number of variants of the Met Office Hadley Centre model, each representing climate processes in a different way within their structure. We also incorporate projections from twelve other international models which have different structures and which have participated in international intercomparisons such as that for IPCC AR4; this allows us to sample the effects of modelling errors which cannot be incorporated by varying the representations in the Met Office model alone. (Obviously errors due to processes missing from all models cannot be sampled by any technique.) The use of alternative climate models also fulfils one of the main user requests identified from a review of UKCIP,* that the projections should not be based solely on the Met Office model.

The progression to probabilistic projections based on large ensembles has meant that not all of the properties and characteristics of the UKCIP02 scenarios could be carried across to UKCP09 — the direct provision of daily time series from climate model output, for example. Thus the new projections are not a "drop in" replacement or straightforward update of UKCIP02.

* http://randd.defra.gov.uk/Document.aspx?Document=GA01070_3619_FRP.pdf

Box 1.3: How are probabilistic projections presented? Explaining PDFs and CDFs

The provision of probabilistic projections is the major improvement which the UKCP09 brings to users. However, to utilise these appropriately, it is essential that users have a good understanding of what they mean and how they are communicated.

Probabilistic projections assign a probability to different possible climate change outcomes, recognising that (a) we cannot give a single answer and (b) giving a range of possible climate change outcomes is better, and can help with making robust adaptation decisions, but would be of limited use if we could not say which outcomes are more or less likely than others.

Within any given range of plausible climate changes, we cannot talk about the absolute probability of climate changing by some exact value — for example a temperature rise of exactly 6.0°C. Instead we talk about the probability of climate change being less than or greater than a certain value, using the Cumulative Distribution Function (CDF). This is defined as the probability* of a climate change being less than a given amount. The climate change at the 50% probability level is that which is as likely as not to be exceeded; it is properly known as the median, but in UKCP09 we refer to it by the more user-friendly name of *central estimate*. Thus in Figure 1.5 (top panel), the CDF (a hypothetical example at a certain location, by a certain future time period, for a given month of the year, under a particular emissions scenario) shows that there is a 10% probability of temperature change being less than about 2.3°C and a 90% probability of temperature change being less than about 3.6°C. These statements conventionally concern the probability of change being less than a given threshold, but of course we can turn them around to give the probability of exceeding that threshold. Thus the CDF in Figure 1.5 (top panel) also shows that there is a 90% probability of temperature change exceeding about 2.3°C and a 10% probability of temperature change exceeding about 3.6°C.

The CDF would be useful for those who want to know the probability of climate change being less than some threshold where an impact of interest starts to occur. However, the CDF is not useful for understanding the relative probability of different specific outcomes. The Probability Density Function (PDF, Figure 1.5, bottom panel) is an alternative representation of the same distribution which is a useful visualisation of the relative likelihood of different climate outcomes. For a given value of climate change, the CDF is the area under the PDF to the left of that value of climate change. As the CDF has a maximum value of 100%, the area under the PDF curve cannot be more than 100%.

As probability is represented by the area under a PDF curve, the *y*-axis in Figure 1.5(b) is referred to as a probability density, with units of "per °C". However, the PDF can be thought of more simply in relative terms by comparing the ratios of probability density for different outcomes. For instance, as the probability density at 2.9°C is about 0.7 (per °C) and the probability density 3.8°C is about 0.2 (per °C) , then a temperature change of 2.9°C is about 3.5 times more likely than one of 3.8°C. Hence, for simplicity, PDF graphs from the User Interface are all labelled *relative probability* rather than *probability density (per °C)*.

* Probabilities in CDFs are conventionally taken to range between 0 and 1, although we refer to them here as percentages between 1 and 100.

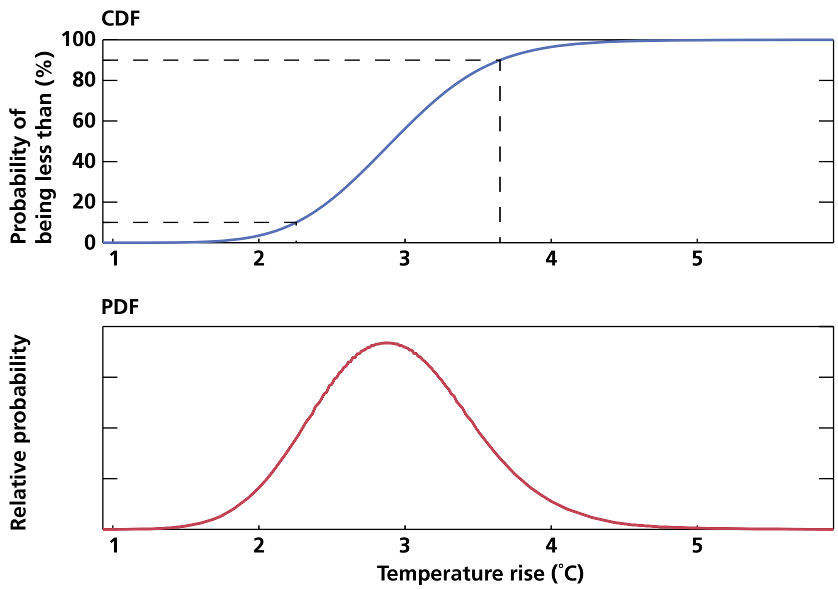


Figure 1.5: Top panel, Cumulative distribution function of temperature change for a hypothetical choice of emission scenario, location, time period and month. Bottom panel, Corresponding probability density function for this hypothetical case.

The hypothetical distribution shown in Figure 1.5 (bottom panel) is smooth and almost symmetrical; in practice the UKCP09 distributions vary in shape, dependent on how the effects of uncertain climate system processes combine to produce different projections for different variables, time periods and locations.

It is very important to understand what a probability means in UKCP09. The interpretation of probability generally falls into two broad categories. The first type of probability relates to the expected frequency of occurrence of some outcome, over a large number of independent trials carried out under the same conditions: for example the chance of getting a 5 (or any other number) when rolling a dice is 1 in 6, that is, a probability of about 17%. This is not the meaning of the probabilities supplied in UKCP09, as there can only be one pathway of future climate. In UKCP09, we use the second type (called *Bayesian probability*) where probability is a measure of the degree to which a particular level of future climate change is consistent with the information used in the analysis, that is, the evidence. In UKCP09, this information comes from observations and outputs from a number of climate models, all with their associated uncertainties. The methodology which allows us to generate probabilities is based on large numbers (*ensembles*) of climate model simulations, but adjusted according to how well different simulations fit historical climate observations in order to make them relevant to the real world. The user can give more consideration to climate change outcomes that are more consistent with the evidence, as measured by the probabilities. Hence, Figure 1.5 (top panel) does not say that the temperature rise will be less than 2.3°C in 10% of future climates, because there will be only one future climate; rather it says that we are 10% certain (based on data, current understanding and chosen methodology) that the temperature rise will be less than 2.3°C. One important consequence of the definition of probability used in UKCP09 is that the probabilistic projections are themselves uncertain, because they are dependent on the information used and how the methodology is formulated. Section 2.6 discusses the uncertainty in the probabilistic projections in more detail and Annex 2 explores their robustness to changes in evidence and methodology.

As mentioned earlier, UKCP09 probabilistic projections also take into account the uncertainties due to natural internal climate variability (sometimes called the *chaotic* behaviour of the earth's climate system), but not the effect of uncertainties in future emissions. The latter, though small over the next two or three decades mainly because of climate system inertia, will be substantial in the second half of the century, but there is currently no accepted method of assigning relative likelihoods to alternative future emissions pathways. We therefore present separate probabilistic projections of future climate change for three scenarios of future emissions. These were selected, after consultation with users, from three scenarios developed by IPCC in its Special Report on Emission Scenarios (SRES) in 2000. In UKCP09 they are labelled High emissions, Medium emissions and Low emissions, and correspond to the A1FI, A1B and B1 scenarios in SRES. Annex 1 gives further detail on these emission scenarios.

1.4 Projections at a daily resolution over land

Changes in daily climate, such as the frequency of hot or very wet days, are likely to be more significant for many climate impacts than changes in monthly or seasonal averages. Whilst we are not able to project changes in storm tracks and anticyclones with confidence, we can project how the characteristics of daily time series could be affected by changes in the more basic aspects of future climate, such as monthly mean temperature and precipitation and other aspects of their distributions, which we have more confidence in projecting.

Our approach, therefore, is to provide a tool known as a weather generator, capable of providing plausible realisations of how future daily time series of several variables could look, consistent with changes in the characteristics of monthly-average climate sampled from the probability distributions. It does not provide a weather forecast for a particular day in the future; it gives statistically credible representations of what may occur given a particular future climate. Despite their limitations (for example, they assume that relationships between different variables remain unchanged in a future climate), we recognised the inevitability of (possibly different varieties of) weather generators being employed by many users, and the advantages for consistency between impact studies that a single weather generator would bring. The UKCP09 weather generator was developed by the Universities of Newcastle and East Anglia, based on a previous version in use by the Environment Agency.

The UKCP09 Weather Generator provides synthetic daily time series of temperature (mean, maximum and minimum), precipitation, relative humidity, vapour pressure, potential evapotranspiration (PET) and sunshine (from which we also estimate diffuse and direct downward solar radiation) at a resolution of 5 km, for each of the three emission scenarios and each of the future 30-yr time periods — 2020s, 2030s, etc. It provides data over land but not for marine regions. The weather generator does not add any additional climate change information over that which is present in the 25 km probabilistic projections. However it does add local topographical information (e.g. hills, valleys) at the 5 km scale, as it is based on observed data which is representative of this scale. The Weather Generator is also able to construct synthetic hourly time series for precipitation, temperature, vapour pressure, relative humidity and sunshine for future time periods. This is a disaggregation of daily data and, again, does not provide any new climate change information at this level. The *UK Climate Projections science report: Projections of future daily climate for the UK from the weather generator* describes the weather generator in detail, with examples of its output, and also considers its limitations.

An entirely different type of projections at a daily resolution (again, not weather forecasts for the future) is also available from an ensemble of transient experiments (that is, run continuously from 1950 to 2099) of the 25 km resolution Met Office regional climate model; the daily time series are spatially coherent and physically consistent across the whole UK and surrounding seas. However, because they are not completely compatible with the probabilistic projections, they are not part of UKCP09, but are available from the Climate Impacts LINK project website, also funded by Defra. Chapter 5 gives more details.

Note that guidance on the application of these projections, including discussion of their limitations, and also some examples of how they could be used, is discussed in a separate publication: UKCP09 User Guidance.

Box 1.4: Confidence in climate projections

There is a cascade of confidence in climate projections. There is very high confidence in the occurrence of global warming due to human emissions of greenhouse gases. There is moderate confidence in aspects of continental scale climate change projections. 25 km scale climate change information is indicative to the extent that it reflects the large-scale changes modified by local conditions. There is no climate change information in the 5 km data beyond that at 25 km. All that can be produced is a range of examples of local climates consistent with current larger-scale model projections. The confidence in the climate change information also depends strongly on the variable under discussion. For example, we have more confidence in projections of mean temperature than we do in those of mean precipitation. The probabilities provided in UKCP09 quantify the degree of confidence in projections of each variable, accounting for uncertainties in both large scale and regional processes as represented in the current generation of climate models. However, the probabilities cannot represent uncertainties arising from deficiencies common to all models, such as a limited ability to represent European blocking. The fact that the UKCP09 projections are presented at a high resolution for the UK should not obscure this, and users should understand that future improvements in global climate modelling may alter the projections, as common deficiencies are steadily resolved.

2 Why do we need probabilistic information? Uncertainties in climate change projections

This chapter describes the uncertainties in projections of climate change and how they arise. It goes into some detail on how climate models are structured, and the reasons why different models give different projections of change. This provides the background to a simplified description of the methodology which has been developed to provide the probabilistic projections for UKCP09. Next, it outlines some of the limitations of these projections. Finally, it describes the three scenarios of future emissions which underlie the projections.

2.1 Background

The development of climate change information over the last two decades has broadly paralleled that in climate science and climate modelling. Planners and decision makers have become increasingly demanding in their requirements over the last decade as the potential severity of impacts is realised, and as UKCIP and others have successfully persuaded more and more stakeholders to bring climate change into the mainstream of their long-term planning process. Successive improvements in models and the way they are used mean that climate scientists are able to come closer to meeting these requirements, but large uncertainties remain which are outlined in this chapter, together with a simplified description of how we are taking account of them in UKCP09. It is the continuing existence of these uncertainties that has largely driven the move away from single projections and towards probabilistic ones.

As outlined in Chapter 1, there are three major sources of uncertainties in estimating future climate change: (i) that due to natural variability, (ii) that due to incomplete understanding of climate system processes and their imperfect representations in models (which we term modelling uncertainty) and (iii) that due to uncertainty in future emissions; these are discussed below in turn. Previous UKCIP climate change scenarios have taken account of some of these uncertainties in different ways (see review by Hulme and Dessai, 2008). UKCIP98 (Hulme and Jenkins, 1998) presented four climate change scenarios, corresponding to four combinations of emissions scenario and global climate sensitivity; the latter was used to scale patterns of change from a single Met Office 300 km resolution global climate projection as an attempt to include model uncertainty. UKCIP02 (Hulme *et al*. 2002) again provided four climate change scenarios, differing only in the emissions scenarios which were again used to scale a single 50 km resolution pattern from the Met Office Hadley Centre regional climate model; no account was taken of model uncertainty as there were no credible techniques then available to do this. Dessai and Hulme (2008) have shown that recent trends in observed UK climate fall broadly within the range of projections of UKCIP (and earlier) scenarios, the greatest ambiguity occurring for summer precipitation.

2.2 Natural variability

Climate, at a global scale and even more at a local scale, can vary substantially from one period (for example, a decade or more) to the next, even in the absence of any human influences. This natural variability of the earth's climate has two causes. The first, natural internal variability, arises from the chaotic nature of the climate system, ranging from individual storms which affect our regional weather to large scale variations over periods of seasons to years. Variability of the latter type results mainly from interactions between ocean and atmosphere, resulting in phenomena such as El Niño. Natural internal variability will continue in future, and be superimposed on longer-term changes due to man's activities. If in a specific future period internal variability happens to act in the same direction as man-made change then the overall change will be that much bigger; if it acts in the opposite direction, the overall change will be that much smaller. Climate models provide realistic simulations of a number of key aspects of natural internal variability in the observed climate (see Annex 3). By running the climate model many times with different initial conditions (a so-called initial condition ensemble) we can estimate the statistical nature of this natural variability on a range of space and time scales, and hence quantify the consequent uncertainty in projections.

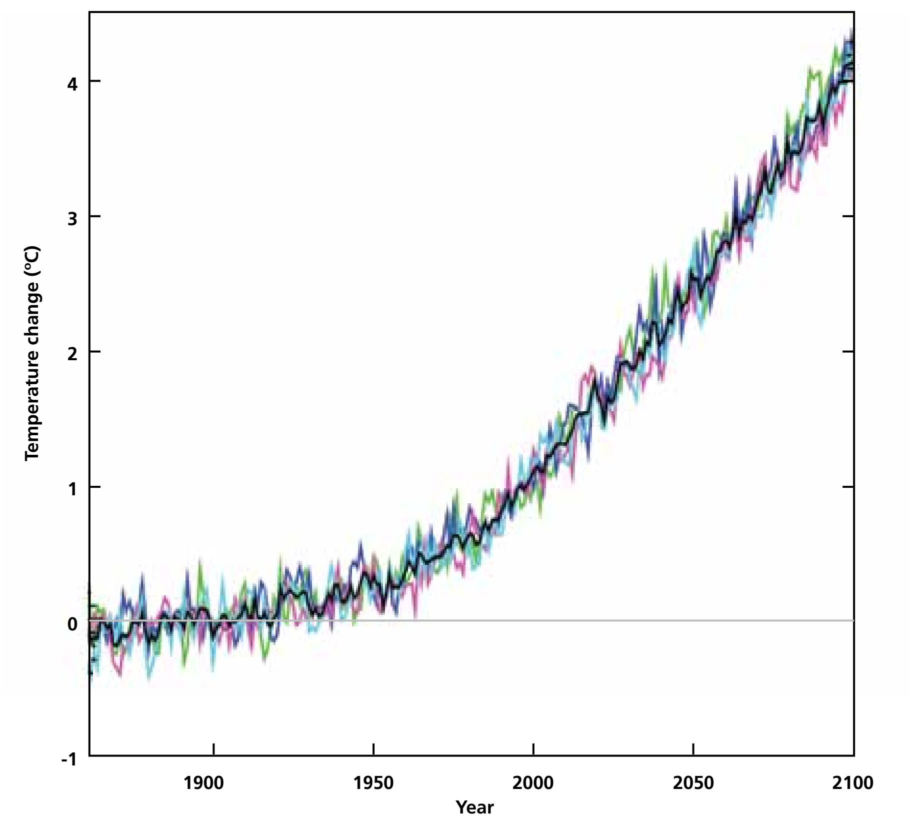


Figure 2.1: Simulations of change in global average temperature for the period 1860–2100 from three experiments with the HadCM3 climate model, shown in the three colours. Each experiment was driven with the UKCIP02 Medium High Emissions scenario but was started with different initial conditions. The black line shows the mean of the three simulations. (Note that influences of changes in solar or volcanic effects are not included.)

Global temperatures projected from a three-member initial condition ensemble, all using the same emissions scenario, are shown in Figure 2.1. It can be seen that, although each experiment shows the same general warming, individual years can be quite different, due to the effect of natural internal variability. If we look at changes at a smaller scale, for example those of winter precipitation over England and Wales (Figure 2.2) we see that, although the three projections show similar upward trends of about 20% through the century, they are very different from year to year and even decade to decade. A common way of reducing the effect of uncertainty due to natural variability on the projections is to average changes over a 30-yr period, as we did in the UKCIP02 scenarios (and do again in UKCP09). But even this still allows large differences in patterns of change, as can be seen from Figure 2.3; for example over Birmingham where two of the model experiments project approximately 30% increases, but the other projects just over 10%. The uncertainty due to projected natural internal variability is included in the overall uncertainty quantified in UKCP09.

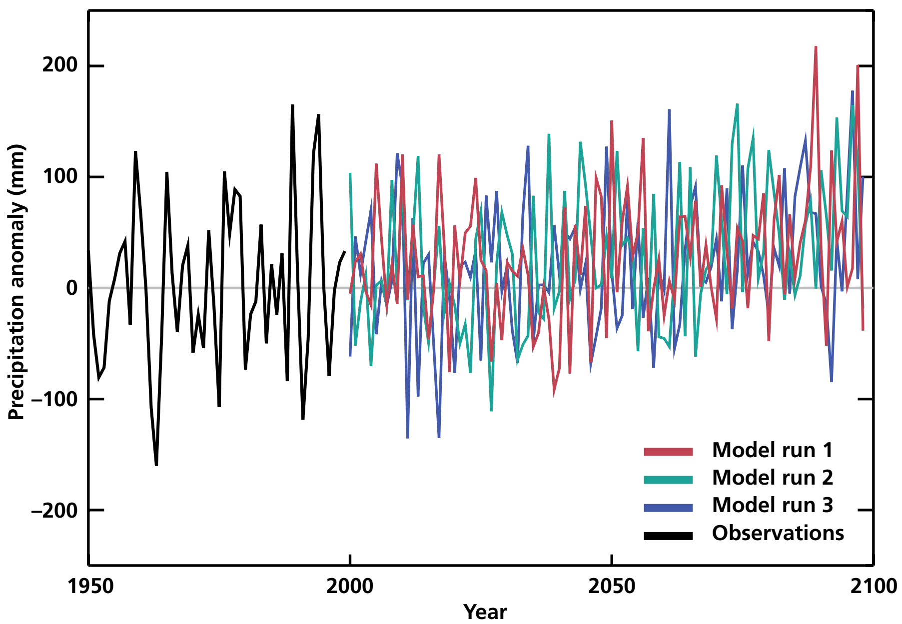


Figure 2.2: The back line shows the observed England and Wales winter precipitation anomaly from 1950–2000, relative to the 1961–1990 average. The three coloured lines show projections of the same variable, from three experiments using the HadCM3 global model. Each experiment was driven with the same (UKCIP02 Medium-High) emissions scenario, but was started with different initial conditions. The differences between the three simulations are due to natural internal variability.

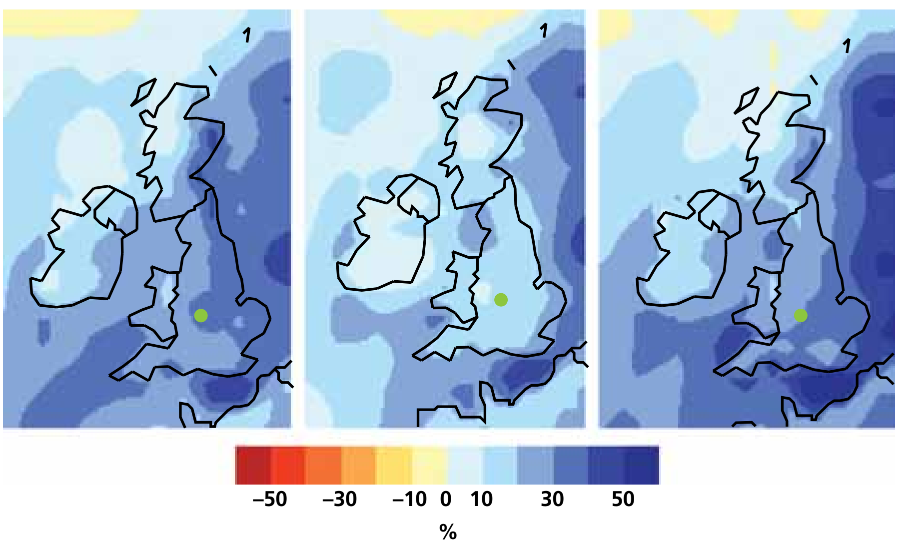


Figure 2.3: Maps of the change in winter precipitation averaged over the period 2071–2100, relative to 1961–1990, taken from the same three model experiments used in Figure 2.2 and described in the caption.

There are some exciting new developments in forecasting natural internal changes in climate over the next decade, suggesting that some details of natural variability may be predictable over the next 30 yr with some skill (Smith *et al.* 2007; Keenlyside *et al.* 2008). (We use the term skill to mean that such techniques, in which observations are used to further determine the initial state of the climate model, produce a narrower range of uncertainty than one would get in the absence of using the observations). Such techniques are still experimental, showing some promise up to a decade or so ahead with predictability beyond that yet to be tested; hence they are not used in UKCP09.

Climate can also vary due to natural external factors (that is, external to the climate system), the main ones being changes in solar radiation and in aerosol (small particles) from volcanoes. The sun is the driving force for the earth's climate so any change in it has the potential to change climate, and indeed we estimate that the rise in global temperatures in the early part of the 20th century may have been partly due to a rise in the amount of energy reaching us from the sun over that period (Stott *et al*. 2003). However, because solar radiation has been relatively constant over the past few decades (apart from changes on the regular 11-yr cycle which are relatively small and are largely smoothed by the inertia of the climate system) we do not attribute recent climate change over this recent period to this factor. Because we cannot forecast with any useable accuracy how the solar radiation will vary in the future, we cannot formally build any changes due to this factor in the projections of future climate; this remains as an uncertainty. However, Stott *et al*. (2003) have estimated that solar radiation changes over the 20th century could have caused between 0.16°C and 0.49°C rise in global temperatures. On the assumption that solar radiation changes over the coming century will be no greater than those in the last, although they could be in either direction, then changes in global temperature due to this factor are unlikely to be greater than ± 0.5°C. (Gareth Jones, pers comm.)

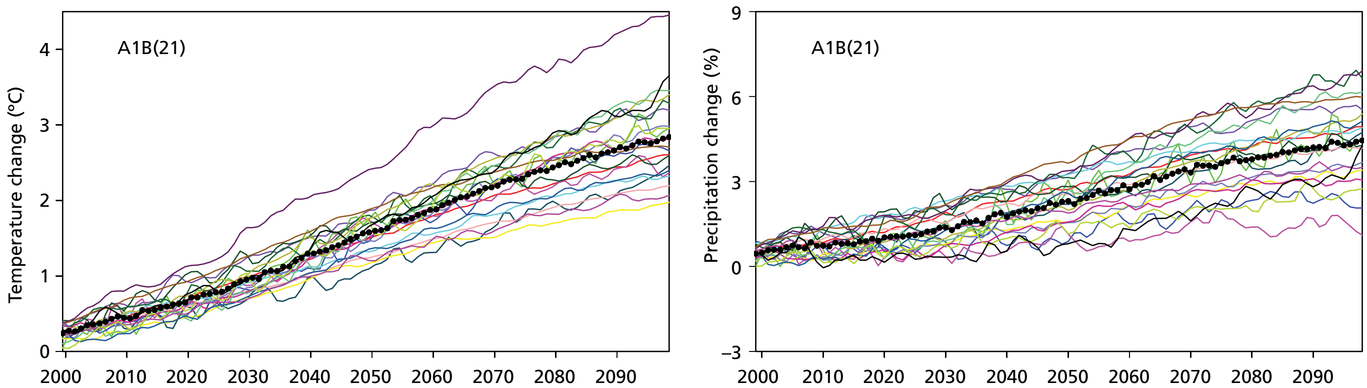
If volcanoes are energetic enough to inject gas into the stratosphere, then the resulting aerosol can remain there for a few years and gradually spread across the globe. Because solar radiation will be reflected back from this aerosol before it can warm the earth, it will have a cooling effect on climate at the surface. The eruption of Mt Pinatubo in the Philippines in 1991 caused global temperatures to drop by about 0.3°C over the following year or two, taking 3–4 yr to recover — and this observed effect has been quite well replicated by climate models (Hansen *et al*. 1996). More energetic volcanoes have an even greater cooling effect. Again, because we do not know the future course of volcanic activity, we have no meaningful way of predicting their effects on climate — apart from being aware that cooling events lasting a few years could occur at any time.

2.3 Uncertainty due to climate models

The second main source of uncertainty in climate projections is modelling uncertainty. This arises from our incomplete knowledge of the climate system and our inability to model it perfectly. As explained in Box 2.1, climate models allow us to calculate the change in climate consequent on a given pathway of future emissions due to human activities. Models provide a mathematical representation of many of the processes in the climate system (atmosphere, land surface, cryosphere and ocean), and allow these processes to interact, hence producing many types of feedback, both positive and negative. The net effect of these will determine how climate evolves in response to changes in greenhouse gases.

These representations are based on a mixture of theory, observations and experimentation, and are inevitably uncertain. All modelling groups seek to represent climate processes in the best possible way in their models and, because this is to an extent a subjective judgement, this leads to different groups adopting different representations. Not surprisingly, this leads to different strengths (and even, in the case of clouds, directions) of feedbacks in the models, and hence different projections of future changes – even when the same pathway of future emissions is assumed. This can be seen from Figure 2.4, which shows changes in global temperature and precipitation from 21 climate models used in IPCC AR4, all under the same emissions scenario. Models with a stronger net positive feedback exhibit a more rapid warming that those with a weaker net feedback; indeed there is a factor of two difference between the highest and lowest projected rates of global warming (Figure 2.4, left panel). Similar comments apply to projected rates of change of global mean precipitation (Figure 2.4, right panel).

Figure 2.4: Smoothed time series of annual change in global temperature (left) and global precipitation, relative to the 1980–1999 average, from 21 global models (including HadCM3, lime green), each driven with the SRES A1B emissions scenario. The mean time series is shown by black dots. The results are not labelled here by model name, but this can be seen in IPCC AR4-WG1. © IPCC AR4-WG1.



Box 2.1: Climate models and how their limitations lead to uncertainties in projections

The climate model

The only way we can calculate how climate will change due to human activities is to use a mathematical model of the earth's climate system, known simply as a global climate model (GCM). This describes the behaviour of the components of the climate and interactions between them. Firstly, the atmosphere; the way it moves horizontally and vertically, plus physical processes that occur in it, such as the formation of clouds and precipitation, and the passage of terrestrial and solar radiation through it. Secondly the ocean, because there is a continual exchange of heat, momentum and water vapour between the ocean and atmosphere and because within it there are large currents which transport heat, water and salt. Thirdly the land, because it affects the flow of air over it, and is important in the hydrological cycle — not just the land surface but soils beneath it — and changes in the land surface (both natural and human-made) affect the climate. Lastly the cryosphere; ice on land (snow, glaciers and ice sheets) and on sea. All of these components of the climate system interact to produce the feedbacks which play a large role in determining how climate will change.

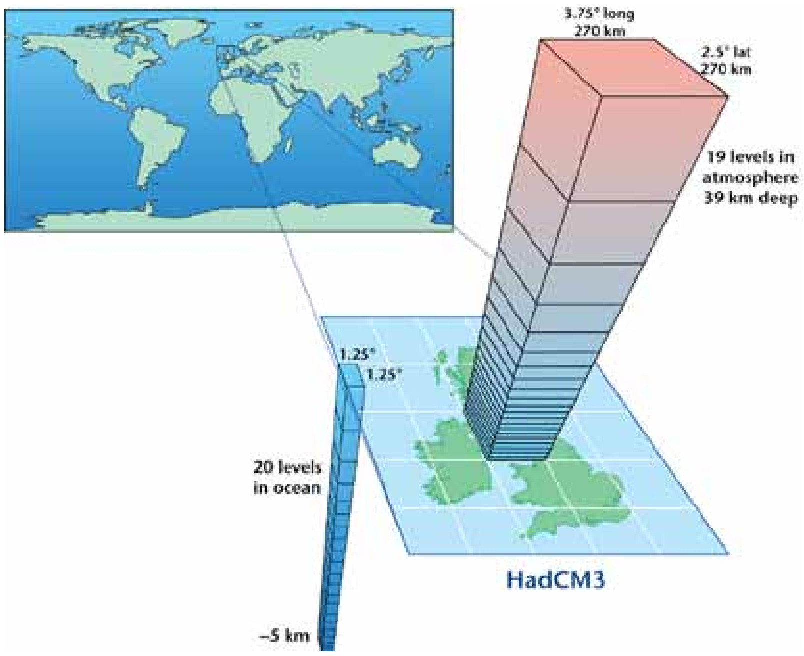


Figure 2.5: The horizontal and vertical structure of the HadCM3 climate model.

Typically, a global climate model breaks up the surface of the earth into a number of latitude/longitude grid boxes. It divides the atmosphere into layers, from the surface to the stratosphere, and does the same for the ocean, from the surface to the deepest waters (Figure 2.5). At each of the points on this three-dimensional grid in the atmosphere a number of equations, derived from the basic laws of physics, are solved which describe the large-scale evolution of momentum, heat and moisture. Similar equations, but including different variables, are solved for the ocean. The third Met Office coupled ocean-atmosphere GCM, HadCM3, has a resolution over land areas of 2.5° latitude x 3.75° longitude, with 19 vertical levels in the atmosphere and four layers in the soil. The ocean model has 20 vertical levels and a grid size of 1.25° latitude x 1.25° longitude. In all, there are about a million grid points in the model. At each of these grid points, equations are solved every time the model steps forward (typically 30 min of *model time*) throughout an experiment which typically lasts 250 *model* yr.

The large ensemble of experiments which form the basis of the UKCP probability projections described in Section 2.3.1 use the *slab model* configuration of HadCM3, known as HadSM3. This represents only the top 50 m of the ocean as one layer and prescribes the effects of ocean heat transport rather than simulating ocean currents explicitly. Hence it is much faster to run on a given computer and so we can run many more experiments. These experiments simulate the long-term *equilibrium* climate (a) at current greenhouse gas concentrations and (b) in a world where these are assumed to be double the current concentrations. Although these simulations do not account for possible changes in ocean circulation, surface and atmospheric processes are widely acknowledged to be the leading drivers of the major features of global patterns of climate change, so slab models are used to provide credible realisations of these patterns. In UKCP09 we are able to run many more experiments (that is, bigger ensembles) using the slab model, and hence explore uncertainties in surface and atmospheric processes more comprehensively. A smaller ensemble of simulations of time-dependent climate change was also produced with the coupled full-ocean model (HadCM3). Relationships between the change patterns simulated between corresponding variants of the slab model and the full ocean model are then used to *timescale* the slab model results, that is, to convert them into a large ensemble of projections of time-dependent changes from 1951 to 2099, whilst also accounting for uncertainties in the projected geographical patterns due to timescaling. We use additional ensembles of HadCM3 simulations to sample uncertainties in ocean transport, sulphur cycle and land carbon cycle processes, and hence also include the effects of these in the projections. We will return to this topic later in this box, and Chapter 3 discusses it in detail.

Parametrisations in climate models

Many of the most important processes in the climate system (for example the drag exerted by hills as air flows over them, and the formation of clouds) take place at a scale much smaller than the grid size of GCMs — these are called subgrid-scale processes. These cannot therefore be described explicitly, so we develop relationships, known as parametrisations, which estimate them from grid scale variables such as winds, temperature, humidity, etc. which are explicitly described in the model.

We illustrate this by taking the example of cloud amount. This is defined as the proportion of each model grid square which is covered by cloud at each level in the atmosphere. To calculate cloud amount in HadCM3, we use the model's calculated mean temperature and water vapour content for that square and level; this is known as *parametrising* cloud amount in terms of the large scale model variables. Now the equation relating water vapour and temperature to cloud amount contains some parameters, the values of which are based on results from, for example, aircraft measurements or high resolution process models such as cloud resolving models. The values of these parameters are uncertain, and this is a major cause of model uncertainty. So, to quantify this model uncertainty, we vary these parameter values between plausible limits to form variants of a number of configurations of the model, in order to generate the ensembles of simulations which form the primary basis for the PDFs in UKCP09.

But the parametrisation which predicts cloud amount from the modelled large scale variables may be different in models from other centres; not just the parameter values but the actual form of the parametrisation scheme itself; this is illustrated schematically in Figure 2.6. This is an example of a structural difference between models; the effect of structural differences cannot be taken account of using variants of a single model alone. In UKCP09 it is taken into account in the probabilistic projections by using a number of models from other centres, as explained in Chapter 3.

Feedbacks

Basic greenhouse theory tells us that when the concentration of a greenhouse gas, such as CO_2, increases in the atmosphere, it alters the balance between the amount of incoming energy from the sun and that leaving the earth as infrared energy (the radiative balance). Given enough

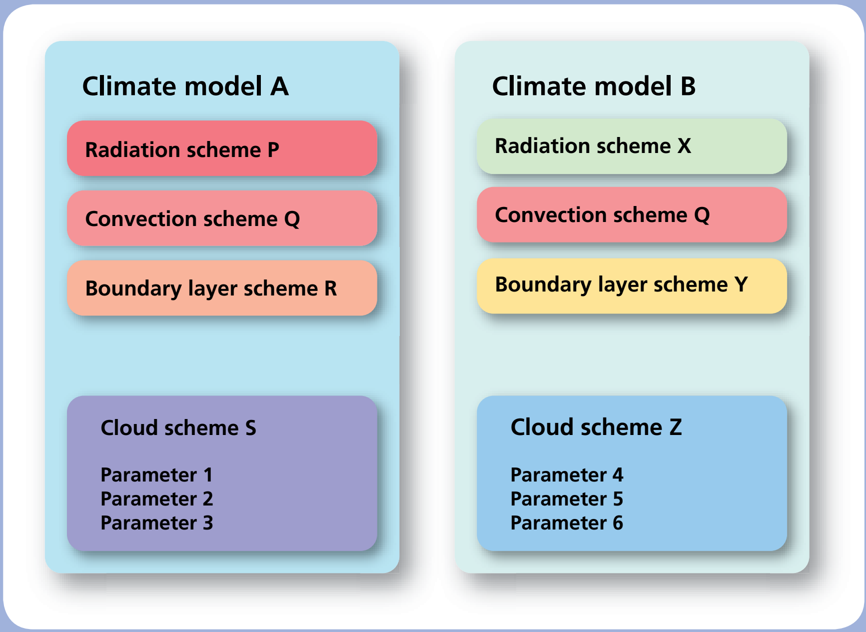


Figure 2.6: Schematic illustration of parametrisation schemes in two different climate models, and the parameter values within one scheme (that for cloud). Note that different models may share one or more parametrisation schemes; in the diagram this is denoted by the convection scheme.

time, the climate system adjusts to this new condition by increasing the surface temperature of the earth. The direct radiative effect of a doubling the concentration of CO_2 in the atmosphere would eventually cause the surface temperature of the earth to increase by about 1°C. However, once a greenhouse warming starts, a number of consequent changes start to happen which can act to either reduce or increase the direct greenhouse warming; these are known as negative or positive feedbacks respectively.

We illustrate this with some examples. Firstly, as the atmosphere starts to warm due to the direct greenhouse effect, it can "hold" more water vapour — and models indicate that water vapour concentration increases to maintain time-averaged relative humidity (which also depends on temperature) approximately constant as climate change proceeds. As water vapour is a powerful greenhouse gas this effect will further increase warming — a positive feedback. Secondly, as the oceans start to warm some sea-ice will melt. Sea-ice reflects back a lot of solar radiation, but the open ocean it exposes when it melts absorbs more radiation; this will reinforce the original warming effect — another positive feedback. Thirdly, one of the most critical feedbacks, but also one of the most complex, is that due to changes in clouds. In the present climate, clouds have a large effect on climate; high clouds act to increase surface temperatures but low clouds tend to cool climate; the net effect is a cooling one. Greenhouse gas — driven climate change can alter many characteristics of clouds at all levels — their amount and altitude, and the properties of their constituent water droplets and ice crystals, for example. Such changes can alter the radiative properties of clouds — the effect they have on incoming solar radiation and outgoing long wave radiation — and the net effect could be either positive or negative. The last example is that of changes of land surface vegetation (from forests to grassland, for example, or desertification) due to changes in rainfall or temperature which in turn can alter local and global climate. There are many other feedbacks, both positive and negative, in different parts of the climate system.

Feedbacks naturally arise in the climate model because the processes which lead to them (in the second example above this is the formation of sea-ice and its reflectivity) are explicitly represented or parametrised. Many feedbacks take place at a small scale and capturing their overall effect in the model therefore depends upon the parametrisations of small scale processes. Hence the strength of the feedbacks, and thus future changes in climate, will depend on the form of the parametrisation used (part of the model structure), and the values of its constituent parameters. This is one of the main causes of the differences between projections from different models. The methodology developed for the UKCP09 projections is designed to sample these uncertainties, to the extent that this is presently possible, in a systematic way.

Biogeochemical cycles

The carbon cycle and the sulphur cycle represent two important processes in climate change, yet, as with standard processes in the atmosphere and oceans, they carry their own large uncertainties. Here we give an overview of the processes, the uncertainties, and how UKCP09 includes them in the final probabilistic projections; more detail resides in Chapter 3.

The carbon cycle

Currently about half of the emissions of CO_2 from human activities (fossil fuel combustion and land use change) are taken up by sinks on land (vegetation and soils) and in the ocean (seawater and ecosystems within it), leaving the remainder of the CO_2 in the atmosphere where it increases concentrations. But as climate starts to change, carbon sinks can also change, so may be able to absorb more, or less, CO_2 from the atmosphere. For example, as soils warm they increase their respiration of CO_2 back to the atmosphere and their ability to remove CO_2 will weaken, leading to atmospheric concentrations being higher than they would otherwise be — a positive feedback. On the other hand, a warmer climate will encourage the growth of boreal forests which would take up more CO_2 from the atmosphere — a negative feedback. There are a host of such feedbacks, both positive and negative, although the net effect is a positive one. Uncertainties in estimating atmospheric concentrations resulting from emissions were not dealt with in the IPCC Third Assessment Report (TAR) in 2001, and hence could not be taken into account in UKCIP02. In UKCP09 these feedbacks are included, and the uncertainty they add to climate change projections is estimated using two sources of information. Firstly, using variants of the Met Office coupled climate — carbon cycle model with different values for the land carbon cycle parameters within it. Secondly, using results from a project (known as C4MIP) which compared results from a number of international models which include the carbon cycle. Further detail is given in Chapter 3. Note that, although UKCP09 projections include the feedback from both land- and ocean-carbon cycle projections, they only include the effect of uncertainties in the feedback from land, which has been estimated (in C4MIP, see Friedlingstein *et al*. 2006) to be several times greater than that from the ocean component. Because the processes involved in climate — carbon cycle feedback are less well understood, and projections are less constrained by observations, our ability to assess the uncertainty in these is more limited than for other aspects of the climate system.

The sulphur cycle

Sulphur gases emitted from fossil fuel burning, and naturally from the oceans, takes part in chemical reactions in the atmosphere to form small particles — sulphate aerosol. These are eventually removed from the atmosphere by rain and clouds, having a typical lifetime of a few days, but whilst in the atmosphere they can have a substantial cooling effect on climate in a direct and an indirect way. The direct cooling effect arises when a suspension of aerosols in the clear atmosphere reflects back some of the incoming solar radiation before it has a chance to warm the ground. The indirect effect arises from the ability of sulphate particles to act as additional nuclei on which water vapour condenses to form clouds. Such clouds would therefore have more water droplets, each of which (for a given amount of available water) would be smaller — the total surface area would therefore be greater and the cloud would reflect back more solar radiation — a further cooling effect. Both the direct and indirect effects described above are included in the HadCM3 model.

A second indirect effect occurs within sulphate-laden clouds. Because their droplets are smaller than those in clean air, the processes which lead the droplets to grow heavy enough to form rain are slower, and hence the clouds persist (and reflect back solar radiation) longer — a further indirect cooling effect. This is a much more complex process, and is only now becoming understood well enough to be included in models (such as the Met Office earth system model, HadGEM1) but is not included in UKCP09. Because atmospheric sulphate burdens are expected to decline in the future, the omission of this effect may lead to an underestimate of changes in the first few decades of the UKCP09 projections.

Constituents included, and not included, in the probabilistic projections

The atmospheric constituents included in HadCM3, its corresponding simple-ocean configuration and the regional climate model, are shown in Table 2.1. With the exception of the cloud persistence effect of sulphate aerosols, the projected combined effect by 2100 of changes in those constituents not included is unlikely to add a significant amount to overall uncertainty. Similarly, although the Met Office model includes the effect of chemical reactions in the atmosphere which determine concentrations of methane and tropospheric (low altitude) ozone, no attempt was made to estimate the consequent uncertainty in concentrations; this would also be expected to have a minor effect. Uncertainty in the climate effect of northern hemisphere stratospheric ozone changes is also likely to be small relative to those quantified.

In contrast, other components of the methane cycle, such as climate-induced emissions from wetlands, melting permafrost and methane hydrates, do have the potential to modify future climate change significantly. However, these feedbacks are so poorly understood as to make estimates of their effect very uncertain, and hence they are not currently integrated into any climate model.

Constituent	Whether included
Carbon dioxide	Yes
Methane	Yes
Nitrous oxide	Yes
CFCs, PFCs, HFCs, HCFCs, SF6	Major ones
Tropospheric ozone	Yes
Stratospheric ozone	Yes
Sulphate aerosols — direct effect	Yes
Sulphate aerosols — cloud albedo effect	Yes
Sulphate aerosols — cloud persistence effect	No
Black carbon aerosol	No
Organic carbon aerosol	No
Mineral dust	No
Sea salt aerosol	No
Land cover (albedo effect)	No

Table 2.1: The atmospheric constituents included in the Met Office models used for UKCP09.

At a local scale, differences between projections are even more obvious. Figure 2.7 shows, as an example, projections of changes in summer precipitation over the UK from 12 climate models, for the same future time period and same emissions scenario. Rainfall over London shows a reduction of about 60% in the projection from one model, but a small increase in another. Note that, because Figure 2.7 shows only single projections — all that is available from most climate models — natural internal variability contributes to the differences between them.

A similar illustration of model differences was shown in UKCIP02. The differences now are no smaller than those shown 7 yr ago — in other words, there has been no apparent convergence of model projections, despite improvements in climate process representations in models made during this period. For this reason, we cannot assume that continuing model improvements will quickly lead to a narrowing of uncertainty in projections.

Figure 2.7: Changes (%) in summer (June–August) precipitation by the period 2071–2100 compared to 1961–1990, from 12 climate models, each of which took part in the IPCC AR4, all driven with the same SRES A2 emissions scenario.

Planners and decision-makers could, of course, use the range of projections such as those in Figure 2.7 as an estimate of the uncertainty which should be taken into account, and the UKCIP02 report recommended this course of action. Of more use to planners would be some indication of the relative credibility of each of the models, but systematic techniques for doing this are difficult to apply to such a small and diverse set of climate models. In UKCP09 we quantify the uncertainties in projections, giving information on the relative likelihood of different climate change outcomes, in the form of probabilistic projections. In this way, rather than give users a single projection of unknown likelihood, we can show the uncertainty in projections in the form of a probability distribution function or PDF. This shows us the relative probability of temperatures changes of, say 2°C or 3°C at a particular location by a certain time period. The interpretation of this probability is important and is discussed in Box 1.3 and Section 2.5. More usefully, it can be used to estimate the probability of a change being greater or less than some threshold. The method gives probabilities of changes in number of variables, both monthly means and some extremes. PDFs, and an alternative method of presenting the same information, the Cumulative Distribution Function (CDF), are explained in more detail in Box 1.3.

The requirement for probabilistic projections has been recognised by the climate modelling community for some time, and they have begun to develop methods based on projections that are available from a number of climate models – the so called *ensemble of opportunity* (Giorgi and Mearns, 2003; Dessai *et al*. 2005; Goodess *et al.* 2007; CSIRO and Bureau of Meteorology, 2007; Frei, 2007). However, whilst such an ensemble (as in Figure 2.7) is sufficient to demonstrate the requirement for probabilistic projections, it is not sufficient to fulfil it. This is because it is assembled on an ad-hoc basis, and has not been designed to sample modelling uncertainties in a systematic and comprehensive manner. The ensemble of opportunity in Figure 2.7 shows some range of projections, but does not indicate in which part of the range the outcome is likely to lie — it may even be outside the model range. We therefore base the UKCP09 on an alternative approach, which nevertheless uses the information from an international set of climate models, described in outline below and in more detail in Chapter 3.

2.3.1 Accounting for modelling uncertainty in UKCP09

As summarised earlier, uncertainties in model projections arise from an incomplete understanding of processes in the Earth's climate system, and an inadequate representation of these processes in climate models. These representations may be limited not only by physical knowledge but also by, for example, computing resources, and these lead to errors in models, which in turn lead to errors in projections. For convenience we group all these under the heading *modelling uncertainty*.

In UKCP09 we sample uncertainties in a range of processes in the atmosphere and at the surface, the carbon and sulphur cycles, and in the ocean. However, we recognise that uncertainties in atmospheric processes are likely to be the major contributor to overall uncertainty at a local level, and hence these are treated in the greatest detail in the UKCP09 methodology. The development of new techniques to sample atmospheric model errors, and hence account for their effects in driving uncertainty in future projections of climate, is a key aspect of the research underpinning UKCP09. In order to understand the approach, it is convenient to separate sources of model error into two types: structural error and parameter error. The UKCP09 approach seeks to sample uncertainties arising from both of these. In the first case, when building a model the modeller will make choices about its basic structure, such as the grid on which atmospheric or oceanic motions are resolved, the numerical integration scheme, the set of physical processes included, etc. Many important processes (such as those in clouds) occur on spatial scales too small to be resolved explicitly on the model grid, and therefore have to be represented in models using relationships with large scale variables which are resolved — so-called *sub-grid scale parametrisations*. The nature of the equations used for a given representation is an important component of its structure. Models containing different structural choices will possess different biases in their simulations of climate processes, and hence give different projections of change — this is the structural component of model error. In the second case, having chosen a particular parametrisation scheme to represent a given small scale process, the modeller has then to choose the values of parameters which control how the process operates in that scheme. These parameters are based on a mixture of theory, observations and experimentation, but the available information is seldom precise enough to allow the appropriate value of a given parameter to be accurately known — this gives rise to the parameter component of model error. This is discussed in rather more detail in Box 2.1.

We explore the effects of uncertainties in atmospheric and land model parameters controlling surface and atmospheric processes using one climate model – in this case the Met Office model HadSM3 (a configuration of HadCM3* having a simplified ocean, see Box 2.1). This is done by identifying parameters controlling the detailed processes likely to have the most effect on model projections. Several parameters are selected from each of the schemes in the model's atmosphere and land: layer cloud, convection, radiation, atmospheric dynamics, boundary layer, land surface and sea-ice. This covers uncertainties in the major aspects of the model's physics. Next we ask experts to define a range of plausible values, together with an intermediate estimate, for each of the uncertain parameters.

We then construct a large number (ensemble) of variants of the model, known as a *perturbed physics ensemble*, each of which contains a different choice of parameter values within these expert-specified bounds, and make a projection of climate change with each. As a first step, we can simply take this projection, for a particular quantity such as change in summer rainfall over some location, from each of the ensemble members and present these in the form of a distribution showing how frequently different outcomes occur — this is represented by the blue histogram in Figure 2.8.

In principle, we would build a different model variant with each possible combination of parameter values, but to make climate simulations with each of these variants would require an unfeasibly large amount of computing resources. Hence we chose a manageable number (280) of variants, to cover as comprehensive a range of outcomes as possible. However, the shape of the histogram in Figure 2.8 depends upon which combinations of parameter changes we choose. To predict the response for all the model variants that it was not possible to run, we build an *emulator* of model output, relating it statistically to the model parameters. This is trained on the model results we do have, and then used to estimate values of model output variables that would be obtained for any desired combination of parameter values. The distribution of projections

* HadCM3, the model used as the basis of the UKCP09 projections, was also used for the UKCIP02 scenarios. It might be thought that, six years on, a better model might have been used. However, a recent comparison of climate models with observations (Reichler and Kim, 2008) shows that HadCM3 ranked second out of 17 models compared in CMIP-2 in 2002, but still ranked joint second out of 21 models compared in the CMIP-3 comparison in 2007, where models were compared with a pre-industrial control climate. The most recent Met Office Hadley Centre model does compare somewhat better with observations, but its higher resolution would have drastically reduced the number of ensemble members which could have been run, and hence given a less-comprehensive estimate of uncertainty.

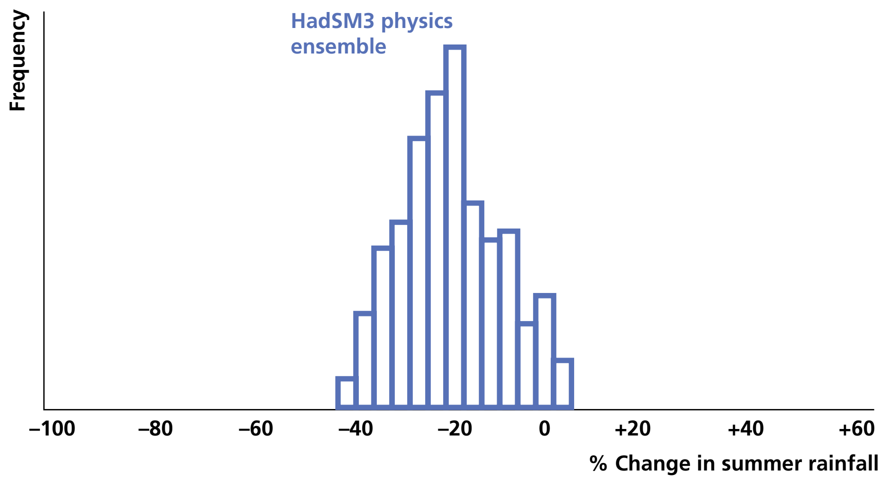


Figure 2.8: Hypothetical histogram showing the frequency of occurrence of different changes in summer rainfall from the 280-member perturbed physics ensemble of HadSM3.

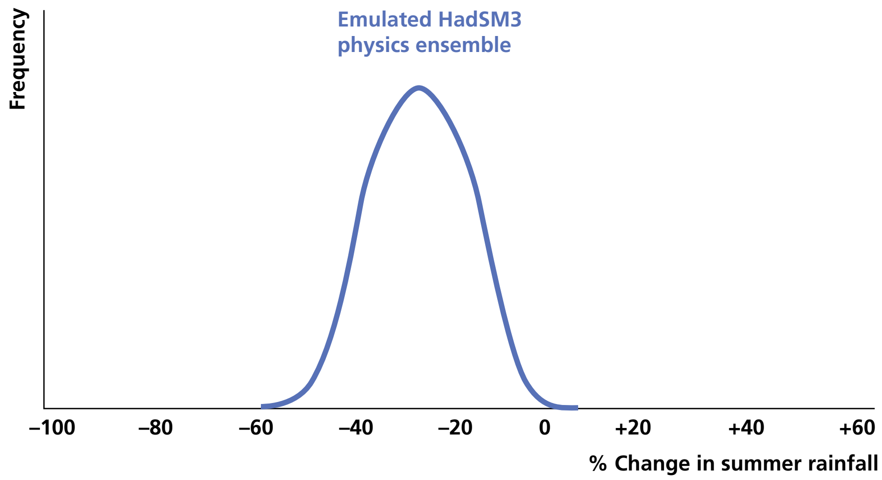


Figure 2.9: Hypothetical distribution showing the frequency of occurrence of different changes from the emulator.

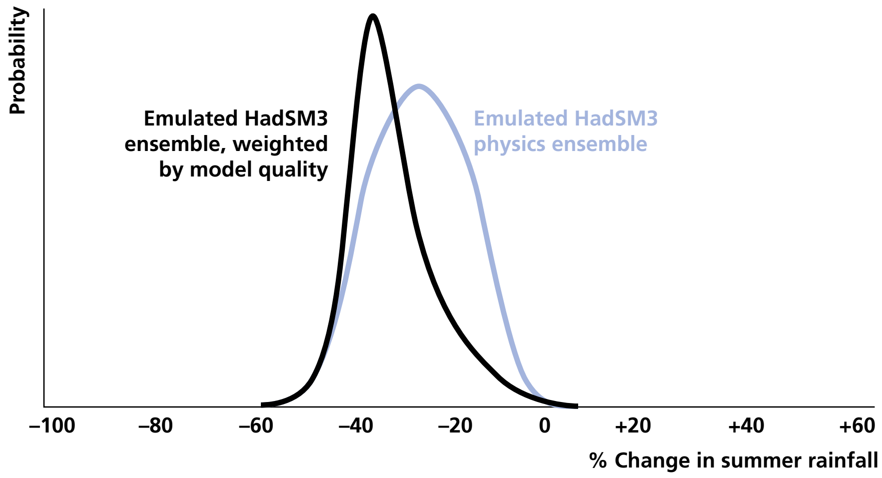


Figure 2.10: Hypothetical distribution showing the probability of different changes from the emulator, weighted according to model credibility based on observations (black curve).

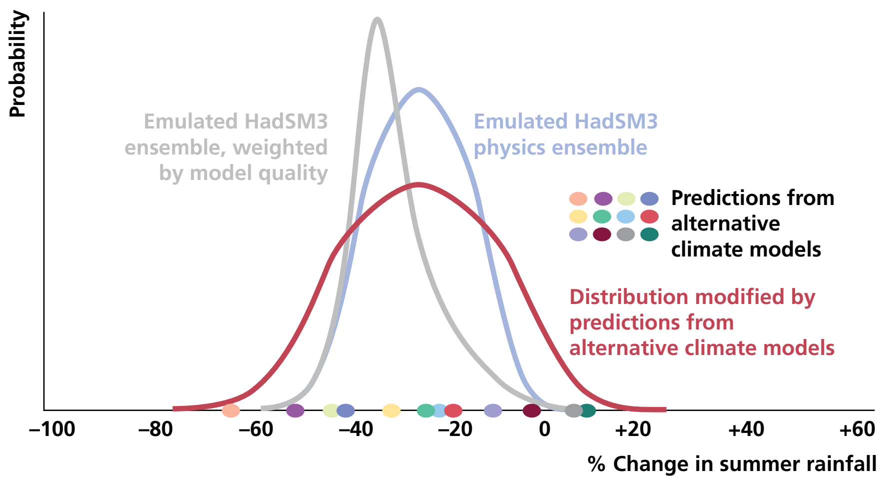


Figure 2.11: The hypothetical probability distribution function of change of summer rainfall (red curve), including projections from both the Met Office perturbed physics ensemble and from alternative international climate models.

from this is illustrated schematically by the blue curve in Figure 2.9, which can take a somewhat different shape from the histogram in Figure 2.8 because the former explores different combinations of parameter values.

Now the model variants will not all give rise to climate simulations of equal credibility, and hence their projections should not be given the same weight. We compare each model's simulation of a wide range of variables for recent climate against observations, and also how well each *hindcasts* large scale patterns of temperature change over the last 90 yr. We use both these pieces of information to weight the projection from each model; this allows us to generate a weighted distribution of outcomes — the black curve in Figure 2.10.*

So far, however, we have described how we use variants of one model to explore the effects of uncertainties in model parameters. However the presence of structural model biases, which cannot be resolved by varying parameters, gives an additional source of uncertainty in model simulations of both past and future climate. This affects both the weights to be assigned to different Met Office model variants, and the spread of possible future projections. We estimate the uncertainty due to these structural errors by using our perturbed physics ensemble to *predict* the results of an alternative set of twelve climate models (all of which have participated in intercomparison exercises such as IPCC AR4) which contain structural assumptions partly independent of those made in the Met Office model. Projections from each of these alternative models are indicated schematically by the coloured dots on Figure 2.11; note that each alternative model is represented by a single projection as no ensemble projections were available. Following IPCC AR4, we assume each of the alternative models has equal validity, bearing in mind that we could not weight the alternative models by re-using the observations employed in determining weights for Met Office model variants, as such double-counting would risk over-constraining our projections.

We assume that differences between the results of the *nearest* few variants of the Met Office model and each of these alternative models gives a reasonable sample of possible differences between the Met Office model and the real world, and hence modify our future projections to account for the resulting estimate of structural model error. These results are then incorporated into our uncertainty analysis, based on a statistical framework devised by Goldstein and Rougier (2004), discussed in Chapter 3. This allows us to create a probability distribution function accounting for uncertainties arising from both model parameters and structural errors, and constrained by observations, shown as the red curve in Figure 2.11.

The above description is an enormously simplified explanation of the methodology. As mentioned earlier, the large ensemble of about 280 members, described above, can only be run using a model configuration with a simple representation of the ocean (known as a slab model, see Box 2.1) which is suitable for the simulation of the long-term *equilibrium* response to an assumed doubling of carbon dioxide, but not for the simulation of time-dependent climate change. Hence additional time-dependent (that is, continuous from 1950 to 2099) simulations are undertaken using the model configuration with atmosphere coupled to a full dynamical ocean (HadCM3). The results from these experiments are used in a technique for matching equilibrium and time-dependent patterns of change so that the very large ensemble of projections using the slab model can be *timescaled*. Further simulations are also needed to sample uncertainties

* Note that in practice the methodology does not involve creation of an interim weighted distribution (as shown in Figure 2.10), prior to the addition of the effects of structural model error; the discussion is presented this way to emphasise the key inputs to the calculations.

arising from ocean transport, carbon cycle and sulphur cycle processes. Finally, to make the projections suitable for impacts and adaptation assessments, we use a further ensemble of the Met Office regional climate model (HadRM3) to *downscale* the projections from the global Met Office model to a resolution of 25 km. A more detailed description of the full methodology is given in Chapter 3. The methodology involves a number of expert choices (for example, the range of values taken for model parameters, and their distribution), the sensitivity to which needs to be tested to establish the robustness of the results. Examples of such sensitivity tests are given in Annex 2.

The relative size of the various contributing factors to the total uncertainty (and hence to the width of the PDF) will be different for different locations, time periods, type of spatial averaging, etc; this is discussed in Annex 2. Figure 2.12 shows two specific examples of the relative contributions, in the case of changes to mean winter precipitation by the 2080s under the Medium emissions scenario, for 25 km squares in south-west England and the west of Scotland. Here we have combined* the proportions of uncertainties due to model parameter values, model structure, the carbon cycle, aerosol physics and ocean physics, and termed this contribution *model uncertainty*. Natural internal variability (*chaos*) is labelled as natural variability. The remaining slice of the pie arises from the timescaling and downscaling procedures in the methodology described above. As can be seen, in these examples modelling uncertainty dominates the other contributions — although this is not true everywhere. A closer time period (the 2020s) would show a relatively bigger contribution from natural variability, and different choices of variables, locations and emissions scenarios would give different pie chart structures. Note that the uncertainty in emissions is not included; this is handled by giving different probability projections for each of three emissions scenarios as described later in this chapter.

The presentation of information in probabilistic terms, rather than giving users a single projection for a given emissions scenario, is a major change in the nature of climate change projections. Whilst they are undoubtedly more complicated to grasp conceptually, and their application in practice demands more of the user, probabilistic projections are a more honest way of representing the substantial uncertainties that are discussed above. Because it is so important to understand, we repeat here the point made in Chapter 1, that a probability given in UKCP09 is not the same as the probability of a given number arising in a game of chance, such as rolling dice. Instead, it is a measure of the degree to which a particular level of future climate change is consistent with the information (observations and model simulations) used in the analysis, that is, the evidence.

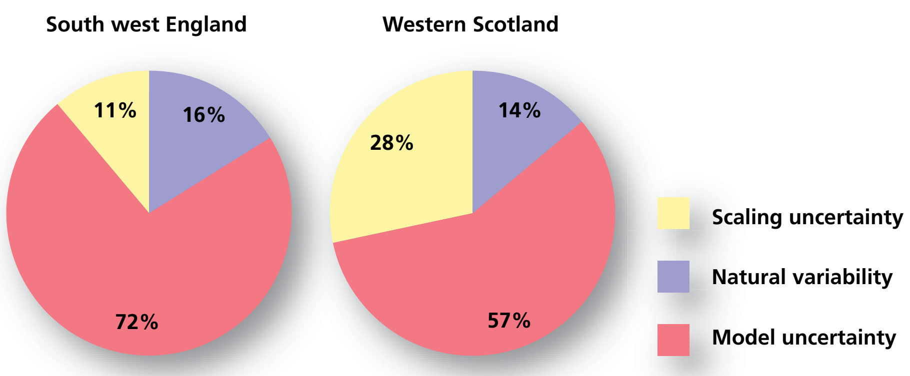


Figure 2.12: The relative contributions to overall uncertainty in change to winter-mean precipitation for 25 km squares in south west England (left) and west Scotland (right) by the 2080s under the Medium emissions scenario, from natural variability, modelling uncertainty and scaling uncertainty. (Contributions do not total 100% due to rounding errors.)

* Because of the way contributions are divided up in Annex 2, this aggregation is a close approximation to, but does not exactly cover, all the terms in model uncertainty.

2.4 Uncertainty due to future emissions

Previous UKCIP reports on climate change projections have discussed uncertainty due to future emissions, and this uncertainty continues to apply to the climate projections in this report. The pathway of future emissions of greenhouse gases (CO_2, methane, nitrous oxide, etc.) and aerosols (or aerosol precursor emissions such as sulphur dioxide) will depend upon many socioeconomic factors such as changes in population, GDP, and energy use, and in technical developments which might influence carbon intensity (the amount CO_2 per unit of energy generated). IPCC published a Special Report on Emissions Scenarios (SRES) (Nakićenović and Swart, 2000), in which climate-relevant emissions were calculated based on a number of *storylines*, each describing a possible pathway of how the world might develop. All scenarios are *non-interventionist*, that is they assume no political action to reduce emissions in order to mitigate climate change; differences between them arise purely from different assumptions about future socioeconomic changes.

There is no agreed method with which to assign a relative probability to different future emissions; SRES made it clear that no relative probability could be attached to different emissions scenarios, but neither were they to be assumed as equally probable (see Annex 1). (Strictly speaking, being scenarios, they have no probability.) This means that the uncertainty due to future emissions cannot be incorporated into a probabilistic projection. However, the uncertainty associated with future emissions is recognised in UKCP09 by giving probabilistic projections which correspond to each of three different emissions scenarios, High, Medium and Low. These scenarios correspond to three of the *marker scenarios* in SRES: A1FI, A1B and B1 respectively, as decided following consultation. This is a change from UKCIP02, where four emissions scenarios were used corresponding to SRES A1FI, A2, B2 and B1. Figure 2.13 shows emissions of CO_2 from the scenarios used in UKCIP02 and UKCP09. Each scenario also includes emissions of other greenhouse gases, and of sulphur dioxide which creates sulphate aerosols that cool climate. Although the three UKCP emissions scenarios span the range of marker scenarios in SRES, there are additional scenarios, both higher and lower, that they do not encompass.

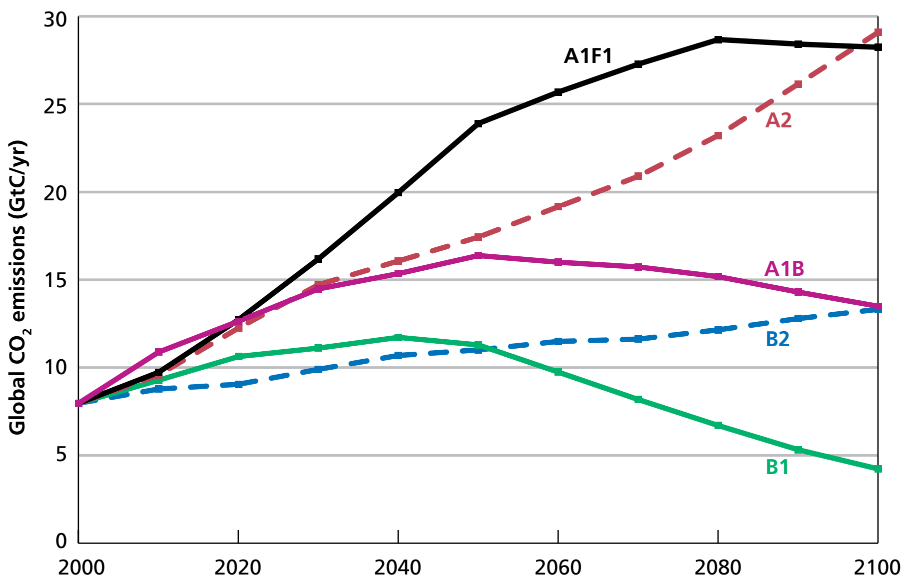


Figure 2.13: Global annual CO_2 emissions (expressed as gigatonnes of carbon) under the three IPCC SRES *marker* scenarios used in UKCP09: A1FI (black: High emissions), A1B (purple: Medium emissions) and B1 (green: Low emissions). Also shown dotted are two SRES emissions scenarios used in UKCIP02 but not in UKCP09: A2 (red: Medium-High Emissions) and B2 (blue: Medium-Low Emissions).

Additional uncertainties arise from the way in which the SRES emissions scenarios were developed, both in the underlying storylines of future changes in society, economies, technology, etc., and in the way in which the emissions are developed from the storylines. These uncertainties are considered here to be part of the overall uncertainty in future emissions.

More detail on the three SRES emissions scenarios, and the socioeconomic futures which underlie them, is given in Annex 1. Of course the question of how to handle results from the three projections from the different emissions scenarios in a risk assessment still remains an issue for users, and this is discussed in the User Guidance.

The differences in projections of global temperature over land which arises from different future emissions is illustrated in Figure 2.14, using the average of 17 variants of the HadCM3 model. Not surprisingly, the High emissions scenario results in the greatest warming by 2100, and the Low emissions scenario gives the smallest warming. But also evident is the relative insensitivity of warming to emissions scenario, over the period to about 2040. This is partly due to the smoothing effect of the long effective lifetime of CO_2 and the thermal inertia of the climate system, but also partly due to the offsetting effects of warming

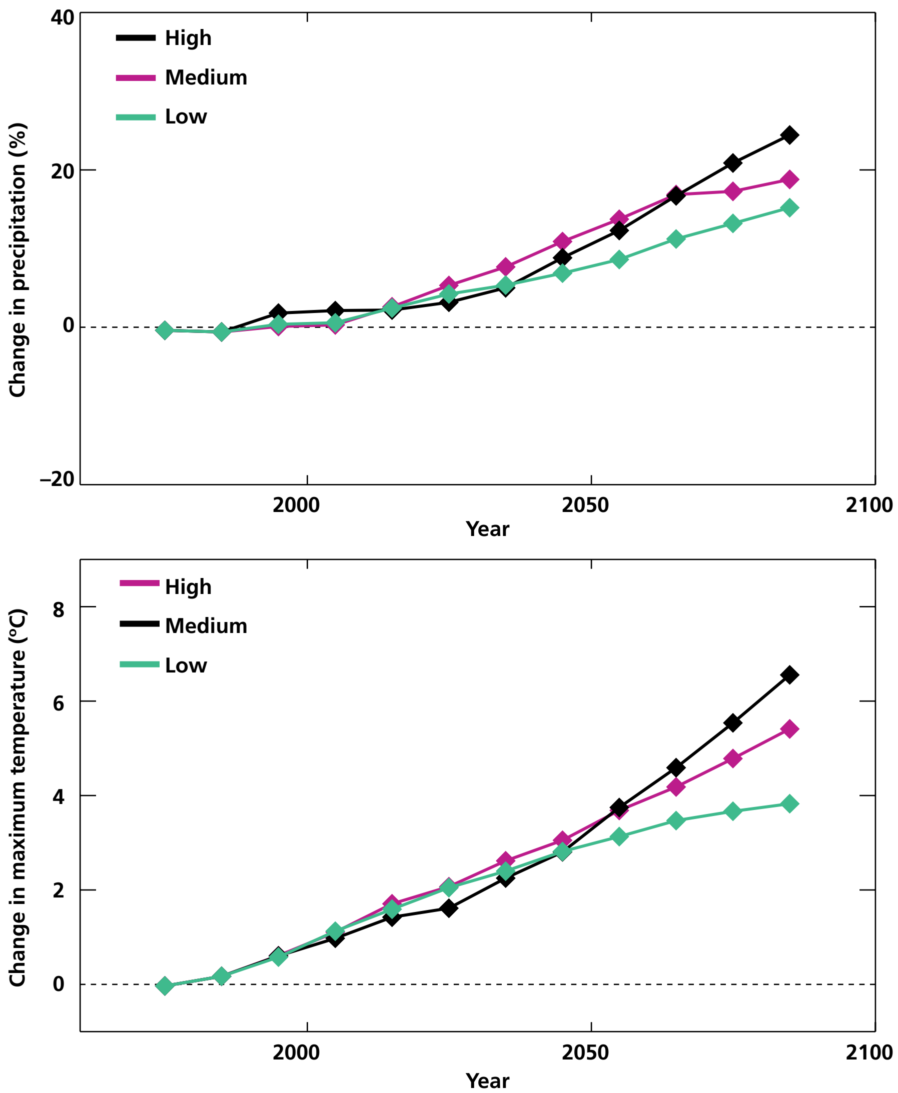


Figure 2.14 Changes in winter-mean precipitation (upper panel), and summer mean daily maximum temperature (lower panel) over Wales, averaged from 17 variants of the HadCM3 global model, for each of three different future emissions scenarios. (Because the purpose here is to show the relative insensitivity of climate change over the next few decades to emissions, the graphs do not reflect the uncertainties in future CO_2 concentrations which are taken into account in UKCP09.)

greenhouse gases and cooling sulphate aerosols in the scenarios. However, after the middle of the century, projections based on the three emissions scenarios become increasingly different.

2.5 Uncertainties in UKCP09 probabilistic projections and future prospects

The procedure used in UKCP09 to convert the ensembles of climate model simulations into probabilistic estimates of future climate necessitates a number of expert choices and assumptions (see Chapter 3 and Annex 2). This implies that the probabilities we specify are themselves uncertain. A system for projecting future climate (unlike one for short-range weather forecasting) cannot be verified on a large sample of past cases. Nevertheless it is possible to check whether or not our probabilistic estimates are robust to reasonable variations within these assumptions; results from some such sensitivity tests are shown in Annex 2.

Although it is important that prospective users understand the limitations and caveats, it is also worth emphasising that (a) current models are capable of simulating many aspects of global and regional climate with considerable skill (see Annex 3); and (b) they do capture, albeit imperfectly, all the major physical and biogeochemical processes known to be likely to exert a significant influence on global and regional climate over the next 100 yr or so.

As explained in the previous section, there are several components of uncertainty which contribute, in varying proportions, to the width of the PDF of change in a particular variable (for a given emissions scenario, location, etc.). These can be thought of as being in three categories:

- uncertainty due to natural variability
- statistical uncertainty inherent in the UKCP09 methodology
- modelling uncertainty (arising from our lack of understanding of the climate system and our inability to model it perfectly) — which includes the carbon cycle, sulphur aerosols and ocean heating.

In the conclusion to Annex 2 we explain how each of these could be reduced in future. By initialising models with recent climate, we should be able to reduce uncertainty due to natural variability, especially for the next 10–20 yr. For long term projections, natural variability represents an irreducible contribution to the overall uncertainty. Uncertainty in the statistical methodology could be reduced with a sizeable increase in computing power. Modelling uncertainty should reduce as our understanding of the climate system and our ability to represent it in climate models gets better, although history shows that this is likely to be slow.

The consequence of these expected improvements is that the shape of a given PDF is likely to change in the future. Users need to understand clearly that, if they choose to adapt to a climate change corresponding to a specific probability level, this is likely to change in future projections — and the changes are likely to be greater at the extremes of probability levels (that is, 10 and 90%). If our understanding of climate processes, and model representations of them, does not change substantially in future, then we foresee a general reduction in uncertainties (except that due to long-term natural variability) because of improvements in our ability to represent processes currently modelled and we would hence expect the shape of the PDF to change, with a reduction in its width. However, we do not know in what way this reduction in width will occur;

in particular it may not be towards what are the most likely values in UKCP09. Although we cannot say what the next generation of PDFs will look like, it is likely that the spread of plausible changes they would indicate would be encompassed by the corresponding PDFs shown in UKCP09. Thus, in the absence of any major change in model projections, users who are incorporating the probabilities given in UKCP09 into their decision making are likely to find that their decisions are robust to changes in the next generation of projections.

On the other hand, there is also the potential for uncertainties to become greater if processes not yet included, or included imperfectly, in the models turn out to exert a substantial influence on climate change. Less than a decade ago, for example, carbon cycle feedbacks were not included in models, yet these are now known not only to change the projections substantially but also to add significantly to the uncertainty in them — which is why they are included in UKCP09. Further such effects, for example, methane feedbacks from land and oceans or the dynamics of ice sheets, may be shown to be important in due course. Uncertainties could also widen if future (improved) models reveal that a process which is represented in the current generation of models, but with a common bias, turns out to exhibit a larger response to man-made forcing than current models suggest (see Box 2.1). However, the consistency between model simulations and observations of change over the last century provides some reassurance that any unknown processes are unlikely to change projections fundamentally, at least for the next few decades.

An obvious follow-up question is: should decisions be made now, based on UKCP09 projections, or should they be delayed in the hope that better projections will be available in a few years time? The risk of deferring a decision is something that can be assessed using the UKCP09 projections. How rapidly will climate projections change in the future? Although modellers have improved many aspects of their models over the past decade or so, the current range of changes over the UK (Figure 2.7) is not significantly narrower than that shown in UKCIP02. In practice, the prospects for better projections will depend on which aspects of future climate users are most interested in. The width of the PDFs in UKCP09 are substantial even for the next few decades, due mainly to natural variability, and grow larger through the century due to uncertainties in climate feedbacks. It may be possible to reduce short-term uncertainties with higher resolution models which may simulate better (for example) the North Atlantic storm track, and by starting model experiments with the recently observed state of the ocean. However, this may not improve projections of (say) changes in surface temperature a hundred years ahead; at these lead times improved projections would come from more faithful representations of climate feedbacks and the carbon cycle in models. Dialogue between decision makers and climate scientists, on the potential for emerging research to update projections, will be essential. However, we reiterate the key point made earlier that the UKCP09 methodology is designed to capture known uncertainties in the climate system built into the current generation of climate models, and is the most comprehensive approach to do so to date. The UKCP09 projections can make a useful contribution to assessing risks posed by future climate; they are appropriate for informing decisions on adaptation to long-term climate change which need to be taken on the basis of current knowledge, and the uncertainty quantified in them is likely to be a conservative estimate.

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3 Construction of probabilistic climate projections

The Met Office Hadley Centre has designed a methodology to provide probabilistic projections for UKCP09 which reflect major known uncertainties in relevant climate system processes. The method uses large ensembles of climate model projections, which are processed using advanced statistical methods to generate thousands of plausible climate outcomes, which are then weighted using historical observations.

This chapter provides a comprehensive review of the methodology used to construct the UKCP09 probabilistic projections, for readers requiring a more complete scientific insight into their basis. It is necessarily written assuming a higher level of scientific understanding than other chapters, although it does not seek to document each aspect of the method to the level of technical detail that would appear in a specialist journal paper. Published papers (cited below where relevant) are already available for some components of the method, and will be provided for remaining components in due course. A technical note will also be supplied after the launch of the projections (by October 2009, contingent on the demand for post-launch scientific advice from users), giving a mathematical description of the methodology to supplement the qualitative description given in this chapter.

Section 3.2 describes the elements of the method, and Section 3.3 provides a discussion of the nature, credibility and interpretation of the projections. A short, less technical summary of this material can also be found in Chapter 2, Section 2.2.

3.1 Introduction

It is clear from Chapters 1 and 2 that future climate over the UK (and elsewhere) will be influenced by an array of factors. Some of these affect external forcing of climate through changes to the Earth's radiation balance resulting from natural changes (e.g. volcanic eruptions or variations in solar output) or man-made changes (emissions of greenhouse gases, aerosols and their precursors), while others affect physical and biogeochemical feedback processes which enhance or reduce the response to this forcing. In addition, internal climate variability exerts a significant influence on climate, in addition to the effects of forced changes. All of these factors introduce uncertainty into projections of future climate because none of them can be predicted perfectly. This is due, in general, to imperfect knowledge of either the detailed behaviour or the current observed states of the relevant systems.

We currently have no agreed method of quantifying the relative likelihood of alternative pathways for future man-made emissions (Section 2.4). For UKCP09, we therefore focus on the task of estimating distributions of future changes in climate for each of three specific emissions scenarios (SRES A1FI, A1B and B1, explained in Section 2.4 and Annex 1, and referred to elsewhere in UKCP09 as High, Medium and Low). These scenarios assume no future changes in natural external forcing, apart from a prescribed repetition of the 11-yr cycle of solar insolation based on past observations. Regional climate changes in response to these emissions will be determined by complex interactions between a number of Earth System processes, plausible projections of which require the use of detailed three-dimensional global climate models (GCMs). As discussed in Section 2.3, ensemble approaches provide an obvious method of exploring the uncertainties associated with GCM projections. Multimodel ensembles (MMEs, e.g. Meehl *et al*. 2005), constructed by pooling projections from alternative GCMs developed at different modelling centres, provide a valuable indication of the range of possible future changes. However, stakeholders faced with climate-sensitive policy and adaptation decisions will typically require more than a simple specification of a possible range (Pittock *et al*. 2001). This is widely recognised in the climate science community, and consequently methods have been suggested to derive probability distributions for regional changes from MME results (e.g. Tebaldi *et al*. 2005; Greene *et al*. 2006; Furrer *et al*. 2007; Watterson, 2008), giving estimates of the relative probability of different future outcomes within the envelope of possible changes. Motivations for such approaches stem from results showing that combining projections from different models can increase the skill of historical climate simulations (e.g. Reichler and Kim, 2008) or seasonal forecasts (e.g. Hagedorn *et al*. 2005), because the errors in different models are partially independent. Furthermore, the models are assembled from a large pool of alternative components, thus sampling to some extent the effects of variations in basic structural assumptions such as choice of model grid, numerical integration scheme or the fundamental physical assumptions employed in the parameterisation of sub-grid scale processes such as convection, boundary layer transports, cloud and precipitation formation, etc. (see Box 2.1). However, multi-model ensembles are rather small in size, consisting typically of 10–20 models, some of which might be run several times from different initial states. Also, the set of models is assembled on an opportunity basis, not being designed to sample systematically some underlying space of possible model formulations (Allen and Stainforth, 2002). This creates the need for substantial assumptions in converting their results into estimated probabilities for climate change, essentially because it is not clear how to identify a distribution of possible outcomes of which the MME is a sample. Different studies address this issue in different ways, and therefore generate significantly different results (see Tebaldi and Knutti, 2007).

Another issue is that probabilistic projections are conditional on the set of uncertainties sampled in the ensemble simulations. In order to provide a credible basis for decision making, a critical prerequisite is that these are designed to sample all sources of uncertainty known to be likely to exert a significant influence on climate over the time frame of interest (here, the 21st century). For a given scenario of future emissions, these would include internal climate variability and uncertainties in atmospheric and oceanic processes, which give rise to different realisations of 21st century climate in the latest MME produced for the IPCC AR4 (Figure 2.5). However additional sources of uncertainty, notably carbon cycle feedbacks (Box 2.1) and the uncertainty in downscaling GCM simulations to local scales, also need to be considered. In order to produce probabilistic projections for UKCP09, we have therefore developed a new approach aimed at sampling the key uncertainties systematically, using a purpose-built set of ensemble simulations involving several different configurations of the HadCM3 climate model.

The method is based on the notion of the *perturbed physics ensemble* (PPE), in which alternative variants of a single GCM are created by altering the values of uncertain model parameters (Murphy *et al*. 2004; Stainforth *et al*. 2005). These parameters control important small scale processes in the model (such as the formation and precipitation of cloud droplets, the reflectivity of sea ice or the transfer of heat, moisture or momentum between the surface and the atmosphere), and are uncertain because we lack sufficiently detailed observations or sufficiently precise theoretical understanding to constrain their values accurately. A major advantage is that PPEs can be designed to ensure that all the key process uncertainties are sampled in a manner consistent with current scientific understanding. This is achieved by asking experts to identify which model parameters control the key processes, and then to specify distributions for the chosen parameters, consistent with the present state of knowledge concerning the identified processes. We can then construct a set of ensemble runs which select alternative values of the parameters drawn from these distributions, ensuring that the relevant uncertainties are well sampled.

The PPE approach therefore facilitates the construction of probabilistic projections consistent with current understanding of model uncertainties (Section 3.3), and it is also possible to test the sensitivity of the results to reasonable variations in the definition of the *space of possible model variants* implied by the specified distributions for model parameters (see Annex 2). However, the model on which the PPE is based (in our case HadCM3) will inevitably contain some structural errors in its physical representation of the real climate system, which cannot be resolved by varying the model parameters (Murphy *et al*. 2004). These structural errors determine how informative the model simulations are about the real system, so it is critical to account for the additional uncertainty implied by their presence (Goldstein and Rougier, 2004). We address this by using our PPE results to *predict* the results of members of a multimodel ensemble developed at other modelling centres, and containing structural assumptions partially independent of HadCM3. This allows us to estimate the effects of structural errors (subject to assumptions discussed in Section 3.2.8), and to present probabilistic projections which combine information from both perturbed physics and multi-model ensemble results.

The methodology is described in Section 3.2, this being a somewhat abridged (though also updated) version of that given by Murphy *et al*. (2007). Section 3.3 provides a brief summary of key strengths and limitations of our approach, and a discussion of how the probabilistic climate change estimates it provides for UKCP09 should be interpreted by users. The robustness of these estimates to plausible variations in key assumptions is discussed in Annex 2.

3.2 Methodology

3.2.1 Overview

The method is based on a general statistical framework for the derivation of probabilistic projections of real systems from simulations carried out using complex but imperfect models of those systems (Goldstein and Rougier, 2004; Rougier, 2007). The approach is Bayesian in nature, seeking to estimate the relative credibility of different future outcomes by updating subjective estimates of uncertainty specified before the experiments with evidence from observations. This is achieved by first defining a space of possible variants of the model (through distributions for model parameters consistent with expert knowledge — see Section 3.1), and then estimating the historical and future climate that the model would give if we could afford to run it at every point within its parameter space. Then we integrate over the parameter space, weighting the projection of future climate at each location according to (a) how likely each combination of parameter values was thought to be before the model simulations were carried out (*prior* information), and (b) the relative likelihood that each point in parameter space gives a true representation of the real climate system (*posterior* information obtained from estimates of how well the model simulates historical climate in practice). This procedure yields probabilities for different outcomes of future climate which are determined by a combination of the complex interactions between physical and biogeochemical processes built into the climate model, expert judgements, structural modelling errors and observational constraints. The interpretation of these probabilities is discussed further in Section 3.3.

Sections 3.2.2–3.2.12 set out a general method for provision of climate projections in any part of the world, at spatial scales skilfully resolved by global climate models (typically regions of approximately 10^6 km^2 or larger, though this is subject to tests of the validity of its key assumptions as applied in specific regions). However the provision of detailed spatial information for UKCP09 also relies on the addition of a downscaling procedure based on high resolution regional climate model simulations, described in Section 3.2.11. The project was allocated considerable computing resources; however these were inevitably finite, so the methodology relies on judgements regarding how best to deploy these to address the main uncertainties. Assumptions and limitations arising from these choices are highlighted in the following sub-sections.

3.2.2 Process uncertainties

The first task is to define the set of Earth System processes likely to contribute significant uncertainty in 21st century climate (see Box 2.1). These would clearly include surface and atmospheric physical processes (for example water vapour, cloud, surface albedo and soil moisture feedbacks continue to be recognised as key determinants of global and/or regional climate change (Bony *et al.* 2006; Soden and Held, 2006)). However, other components are also likely to be important. Changes in ocean heat transport have potential to influence both global and regional changes (Raper *et al*. 2002; Boer and Yu, 2003), while imperfect knowledge of the radiative forcing due to sulphate aerosols (Anderson *et al*. 2003) is recognised as a significant source of uncertainty, both in determining recent observed climate change and in predicting future changes (Andreae *et al*. 2005). Uncertainties in the fraction of man-made carbon dioxide emissions likely to remain in the atmosphere (due in particular to terrestrial carbon cycle feedbacks) have also emerged as an important source of divergence in future projections by different models, particularly in changes expected during the second half of the 21st century (Cox *et al*. 2000; Friedlingstein *et al*. 2006). We therefore designed our ensemble experiments to sample uncertainties in the atmosphere, ocean, sulphur cycle and terrestrial carbon cycle modules available in the family of HadCM3 components. This covers the major known sources of uncertainty in climate change out to a century or so ahead. Inevitably, however, limitations of computational resource, modelling capability and current understanding imply that some additional drivers of climate change have to be omitted, or included without sampling of the associated uncertainty. For example, our carbon cycle simulations account for feedbacks associated with ocean as well as terrestrial carbon uptake; however, uncertainties in processes affecting oceanic uptake are not sampled (see Section 3.2.5). Our simulations do not include forcing from carbonaceous aerosols (e.g. Jones *et al*. 2005), non-aerosol atmospheric chemistry (e.g. Johnson *et al*. 2001) or methane cycle feedbacks (Christensen *et al*. 2004; Archer and Buffett, 2005). The sampling of sulphur cycle feedbacks omits the *second indirect effect* arising from the effects of reduced cloud droplet size on precipitation efficiency, and hence cloud persistence, as this process is not included in HadCM3, or indeed in most current climate models (see Table 10.1 of Meehl *et al*. 2007)

Designing ensemble climate projections given finite computing resources

The standard approach to modelling time-dependent climate changes involves simulations which run from pre-industrial conditions up to the end of the period of interest (say from 1860–2100), specifying observed time-dependent changes in external forcing agents (typically man-made changes in greenhouse gases and aerosol precursors, and natural variations arising from solar variability and volcanic eruptions) up to present day, switching to some future scenario of man-made forcings to 2100. The ideal method of sampling modelling uncertainties would be to run a very large ensemble of such *transient* climate change simulations, in which all the relevant Earth System modules (atmosphere, ocean, sulphur and carbon cycle) are coupled together dynamically, and in which different ensemble members sample multiple perturbations to uncertain parameters in all modules simultaneously, in such a way as to ensure comprehensive coverage of the entire parameter space of each module. Such an experiment would ensure that non-linear interactions between all uncertain processes in all modules were thoroughly sampled. Unfortunately, such an experiment is well beyond the available computing resources, so compromises have to be made based on expert judgement of the relative importance of different sources of uncertainty.

Figure 3.1: Elements of our methodology to sample modelling uncertainties using perturbed physics ensembles (PPEs) based on configurations of the HadCM3 climate model. Blue boxes denote ensemble simulations using various model configurations derived from HadCM3. Yellow boxes denote statistical tools required to generate alternative estimates of climate change which combine the sources of uncertainty sampled in the various ensemble experiments. Boxes A and B are described in Section 3.2.3. Boxes C, D and E are explained in Sections 3.2.4, 3.2.5 and 3.2.11 respectively. Boxes F and G represent our timescaling procedure for deriving very large ensembles of realisations of time-dependent climate change from smaller ensembles of climate model simulations, covered in Sections 3.2.4 and 3.2.6. Box H denotes our downscaling procedure (see Section 3.2.11) for the generation of probabilistic projections at the 25 km resolution required for UKCP09, derived from information at larger scales obtained from global climate model simulations.

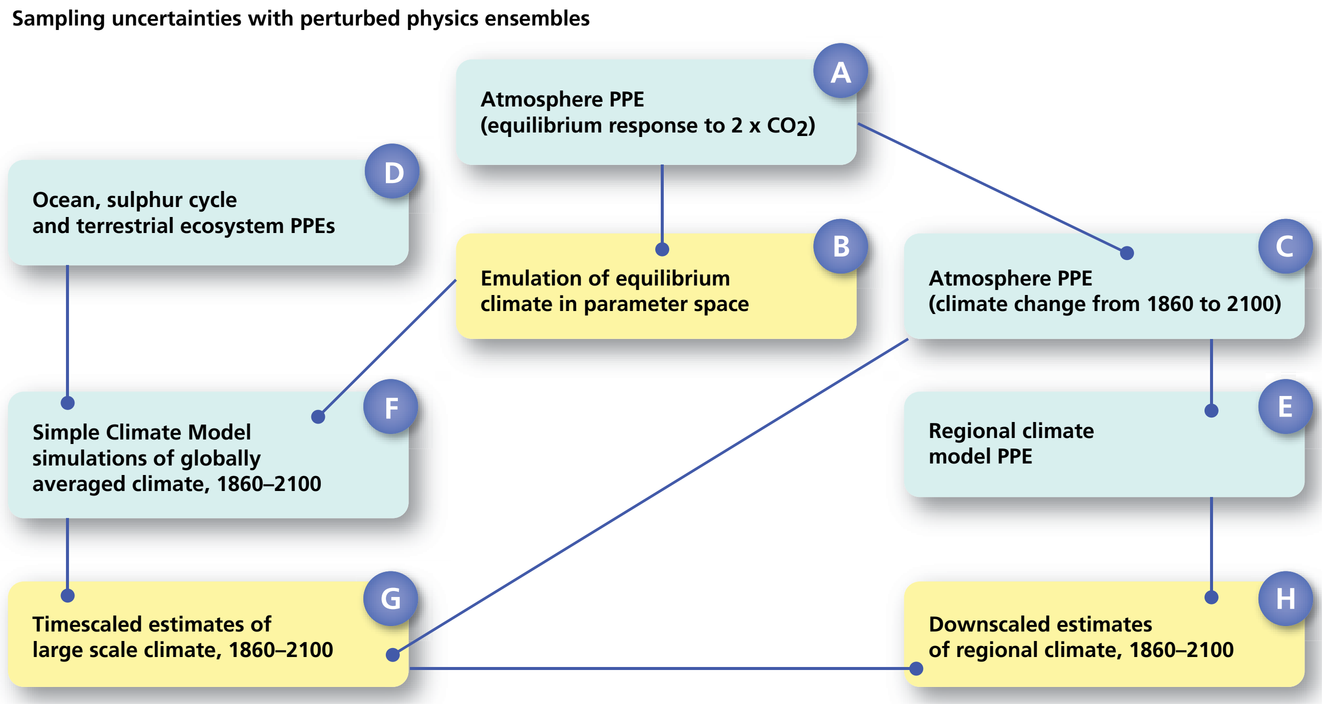


Figure 3.1 gives a schematic summary of the major components of our strategy for sampling modelling uncertainties, through the combination of a number of ensemble climate projection experiments. These experiments use several model configurations derived from HadCM3 to sample uncertainties in climate change during the 21st century, and are described below in Sections 3.2.3–3.2.6, and 3.2.11.

3.2.3 Sampling uncertainties in surface and atmospheric processes

Based on the assessment that surface and atmospheric feedbacks are likely to provide the largest source of uncertainty in regional changes during the coming century, we focus our resources on sampling the parameter space of these processes more comprehensively than those of the ocean, sulphur cycle or carbon cycle modules. The atmosphere module of HadCM3, which also includes land surface processes and surface–atmosphere exchanges, contains 100 or more parameters controlling the model parameterisations of small scale processes (which cannot be resolved explicitly on the model grid) in terms of grid box variables. It would not be computationally feasible to explore the combined effects of perturbing all these parameters, and in any case some parameters exert a much more significant influence than others on the simulated outputs of the model. Parameterisation experts were therefore asked to identify a subset of these which control the main processes most important for the simulation of (both global and regional) climate, and then to estimate plausible minimum, intermediate and maximum values (accepting that, in general, there would be insufficient evidence to provide a unique specification of the likely distribution of parameter values between the minimum and maximum values). This exercise resulted in a subset of 31 key parameters for perturbation. We assume that neglect of possible perturbations to additional parameters does not significantly affect the spread of model behaviour generated from our simulations.

Simulations of equilibrium climate changes in response to doubled CO_2

A large ensemble of (at minimum) a few hundred members is required to provide a reasonable first-order estimate of how the model behaviour varies within this 31-dimensional space, given that both the linear effects of each parameter (Murphy *et al*. 2004), and non-linear interactions between them (Stainforth *et al*. 2005), can have important influences on the model simulations. Resource limitations prevented us from undertaking ensembles of transient climate change simulations of this size, so the required large ensemble was run using a computationally less demanding model configuration (HadSM3) in which the atmosphere module is coupled to a simple thermodynamic model of the near-surface ocean, which warms or cools in response to surface heat exchanges with the atmosphere, and in which horizontal and vertical transport within the ocean is prescribed. Such a model configuration is widely accepted as a suitable set-up for the simulation of equilibrium climate changes, including the climate sensitivity, a standard benchmark of climate change defined as the global mean equilibrium response of surface temperature to doubled carbon dioxide. However, this simplified approach neglects climate change feedbacks involving changes in regional ocean heat transport (Boer and Yu, 2003), and implies the need for a method of converting simulated equilibrium changes into corresponding estimates of transient climate change. This conversion relies on the assumption that a reasonable relationship exists between patterns of time-dependent and equilibrium climate changes in response to increasing greenhouse gas concentrations. Harris *et al.* (2006) find a close relationship for multiyear averages of surface temperature changes, whereas for precipitation the degree of correspondence varies significantly with location, though it is quite good for the UK and Europe. Note, however, that our conversion method (described in

Section 3.2.4) also accounts for random and systematic differences between simulated patterns of time-dependent and equilibrium changes.

An ensemble of 280 HadSM3 experiments was run, sampling the effects of perturbing these parameters relative to the settings used in the standard published variant of HadCM3 (Gordon *et al*. 2000). These settings are referred to hereafter as the *standard* parameter values, though a number of these values actually correspond to extremes of the ranges identified by experts, due to the practice of *tuning* the model to improve its simulation of certain basic aspects of climate, such as the planetary radiation balance. Each experiment consisted of a *control* simulation of recent climate, and a simulation of the response to a doubled carbon dioxide concentration, run for a sufficient length of time to allow the resulting climate change to reach equilibrium. Murphy *et al.* (2004) carried out an initial ensemble of 53 members in which one parameter was perturbed at a time. This was subsequently augmented by a second ensemble of 128 members containing multiple parameter perturbations chosen to sample a wide range of climate sensitivities, achieve skilful simulations of present climate and maximise coverage of parameter space (details in Webb *et al*. 2006). Further HadSM3 simulations were then run to achieve improved sampling of parts of parameter space influenced by key interactions between parameters (Rougier *et al*. 2008). Together, these ensembles provide the 280 simulations used in UKCP09.

Emulation of equilibrium climate changes in response to doubled CO_2

This set of simulations is sufficient to sample the main effects of parameter variations within our 31-dimensional space, but not to cover it comprehensively. We therefore use a statistical tool called an emulator (e.g. Rougier *et al*. 2008), to help us estimate the values of the required set of climate variables at any given point in parameter space. The emulator is trained on the available GCM simulations to estimate the results of a set of historical and future climate variables required in the production of our probabilistic projections. Each climate variable is emulated using an equation which provides a best estimate value and associated errors for any combination of model parameter values. This is done by using the available GCM simulations to train multiple regression relationships which express the required climate variables as functions of the model parameters, where the set of regressors capture key interactions between the effects of different parameters, as well as the effects of each parameter in isolation. Emulation errors are guaranteed to be greater than or equal to internal climate variability, and are typically 20–50% larger.

Using the emulator, we are then in a position to integrate over the whole of our parameter space, estimating values of both historical climate variables (required to weight each location according to how well the GCM would simulate historical climate given that particular combination of parameter settings), and future climate changes. This integration allows us to estimate observationally constrained probabilities for different changes, accounting for model uncertainties. It provides the bedrock of our approach to probabilistic projection; however, a number of additional elements are required to convert the results into user-relevant estimates of climate change for specific 21st century periods, and to ensure that additional sources of uncertainty are included. These are described in Sections 3.2.4–3.2.11. Several aspects of the methodology (in addition to the emulation stage described here) require the estimation of uncertainties from the residual errors of statistical regression or optimisation procedures. These statistical errors are assumed to be Gaussian, and they are all included in the uncertainty expressed in the projections. In view of this, several of the UKCP variables are transformed prior to the calculation of projected changes, the inverse transformation being applied afterwards to recover projected changes in the original variables. These transformations are made either to reduce the risk of non-Gaussian error characteristics, or to ensure that absolute bounds in some of the projection variables cannot be exceeded by the addition of several sources of statistical error. In particular, this ensures that variables presented as percentage changes relative to the UKCP baseline period cannot go beyond –100%.

3.2.4 Sampling uncertainties in transient climate change

The experiments described in Section 3.2.3 provide estimates of the equilibrium climate change in response to doubled carbon dioxide, which must be converted into estimates of 21st century changes. This is done by running a smaller ensemble of simulations of transient climate change, in which the atmosphere module is coupled to the full three-dimensional ocean module of HadCM3, which simulates horizontal and vertical transport processes dynamically. The configuration of HadCM3 for these experiments is as described by Gordon *et al*. (2000), except that the representation of the atmospheric sulphur cycle is upgraded to use the fully interactive module of Jones *et al*. (2001), thus avoiding the need to approximate the effect of sulphate aerosol on cloud albedo using an offline calculation (Johns *et al*. 2003).

The approach involves a 17 member ensemble (PPE_A1B) which samples a subset of the atmospheric module parameter combinations used in the larger HadSM3 ensemble described above. One member used the standard HadCM3 parameter settings, the sixteen additional members using combinations of perturbed settings chosen to sample a wide range of climate sensitivities, while also sampling a wide range of alternative parameter values and providing credible simulations of historical climate. Flux adjustments are used to limit simulation biases in sea

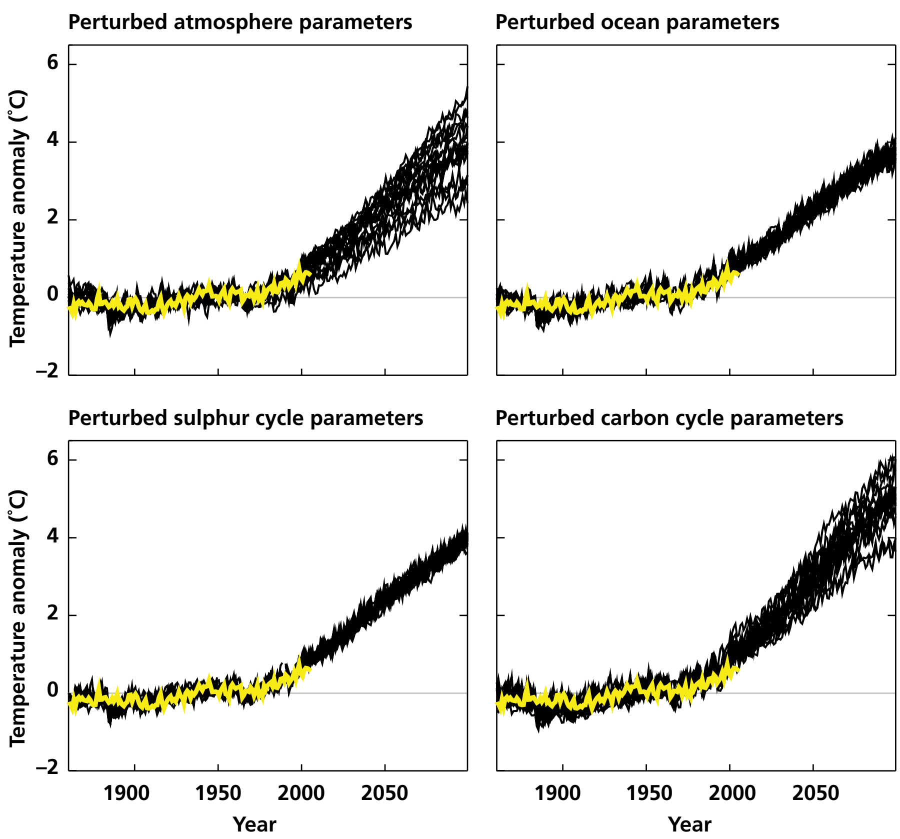


Figure 3.2: Global, annual mean 1.5 m temperature anomalies (°C) from different perturbed physics ensembles of time-dependent climate change under SRES A1B emissions, from 1860 to 2100. Anomalies are expressed with respect to the 1860–2000 mean. Each plot shows observations in yellow, with ensemble projections in black. Top left: Ensemble PPE_A1B, sampling perturbations to atmosphere model parameters. Top right: Ensemble with perturbations to ocean model parameters. Bottom left: Ensemble with perturbations to sulphur cycle parameters. Bottom right: Ensemble with perturbations to terrestrial ecosystem (carbon cycle) parameters.

surface temperature and salinity. The sampling of parameter space and climate sensitivity, and the calculation of flux adjustments, was based on (but updated from) an earlier PPE of HadCM3 variants described by Collins *et al.* (2006). Perturbed model variants in PPE_A1B give global simulations of historical climate of comparable quality to the standard model variant, as was also found in the Collins *et al* (2006) experiment; however, improvements to the flux adjustment technique in PPE_A1B removed biases in sea surface temperature and salinity found in the North Atlantic and Arctic Oceans in the simulations of Collins *et al*. By reducing regional systematic errors the flux adjustment process helps to ensure that the ensemble projects credible regional climate changes, and it also allows the effects of parameter perturbations on the transient response to be explored without being excessively constrained by the need to achieve precise balance in the planetary radiation budget. The simulations were started in the year 1860, and driven up to 2000 by historical time series of concentrations of greenhouse gases (carbon dioxide, methane, nitrous oxide, chlorofluorocarbons and ozone), sulphur emissions, and reconstructions of variations in solar activity and volcanic aerosol. From 2000 to 2100 they were driven by future concentrations of greenhouse gases and sulphur emissions from the SRES A1B scenario. The results show a substantial spread in projections of future global temperature rise (Figure 3.2). Here, and in Sections 3.2.5–3.2.12 we describe the entire methodology as applied in the case of the A1B scenario. Extensions to cover the A1FI and B1 scenarios are summarised in Section 3.2.13.

Estimating transient changes from equilibrium changes using timescaling

While these 17 transient simulations provide a limited sample of direct realisations of time-dependent climate change, our methodology requires that we estimate the time-dependent response from any point in the model parameter space referred to above. This is achieved by developing relationships between the equilibrium response of HadSM3, and the transient response of HadCM3, using the PPE_A1B HadCM3 simulations and the 17 member subset of the larger HadSM3 ensemble containing corresponding parameter perturbations to the PPE_A1B members. Once calibrated, these relationships can then be used to estimate the regional transient response of relevant climate variables (see Table 1.1) that would be obtained with any desired combination of parameter settings, thus providing the basis for the generation of probabilities for regional, time-dependent climate change through the integration over model parameter space referred to above.

The method, which we term *timescaling*, has been developed from earlier work by Harris *et al.* (2006): It involves normalising the regional equilibrium response of HadSM3 simulations by their climate sensitivities, and then scaling the normalised response according to the transient response of global average surface temperature, which is simulated using a simple climate model tuned to the climate sensitivity of the relevant ensemble member. The simple model is based on that of Rowntree (1998) and simulates globally-averaged land and ocean surface temperatures in response to imposed radiative forcing anomalies, representing vertical heat transfer in the ocean via a globally averaged heat diffusion equation, modified to include upwelling and downwelling following Schlesinger *et al*. (1997). This procedure provides time-dependent estimates of regional climate change, which are modified by a correction term (also scaled according to global mean temperature) which allows for differences between the characteristic patterns of equilibrium and transient climate change arising from the effects of oceanic thermal inertia and changes in ocean circulation. In principle the correction term is liable to depend on the values of the model parameters; however, we neglect such dependencies as we do not possess enough transient HadCM3 simulations to quantify them robustly. Also, this approach will not be able to replicate time-dependent responses which are non-linearly related to changes in global mean temperature, for example over northern Australia, where precipitation initially increases with global temperature in our perturbed physics simulations, but later reduces as the global response becomes larger (Harris *et al*. 2006). Over the UK, we do not see evidence of substantial non-linearities of this nature. However the method does include an error term which captures bias and uncertainty in our timescaled estimates of regional changes. This adjusts the projections to allow for the estimated effects of errors associated with our assumption in that the transient response is linearly related to global temperature, and also accounts for the effects of internal climate variability, errors in our simple climate model projections of the global temperature response found in HadCM3 simulations, and our assumption that the correction term is invariant across parameter space. It is assumed to take the form of a Gaussian distribution, noting that some variables are transformed to ensure that this assumption is reasonable (see Section 3.2.3). The time-dependent means and variances of these distributions are calculated by using the PPE_A1B simulations to verify timescaled estimates derived from equilibrium changes simulated by HadSM3 ensemble members containing corresponding sets of parameter perturbations. The correction term is also obtained in this fashion.

The timescaling process is illustrated by Figure 3.3(a), which shows projections of summer temperature changes over the global climate model grid box corresponding to Wales from the 17 HadCM3 projections (left panel), compared against corresponding timescaled projections (right panel). The coloured lines in the right panel represent projections obtained by scaling the relevant HadSM3 equilibrium responses according to global mean temperature, and adding the correction term accounting for differences between the characteristic patterns of equilibrium and transient climate change (see above). These lines can be interpreted as estimates of the forced transient component of climate change, in the absence of non-linear dependencies of the forced response on global mean

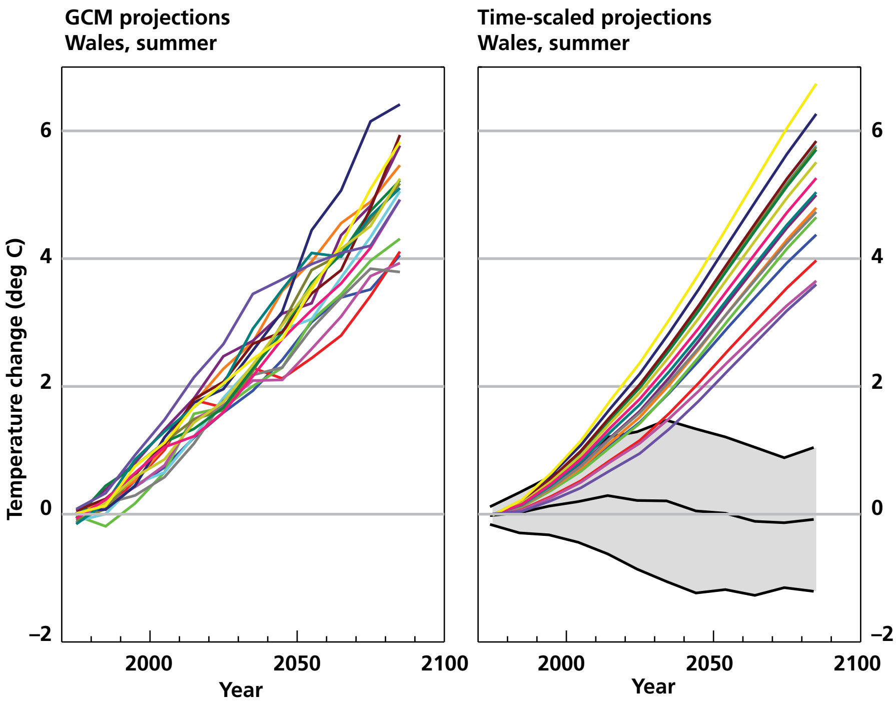


Figure 3.3(a): Left panel shows projected changes in 30-yr averages of surface temperature (°C) relative to 1961–1990 over the global climate model grid box corresponding to Wales, in summer, for the 17 members of the PPE_A1B ensemble of perturbed HadCM3 variants. Right panel shows estimates of the changes derived from the timescaling procedure described in the text (coloured lines). The grey shading illustrates the range of timescaling uncertainties, defined as plus and minus two standard deviations of the errors found by timescaling each of the 17 HadCM3 projections in turn, using statistics obtained by calibrating the procedure using equilibrium and time-dependent climate changes from the other 16 ensemble members.

temperature. In this case, the envelope of timescaled projections corresponds quite closely with that defined by the climate model projections. However the smoothed coloured lines of the timescaled estimates deviate in detail from their climate model counterparts at any given time period, due to the effects of internal variability, non-linear dependencies on global temperature, and other uncertainties in the timescaling process. For this reason, the order of the coloured lines in the timescaled estimates differs somewhat from their HadCM3 counterparts, at any given time level. However, the effects of these timescaling errors (shown separately as grey shading in Figure 3.3(a)) are included in the UKCP09 projections as described above, by adding time-dependent uncertainties sampled from our error estimates to the basic timescaled projections shown by the coloured lines. Results for winter precipitation changes (Figure 3.3(b)) are similar in character, except that the envelope of climate model projections is significantly wider than that of the timescaled projections out to about the 2050s. This is mainly because the forced climate change for the next few decades (estimated in isolation by the coloured lines in the right panel) is relatively small compared to the component of the spread in the climate model projections explained by internal variability. However, we emphasise that the timescaling error term (grey shading) does capture the effects of internal variability, so this component of uncertainty is included in the full envelope of timescaled projections (not shown in Figures 3.3(a) and (b), but obtained by combining the coloured lines and the grey shading).

While changes in well-mixed greenhouse gases such as carbon dioxide give rise to spatially uniform changes in radiative forcing, this is not the case for other forcing agents included in our transient simulations (historical and future changes in sulphate aerosols and ozone, and historical changes in solar and volcanic activity). The forcing due to sulphate aerosols, in particular, is concentrated over and downstream of industrialised regions of the northern hemisphere (Forster *et al*. 2007). The patterns of climate change in response to spatially heterogeneous forcings cannot be assumed to follow that found in response to well-mixed greenhouse gases. We account for this by running an additional

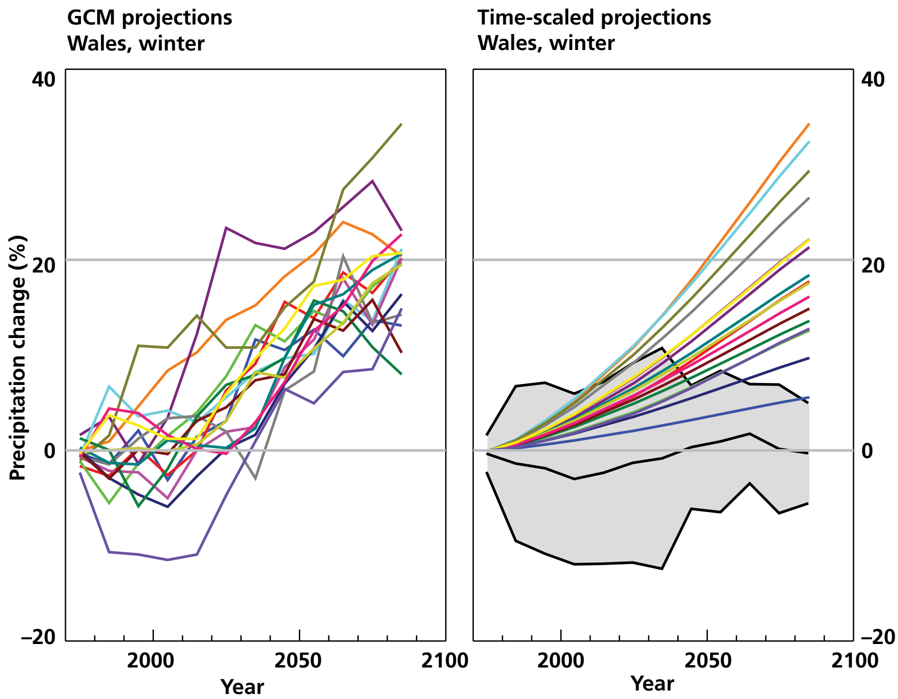


Figure 3.3(b): As Figure 3.3(a), but for precipitation changes (%) over Wales in winter.

17 member perturbed physics ensemble of HadCM3 simulations from 1860 to 2100, identical to PPE_A1B except that concentrations of well-mixed greenhouse gases are held fixed at pre-industrial levels, allowing the climate response to the heterogeneous aspects of the forcing to be isolated. Results from this ensemble (PPE_A1B_NOGHG) are used to estimate the regional response to these forcings (per unit global temperature change) as a function of time, which then forms a potential additional contribution to our timescaled estimates of transient climate change. We do not possess sufficient simulations to estimate how the normalised response to heterogeneous forcing agents might vary across the model parameter space. However, future changes in forcing in the emissions scenarios considered for UKCP09 are dominated by well-mixed greenhouse gases, and for these we do estimate variations across parameter space in greater detail.

In practice, the added refinement of including a separate term for the heterogeneous forcings is found to be important for some variables, but not others. Use of this term is therefore determined on a case-by-case basis, dependent on whether its inclusion leads to a statistically significant reduction in the uncertainty associated with our climate change estimates.

3.2.5 Sampling uncertainties in additional Earth System processes

We sample uncertainties in ocean, sulphur cycle and terrestrial carbon cycle processes by running three additional perturbed physics ensembles, each consisting of 16 perturbed variants of HadCM3. Each of these ensembles is driven from 1860 to 2100 by the same time series of forcing agents used in PPE_A1B. In each of these ensembles parameters in the module targeted for perturbation are varied within ranges obtained by consultation with experts, while parameters in other modules are held fixed at values used in the standard model variant. In all cases parameter combinations were determined using a Latin Hypercube sampling design (McKay *et al*. 1979).

Ocean transport

The first ensemble addresses uncertainties in ocean transport, building on preliminary simulations reported by Collins *et al.* (2007). The ensemble members sample perturbations to parameters controlling various aspects of the resolved and subgrid-scale transports of heat, salt and momentum in both the horizontal and vertical. In these simulations, future global mean temperature rise shows a limited dependence on these ocean parameters (Figure 3.2), much smaller than the uncertainties arising from atmospheric processes.

Sulphur cycle

The second ensemble samples uncertainties in atmospheric sulphur cycle processes, represented in HadCM3 using the module described by Jones *et al.* (2001). It simulates sulphate aerosol concentrations from prescribed emission fields of anthropogenic sulphur dioxide (SO_2), natural dimethyl sulphide and tropospheric sulphur arising from quasi-regular volcanic eruptions. Three modes of aerosol are represented, comprising sulphate dissolved in cloud droplets plus two free particle modes. The model simulates production of sulphate by oxidation of SO_2, transport within the atmosphere, rain out and transfers between the different aerosol modes. The atmospheric sulphur burden affects radiation via the direct (cooling) influence of scattering and absorption of incoming solar radiation, and through increases in cloud albedo resulting from the action of sulphate aerosols as cloud condensation nuclei (the *first indirect effect*). As mentioned earlier, the *second indirect effect*, in which reductions in cloud droplet size reduce precipitation efficiency and increase cloud lifetime, is not included since the calculation of precipitation in HadCM3 does not allow for any dependence on cloud droplet number concentrations. The 16 member ensemble of HadCM3 simulations samples simultaneous perturbations to parameters controlling key aspects of the processes outlined above, including emissions of aerosol precursors. All ensemble members used the settings for atmosphere and ocean module parameters employed in the standard variant of HadCM3. This ensemble simulates a wide range of atmospheric sulphur burdens (although perturbations to some of the atmosphere module parameters in PPE_A1B and PPE_A1B_NOGHG also have a significant impact on these). The impact of sulphur cycle perturbations on global mean temperature changes is modest compared with that in PPE_A1B (Figure 3.2).

Terrestrial ecosystem

Uncertainties in terrestrial ecosystem processes are sampled in a third ensemble in which the TRIFFID dynamic vegetation module of Cox (2001) is added to HadCM3, to form an Earth System model HadCM3C. TRIFFID simulates soil carbon, and the growth and replacement of five functional types of vegetation (broadleaf tree, needleleaf tree, C3 grass, C4 grass and shrubs). The functional types vary according to the net available carbon and competition between plant types, parameterised using empirical relationships. Soil carbon can be increased by litterfall and is returned to the atmosphere by microbial respiration, which depends on temperature and soil moisture. CO_2 fluxes at the land–atmosphere interface are determined by photosynthesis and plant and microbial respiration. In order to simulate carbon fluxes at the ocean–atmosphere interface, an ocean carbon cycle module (Cox *et al*. 2001) is also included. This simulates exchange of gaseous CO_2 with the atmosphere, the transport of dissolved inorganic carbon and cycling of carbon by marine biota via a nutrient–phytoplankton–zooplankton–detritus ecosystem module (Palmer and Totterdell, 2001) that accounts for the effects of light penetration, alkalinity and nutrient availability on biological carbon uptake. In previous carbon cycle experiments using HadCM3 (e.g. Cox *et al*. 2000; Jones *et al*. 2003), the horizontal resolution of the ocean module was reduced; however, here we maintain the standard resolution of 1.25 x 1.25 degrees in order to ensure that our carbon cycle simulations are physically consistent with the other coupled ocean–atmosphere ensembles included in our methodology.

A 16-member ensemble was produced, sampling simultaneous perturbations to TRIFFID parameters controlling soil carbon and the five vegetation functional types. A further ensemble member with standard TRIFFID settings was also run. Parameters in the ocean carbon cycle module were held fixed at standard values in these simulations, because resource and time limitations made it impractical to perform the ensemble of long preliminary integrations (e.g. Cox *et al*. 2001) which would have been required to achieve equilibrium in ocean–atmosphere carbon fluxes. The specification of forcing agents was as in PPE_A1B, except that CO_2 was input as a time series of emissions rather than concentrations, in order to allow carbon cycle feedbacks to operate. This ensemble simulates a substantial range of future changes in CO_2 concentration (669–1130 ppm at the year 2100, for example), and therefore of global mean surface temperature (Figure 3.2), comparable to the spread found by sampling physical surface and atmospheric processes in PPE_A1B. Uncertainties in the ocean carbon sink are not sampled in our simulations (as explained above); however, the spread of responses obtained is similar to that found in a previous multi-model ensemble of carbon cycle simulations carried out in the Coupled Climate Carbon Cycle Intercomparison Project (C^4MIP) by Friedlingstein *et al.* (2006). The C^4MIP ensemble sampled variations in both terrestrial and ocean carbon cycle processes and found that climate-induced changes in carbon storage were explained mainly by the former.

In addition to their impacts on global mean surface temperature (Figure 3.2), the ocean, sulphur cycle and terrestrial ecosystem PPEs all show some statistically significant impacts on patterns of regional change in some parts of the world. For example, the sulphur cycle PPE shows a significant spread in temperature changes in the Arctic Ocean and over interior regions of the northern Eurasian landmass (because surface albedo feedbacks amplify the effects of perturbations to the response of surface temperature), and in precipitation changes over tropical regions of the central and western Pacific Ocean (due to the strong coupling with sea surface temperature changes in these regions). The ocean PPE shows similar impacts over the Arctic and tropical Pacific Oceans, while the terrestrial carbon cycle PPE shows a large spread of precipitation changes over Amazonia, due to the regional influence of ecosystem-atmosphere interactions (Betts *et al*. 2004). However the impacts on changes over the UK (beyond those directly explained by variations in the global mean warming) turn out to be relatively minor.

3.2.6 Combining uncertainties in different Earth System processes

The Earth System ensembles described in Section 3.2.5 are not large enough to provide a basis for training an emulator capable of estimating the model response at any point in the parameter space of ocean, sulphur cycle or carbon cycle processes (cf Section 3.2.3). This prevents us from including the relevant uncertainties via a formal application of Bayes theorem in an integration over the model parameter space (cf. Section 3.2.7 below). However, we do include uncertainty estimates obtained from these ensembles in a simpler manner, by generalising the timescaling technique described in Section 3.2.4. This is done by configuring the simple climate model used in timescaling to include sulphate aerosol forcing, and simple globally averaged parameterisations of processes associated with the effects of terrestrial carbon cycle feedbacks on the atmospheric CO_2 concentration. When running the simple model to estimate the transient climate response for some specified set of surface and atmospheric HadCM3 parameters, we sample the effects of additional Earth System processes by selecting from a distribution of possible values for the simple model parameters controlling global mean ocean heat uptake, sulphate forcing or CO_2 concentration. For heat uptake, this is done by calculating values of ocean diffusivity for each of the 17 members of our ocean perturbed physics ensemble (Section 3.2.5), and also from 20 alternative simulations derived from the multi-model ensemble of coupled ocean-atmosphere models submitted to the IPCC AR4. The multi-model ensemble values were taken from the 23 models listed in Table 8.1 of Randall *et al*. (2007), omitting two models because data required for the calculation were not available, and one because the wrong climate change forcing was applied in the relevant experiment. Inclusion of the multi-model ensemble results enabled us to account in a simple way for structural uncertainties in ocean transport pro cesses not sampled in our perturbed ocean ensemble. Values are then selected from these 37 possible values, assuming each to be equally plausible.

Including sulphate aerosol forcing uncertainties in timescaled projections

For sulphate aerosol forcing the approach is somewhat more complicated, because variations in physical atmospheric parameters (particularly those associated with cloud) are found to exert a significant influence on the forcing, in addition to variations in parameters directly associated with the sulphur cycle. Furthermore, a significant relationship between global mean aerosol forcing and climate sensitivity was found in our PPE_A1B_NOGHG ensemble (low sensitivity model variants tend to simulate high levels of low cloud, and therefore simulate larger changes in forcing in response to aerosols). We accounted for these factors by developing a regression relationship between a transformed function of aerosol forcing, and global climate feedback (the reciprocal of climate sensitivity). The distribution of forcing values is Gaussian in the transformed units. Variations in transformed aerosol forcing, diagnosed from the 16-member perturbed sulphur cycle ensemble, were assumed independent of atmospheric perturbations and added to each member of our PPE_A1B_NOGHG ensemble, thus forming a dataset for regression which sampled uncertainty arising from both atmospheric and sulphur cycle processes. When running the simple climate model for a given location in parameter space (and hence a given climate sensitivity), we then sampled alternative aerosol forcing values from the error statistics of the regression relationship. This method gives a distribution of aerosol forcing values for present day climate (relative to pre-industrial conditions) similar to that given in the IPCC AR4 (see Figure 2.20 of Forster *et al*. 2007), based on the statistical assessment of the uncertainty of radiative forcing mechanisms documented by Haywood and Schulz (2007).

Including carbon cycle feedback uncertainties in timescaled projections

Given that carbon cycle uncertainties provide a leading order contribution to the uncertainty in global mean changes, and recognising that our perturbed physics ensemble does not sample uncertainties associated with structural carbon cycle assumptions in HadCM3C, we also include results from the C^4MIP multi-model simulations in our sampling of possible feedbacks. We performed a pre-screening exercise in which the historical simulations of global carbon budget components (fraction of anthropogenic emissions stored in atmosphere, land and ocean) were compared with an observational constraint based on records of atmospheric CO_2 increase, estimates of total emissions (fossil fuel plus land use emissions) and the oceanic uptake of anthropogenic CO_2 (Sabine *et al*. 2004). Two of the perturbed physics simulations and one of the C^4MIP simulations were found to be inconsistent with the spread of plausible values implied by estimates of observational uncertainty, so these were excluded. We also excluded results of the HadCM3LC model contributed to C^4MIP, as this model is strongly related to that used for our perturbed physics simulations. This left 9 members of the C^4MIP ensemble and 15 members of the perturbed physics ensembles, whose simulated global mean feedbacks were sampled in the timescaling procedure, assuming all 24 estimates to be equally plausible.

The parameterisation of carbon cycle feedbacks in the simple climate model contains explicit temperature dependences, allowing the (significant) effect of variations in the global temperature response on the global mean carbon cycle response to be captured (e.g. Andreae *et al*. 2005). This is achieved using globally averaged calculations of changes to the vegetation and soil carbon stores consistent with the main features of the corresponding calculations used in the terrestrial ecosystem module of HadCM3 (Jones *et al*. 2003), which contains temperature-dependent parameterisations of photosynthesis and plant and soil respiration. With the exception of this carbon cycle–temperature relationship, and the aerosol forcing–climate sensitivity relationship described above, our timescaling method does not account for non-linear interactions between the global feedbacks in different Earth System modules. This is because time and resource limitations prevented us from running HadCM3 ensemble simulations in which parameters in all component modules were varied simultaneously. The UKCP09 projections are conditional on the assumption that additional non-linear interactions are likely to be small compared with the two significant known relationships referred to above. This issue is a subject of current research.

Potential contributions of ocean, sulphur cycle and carbon cycle processes to uncertainties in regional climate changes (beyond the effects directly attributable to uncertainties in global mean surface temperature) are not accounted for in the generalised timescaling technique. This is because results from the relevant ensembles indicate that such contributions would be relatively minor for changes over the UK (Section 3.2.5), and also because quantification of the impacts of non-linear interactions is beyond the scope of the experimental design for UKCP09 (see above). In some regions neglect of such regional effects would not be realistic, a good example being Amazonia where carbon release from forest dieback is dependent on regional changes in precipitation (Betts *et al*. 2004). The extent to which the UKCP methodology could be applied in other parts of the world will therefore depend upon careful evaluation of the potential impacts of regional effects not covered by our timescaling procedure, in addition to the validity of further assumptions required by our technique, such as the use of a linear scaling to global mean temperature changes (see Section 3.2.4).

3.2.7 Probabilistic projections of the equilibrium response to doubled CO_2

In Sections 3.2.7–3.2.9 we describe how we obtain probabilistic projections for the equilibrium response to doubled CO_2 concentration. This exercise provides marginal probabilities for changes in individual variables, or joint probabilities for changes in two or more variables (e.g. temperature and precipitation in some specific region), at the spatial scale of HadSM3 grid boxes (approximately 300 x 300 km^2). However it is also necessary to apply our timescaling procedure (Sections 3.2.4 and 3.2.6), and the downscaling procedure (described in Section 3.2.11 below), to obtain estimates of 21st century changes at the local scales required by UKCP09 users. The combination of these elements is outlined later, in Section 3.2.12.

Probabilistic projections are obtained using the Bayesian statistical framework introduced in Section 3.2.1, described here in general terms, omitting technical details. The calculation is based on values of variables of historical and future climate obtained from a climate model whose outputs depend upon a set of parameters controlling processes judged to be important determinants of the quality of its simulations. Observed values of the historical variables and their associated errors are also required, in order to weight model outputs according to their quality. Probabilities for different values of future variables are obtained by applying Bayes Theorem through an integration over the model parameter space of surface and atmospheric processes (henceforth referred to as *parameter space*), as outlined in Section 3.2.1 (see Rougier (2007) for more details). However, we cannot afford to run the climate model itself at every point within this space, so we train an emulator to replicate the model outputs (see Section 3.2.3), and then use the emulator to estimate values of the required variables for any given combination of parameter settings.

The Bayesian framework allows (and requires) us to account for relationships between the various elements involved in the calculation. Some simplifying assumptions are necessary to make the calculation tractable: for example there is no obvious reason to expect that errors in emulated estimates of climate model output would be correlated with errors in observed estimates of the true historical climate, so we assume these to be independent. On the other hand, our method relies on the basic assumption that relationships can be found between variations across parameter space in the modelled values of historical climate and future changes (e.g. Piani *et al*. 2005; Knutti *et al*. 2006), so we would want to account for these in the calculation. In our Bayesian approach, this is achieved by calculating weights for different combinations of parameter values according to how well the model simulates a set of historical observations given those values. These posterior weights constrain the model parameter space to regions giving rise to relatively skilful simulations, and thus also constrain projections of future climate variables, to an extent which depends on how strongly the future variables are controlled by values of model parameters. This helps to reduce the dependence of the projections on expert prior choices imposed by the experimenters (see Annex 2). Also, the simulated changes, and their associated uncertainties, can be adjusted according to the errors in the simulated values of historical observables, according to the strengths of the correlations between them. This ability to pick out key relationships from a range of possible influences is a critical strength of the procedure, because future changes in climate over the UK (indeed in any region) are influenced by an array of feedback processes, some of which are local in origin, and some of which involve remote influences. Rowell and Jones (2006) demonstrate this in relation to future summer drying over Europe, for example, showing that this is affected by large scale thermodynamic feedbacks, changes in atmospheric circulation, and regional changes in soil moisture influenced by surface–atmosphere coupling in summer, and also by changes in the annual cycle of surface hydrological components dependent on changes in temperature, snowmelt and precipitation at other times of the year. Thus it would not be possible to determine the credibility of projected future changes by focusing solely, for example, on simulated values of historical metrics limited to the region and season of interest (e.g. Moberg and Jones, 2004). The set of observations used to constrain the UKCP09 projections is described in Section 3.2.9.

The complex and interconnected nature of changes in different variables (illustrated by the example above) also suggests that it would be difficult to justify assigning different weights to projections of different variables from the same model variant. Our statistical framework reflects this, being based on the assumption that each model variant should be assigned a universal weight which reflects the quality of its ability to simulate climate as a whole. This weight quantifies the relative likelihood that a given combination of parameter settings provides a representation of climate system processes consistent with our observations of the real world. The likelihood depends on the difference between the emulated values of our set of historical variables and the corresponding observations, accounting for covariances between the variables, and normalized by the uncertainty in the differences, obtained by adding contributions from emulator error, observational error and structural modelling error. The sizes of the covariances determine how rapidly the weight drops as the emulated values move away from observations. The structural error arises from the recognition that HadCM3 (like any climate model) contains certain fundamental biases which cannot be resolved by varying its uncertain parameters, so the framework includes a key term called *discrepancy* which captures the additional uncertainty in model projections arising from such errors.

In our integration over model parameter space, we assume that climate model parameters are *a priori* 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. It is recognised that alternative and equally defensible prior distributions could be proposed (e.g. Rougier and Sexton, 2007); however, the results are quite robust to a number of reasonable alternative choices (see Annex 2).

3.2.8 Structural model errors (discrepancy)

What is discrepancy, and why is it important?

The discrepancy term, introduced in Section 3.2.7, is a measure of how informative the climate model is about the real world. Formally, it represents the mismatch we would find between the model and the real world if we could locate precisely the combination of model parameter settings giving the best overall simulation of climate that the model is capable of providing. Discrepancy applies to simulations of both historical and future climate. It is also a prior input to the Bayesian framework, and should therefore be specified using a method as independent as possible from the specific observations used to weight the (emulated) climate model projections, in order to avoid double counting the observations. Discrepancy is itself uncertain, and is therefore specified as a distribution (in common with other uncertain inputs to the Bayesian calculation). Values must be specified for all historical and future variables involved in the calculation, including covariances between the variables. Discrepancy in historical variables focuses the weight on the well modelled variables and prevents small variations in the poorly modelled variables from having an unduly large impact on the weighting. Discrepancy in future variables increases the uncertainty associated with the projections, and mitigates the risk of making overconfident projections. Specifying the discrepancy is an extremely demanding task in principle, given the inherent difficulty of anticipating the effects on particular climate variables of missing or inadequately understood processes, and their complex interactions.

Estimation of discrepancy in UKCP09

In practice we estimate discrepancy by using results from our large ensemble of HadSM3 simulations of present day and doubled CO_2 climates (see Section 3.2.3) to predict the results of an ensemble of different climate models, whose members consist of coupled atmosphere–mixed layer ocean (*slab*) models of similar complexity and credibility as HadSM3, but employing different basic assumptions in some of their parameterisations of physical processes. Note that this exercise must be carried out using ensembles of slab model simulations, rather than ensembles of coupled models containing a full dynamical ocean (e.g. Figure 3.2), because our perturbed physics ensembles using HadCM3 are too small to support a direct application of the Bayesian framework to their results. Nevertheless, our approach confers the benefit of allowing us to provide projections which combine results from perturbed physics and multi-model ensembles, hence adjusting the projections to account for likely biases arising from structural errors in HadCM3. It is based on the judgement that the effects of structural differences between models can be assumed to provide reasonable *a priori* estimates of possible structural differences between HadSM3 and the real world. We take a given multi-model ensemble member as a proxy for the true climate, and use our emulator of HadSM3 to locate a point in the HadSM3 parameter space which achieves the best multivariate fit between HadSM3 and the multi-model member, based on a set of climate variables described in Section 3.2.9. The fit is determined using an optimisation procedure starting from a randomly-selected initial point in parameter space. The difference represents one estimate of discrepancy, under the above judgement. This process is repeated four times for each multi-model member, in order to sample the sensitivity of the optimisation process to the initial point. These difference estimates are then pooled across the multimodel ensemble, giving a sample of four times the number of ensemble members. The mean of these is taken as our estimate of the mean value of discrepancy, and the covariances of the differences about the ensemble mean serve as our estimate of the discrepancy covariance matrix, after allowing for a component due to internal climate variability.

This approach allows us to provide projections combining results from perturbed physics and multi-model ensembles, thus avoiding exclusive reliance on results from the Hadley Centre model. The slab models used in the discrepancy calculation were selected from those contributed to the IPCC AR4 (Randall *et al*. 2007), and the Cloud Feedback Model Intercomparison Project (CFMIP) (e.g.

Webb *et al*. 2006), using data interpolated to the HadSM3 model grid. Some models could not be used as insufficient data was available, and one model was excluded because the design of its simulation of the response to doubled CO_2 excluded the contribution of surface albedo changes from melting sea-ice, this being a process of known importance included in the other models. In the remaining 14 models, data was available for nearly all of the required variables, but with isolated exceptions (mainly daily data required to calculate the required indicators of temperature and precipitation extremes, which was missing from five of the models). Here, values of the missing variables were estimated from inter-variable correlations derived from the multi-model ensemble. In two cases where more than one model was potentially available from a given institute, statistical tests showed that these models could not reasonably be assumed to give quasi-independent estimates of model error, so the model variant thought to be less credible (based on criteria of lower resolution in one case, and published assessments by the relevant modelling centre in the other) was excluded. This left 12 models to be used in the discrepancy calculation (Table 3.1).

Model Name	Modelling Centre	Source
UIUC	University of Illinois, USA	CFMIP
MIROC3.2medres	Centre for Climate System Research, National Institute for Environmental Studies, Frontier Research Centre for Global Change, Japan	CFMIP
MIROC3.2hires	Centre for Climate System Research, National Institute for Environmental Studies, Frontier Research Centre for Global Change, Japan	IPCC
HadGSM1	Met Office Hadley Centre, UK	IPCC
CGCM3.1 T63	Canadian Centre for Climate Modelling and Analysis, Canada	IPCC
CSIRO-MK3.0	Commonwealth Scientific and Industrial Research Organisation, Australia	IPCC
ECHAM5/MPI-OM	Max Planck Institute for Meteorology, Germany	IPCC
GFDL-CM2.0	Geophysical Fluid Dynamics Laboratory, USA	IPCC
GISS-ER	Goddard Institute for Space Studies, USA	IPCC
INM-CM3.0	Institute for Numerical Mathematics, Russia	IPCC
MRI-CGCM2.3.2	Meteorological Research Institute, Japan	IPCC
NCAR-CCSM3.0	National Center for Atmospheric Research, USA	IPCC

Table 3.1: Climate models used in the estimation of structural errors (discrepancy). Randall *et al.* (2007) (Table 8.1 therein) and Webb *et al.* (2006) summarise some basic features of models sourced from IPCC and CFMIP, respectively, and also provide supporting references for papers giving detailed model descriptions. Note that Table 8.1 of Randall *et al.* describes dynamical ocean–atmosphere configurations of the models, from which are derived the mixed layer ocean–atmosphere (*slab*) configurations used here.

Assumptions and limitations

Whilst this method of calculating discrepancy provides an appropriate means of quantifying uncertainties in projected future changes consistent with current climate modelling technology, it is important to recognise caveats associated with the approach. Firstly, it assumes that the structural errors in different models can be taken to be independent. Whilst there is evidence for a degree of independence (for example, model errors in multiyear climate averages reduce significantly when ensembles of different models are averaged together (e.g. Lambert and Boer, 2001; Reichler and Kim, 2008)), there is also evidence that some errors are common to all models (see Annex 3), due to shared limitations such as insufficient resolution or the widespread adoption of an imperfect parameterisation scheme. From this perspective, our estimates of discrepancy can be viewed as a likely lower bound to the true level of uncertainty associated with structural model errors. However, another caveat is that we do not take into account variations in the credibility of different multi-model ensemble members when calculating discrepancy, partly because there is no widely recognized means of quantifying such variations (Randall *et al*. 2007), and partly because such an exercise would introduce an element of double counting in the use of observations in our Bayesian framework. Nevertheless, the assumption of equal credibility carries the risk that models which simulate climate relatively poorly could yield excessively large estimates of discrepancy, thus overestimating the impact of structural errors.

It is clear, therefore, that the sensitivity of our projections to plausible variations in discrepancy is an important test of their robustness (see Annex 2, and further discussion in Section 3.3). In the case of the historical component of discrepancy, such tests can be augmented by diagnostic checks, since the magnitude of biases in our model simulations can be calculated *a posteriori*. We used our emulator to estimate the location in the model parameter space which gives the best simulation of historical climate, and then calculated the squared error between emulated and observed values found in practice, for each of the variables used in our weighting of different model variants (see Section 3.2.9). For each variable, the squared error was then divided by our *a priori* estimate of its expected value, this consisting of the sum of the variances arising from our prior estimate of discrepancy, observational errors, and emulation errors. The average value of these normalised squared errors was found to be ~0.3, indicating that the structural component of model error may be rather smaller than our *a priori* estimates derived from other climate models without reference to the observations. This suggests that the potential risk that the presence of common systematic errors in models might lead us to underestimate historical discrepancy is not realized in practice, at least for the set of historical observables considered. Obviously we cannot perform corresponding diagnostic checks on the discrepancy attached to future variables, and there is no guarantee that an overestimate in historical discrepancy would necessarily imply a corresponding overestimate of future values.

3.2.9 Use of climate variables to estimate discrepancy and weight projections

The calculation of weights for different locations in the HadSM3 parameter space (Section 3.2.7) requires us to compare emulated estimates of historical climate against some set of corresponding observations. In addition, the calculation of discrepancy (Section 3.2.8) requires us to compare emulated estimates of both historical climate and the response to doubled CO_2 against simulated values from multimodel ensemble members. In this sub-section we describe the set of variables upon which these comparisons are based.

Which observations are used to weight UKCP09 projections?

Our choice of potential observational constraints is restricted to historical variables which can be simulated by our ensemble of HadSM3 simulations, or which can be inferred with acceptable accuracy via the timescaling procedure of Sections 3.2.4 and 3.2.6. This precludes, for example, the use of observations of properties relating to sub-surface ocean, sulphur cycle or terrestrial ecosystem processes (e.g. ocean salinity or temperature cross-sections, net primary productivity of the biosphere, etc.) or of coupled ocean–atmosphere modes of variability in which ocean transport plays a role, such as the El Niño–Southern Oscillation. In the main, therefore, we are restricted to the use of spatial fields of multiannual seasonal means of physical variables describing surface and atmospheric characteristics of recent historical climate. We are also restricted by the set of fields available from the multi-model ensemble used to generate our discrepancy estimates (Section 3.2.8). Nevertheless, this still constitutes a substantial subset of the metrics typically used to assess climate simulations (e.g. Taylor, 2001; Reichler and Kim, 2008). Specifically, we use observed latitude–longitude fields of sea surface temperature, land surface air temperature, precipitation, pressure at mean sea level, shortwave and longwave radiation at the top of the atmosphere, shortwave and longwave cloud radiative forcing, total cloud amount, surface fluxes of sensible and latent heat, and latitude-height distributions of zonally averaged atmospheric relative humidity. This amounts to a very large number of variables, given that a single spatial field consists of ~7000 grid box values. However there are significant spatial relationships within each field, and also relationships between different fields, so it is possible (and necessary, for computational reasons) to capture the main variations found in our ensemble simulations of these observables in a smaller number of independent variables, as described in the following sub-section.

In addition, we also include changes in large-scale features of surface temperature patterns observed during the twentieth century as an additional constraint. This is desirable because the ability to replicate historical temperature changes is widely recognised as an important test of the credibility of projected future changes, and has been used as a formal observational constraint in a number of studies (e.g. Allen *et al*. 2000; Stott *et al*. 2006a,b). It is feasible to do this in UKCP09 because our timescaling technique allows us to infer this aspect of time-dependent historical climate change for any given point in parameter space, by using our simple climate model tuned to the relevant climate sensitivity (Section 3.2.4). We therefore include historical changes in four indices identified by Braganza *et al*. (2003), which capture key features of the characteristic response to increasing greenhouse gases found in climate model simulations, these being the global mean, land–ocean and interhemispheric temperature contrasts and the zonally averaged meridional temperature gradient in Northern Hemisphere mid-latitudes. Stott *et al*. (2006a) show that these indices capture most of the information obtained from comprehensive spatiotemporal analyses of the past warming attributable to forcing from greenhouse gases, aerosols and natural forcing agents, and therefore provide an important constraint on future temperature changes at continental to global scales (e.g. Stott *et al*. 2006b; Kettleborough *et al*. 2007). We also account for structural error in our estimates of the Braganza indices, by combining our emulation and timescaling techniques to *predict* the results of estimates derived from multimodel ensemble members, using an approach consistent with that used to calculate other aspects of discrepancy (see Section 3.2.8).

Expressing observational constraints through a limited set of key variables

Our set of observables, whilst incomplete, constitutes a large collection of variables covering a variety of physical climate characteristics. This should substantially reduce the risk of erroneously assigning a high weight to a location in parameter space which achieves a good fit to observations through a fortuitous compensation of errors. In order to make our calculations tractable, it is necessary to reduce the number of historical multiannual mean climate variables used in the calculation of relative likelihoods for different parts of parameter space. This is done through an eigenvector analysis, identifying a limited set of orthogonal multivariate patterns which explain the main variations in behaviour found within our ensemble of HadSM3 simulations. Fields of values for each climate variable are expressed in dimensionless units prior to the eigenvector analysis, by normalizing values at each location by the globally averaged value of the standard deviation of the relevant variable across the HadSM3 ensemble. The choice of cutoff for the number of retained eigenvectors is determined by a balance between: (i) the need to include a wide range of historical information in order to identify physically and statistically significant variations in the fit to observations found in different parts of parameter space; and (ii) the need to ensure that a reasonable proportion of points in parameter space receive a non-negligible weight, so that robust projections can be obtained by sampling a large but finite sample of points. Statistical tests indicate that six eigenvectors is the appropriate choice (see also Annex 2). The retained eigenvectors explain 66% of the variance found within the HadSM3 ensemble. The projections of emulated multiyear mean climate onto these six eigenvectors, plus the four Braganza *et al.* indices of large scale historical surface temperature trends, form the set of observables from which the weights are calculated.

Observational uncertainties

The specification of uncertainties associated with the verifying historical observations is in principle an important consideration. For the indices of historical surface temperature changes, the estimates are derived from the error estimates supplied by Brohan *et al.* (2006) for the HadCRUT3 dataset. The available observational climatologies for the multiyear mean variables do not possess comprehensive error estimates, so we take the simpler approach of using two alternative verifying datasets for each variable, and randomly generating plausible alternative observed values by interpolating between the two datasets. Improving the specification of observational uncertainties is an issue for future research.

Which climate variables are used to find perturbed physics analogues to multimodel ensemble members?

As explained in Section 3.2.8, we estimate discrepancy by finding locations in the HadSM3 parameter space which produce emulated estimates of climate which best fit results from the simulations of an ensemble of alternative models. The fit is calculated by combining information from simulations of both historical climate and future climate change. The historical information is based on projections onto the six eigenvectors of spatial patterns of time-averaged climate described above. The future climate change information is provided from six multivariate eigenvectors of the simulated response to doubled CO_2. These are obtained from an eigenvector analysis of patterns of change in the ensemble of perturbed physics simulations, based on the same set of variables used to determine eigenvectors of historical climate (see above). The simulated climate changes of multimodel ensemble members are then projected onto these eigenvectors, as are emulated changes from different points in the HadSM3 parameter space, allowing us to add six coefficients of future climate change to the six historical variables used to determine the best perturbed physics analogues to any given multimodel ensemble member.

Although we use only twelve derived variables in this matching process, these encapsulate information from global patterns of historical climate and future change of a range of basic climate variables. This ensures that it would only be possible to find a good overall match (over different variables and regions) if HadSM3 analogues can be found which closely replicate all aspects of the representations of physical processes found in any given multimodel ensemble member. Any outstanding mismatch (beyond the effects of internal climate variability) should then arise from the true effects of structural differences between HadSM3 and the multimodel ensemble member, and can be taken as an estimate of discrepancy.

3.2.10 Probabilistic projections of the equilibrium response to doubled carbon dioxide

As explained in Sections 3.2.7–3.2.9, probabilistic projections of equilibrium climate changes in response to doubled CO_2 provide the cornerstone of the UKCP09 methodology. This process produces projections of changes in the UKCP09 variables at five global climate model (HadSM3) grid boxes covering the UK landmass (and also a further nine points covering surrounding marine regions), for every month of the year. Here we provide a few illustrations of how this part of the method works in practice, and what criteria are considered in assessing the credibility of the results.

Figure 3.4 shows an example, for changes in the 20-yr average of surface air temperature (Tmean) over Wales, in March. The green histogram shows our perturbed physics ensemble of 280 HadSM3 simulations, while the multi-model ensemble (MME) results are shown as black ticks along the *x*-axis. The MME results provide a means of estimating the impact of structural errors in HadSM3, via the discrepancy term described in Section 3.2.8. We estimate discrepancy by taking each MME member in turn, and use a search algorithm to find four locations within the HadSM3 parameter space which match the results of the MME member most closely, based on multivariate global patterns of both historical climate and changes in response to doubled CO_2 (see Section 3.2.9). Once the four HadSM3 analogues have been found, discrepancy values can be calculated

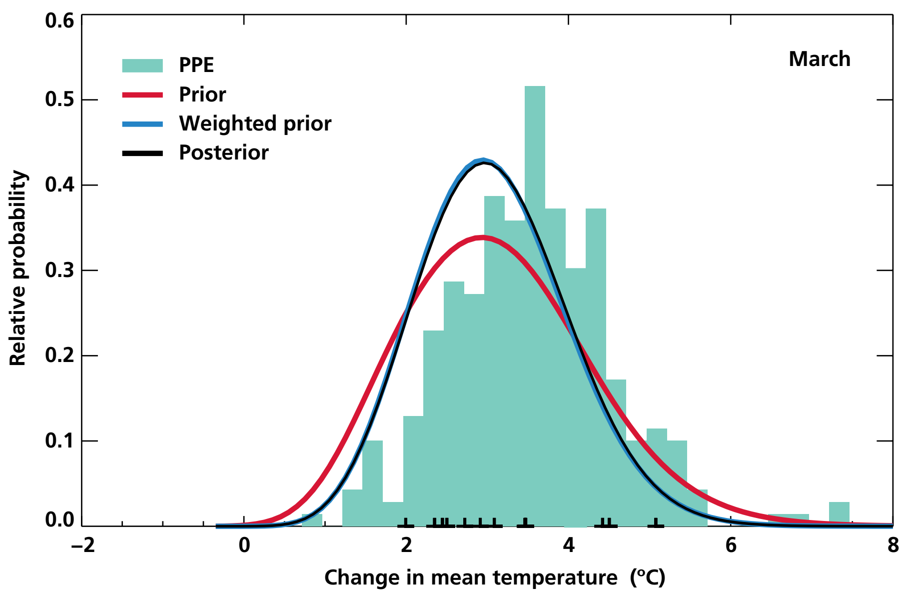


Figure 3.4: Changes in 20 yr-mean surface air temperature (Tmean, °C) over the HadSM3 grid box corresponding to Wales, in March, in response to doubled CO_2. Green histogram shows 280 perturbed physics simulations of HadSM3. Black ticks show corresponding changes simulated by 12 multi-model ensemble members. Red curve shows the distribution obtained by emulating responses across the full parameter space of surface and atmospheric processes in HadSM3. The red curve also includes the broadening effect of adding the variance (but not the mean) of discrepancy. The blue curve shows the effects of weighting the emulated responses according to observational constraints (see Section 3.2.9). The black curve shows the posterior distribution, which includes the shift arising from adding in the mean effect of discrepancy.

for any variable of interest (e.g. temperature change over Wales in March). This is done by applying our emulator to estimate projected changes from the four HadSM3 variants, and comparing those with the simulated projection of the corresponding variable from the target MME member. Repeating this procedure for each of the 12 MME members gives 48 discrepancy estimates in total, from which a mean and variance can be calculated (we assume the discrepancy distribution to be Gaussian).

The coloured curves in Figure 3.4 show how we build up our probabilistic projection from the model simulations. We use our emulator trained on the perturbed physics ensemble results (see Section 3.2.3) to estimate results for a much larger ensemble of model variants sampling the full parameter space of HadSM3. This gives us the red curve, which also contains the impact of the variance of discrepancy (but not the mean value of discrepancy, as we wish to illustrate the impact of this separately). In Figure 3.4 the sampling of the full parameter space, combined with the addition of discrepancy variance, leads to a slight broadening of the distribution of possible changes (red curve cf. green histogram). The median value is also shifted slightly towards a smaller warming, this being an effect of the improved sampling of parameter space inherent in the red curve. We also weight points in parameter space according to emulated estimates of the set of historical climate variables described in Section 3.2.9. This weighting process constrains the emulated projections according to the fit to observations, and will in general alter the characteristics of the probability distribution of projected changes. In Figure 3.4 the probabilities of small or large temperature increases are reduced by the weighting (blue curve cf. red curve), while the probabilities of intermediate changes increase somewhat. The mean discrepancy is then added to the projected changes at each location in the HadSM3 parameter space, to produce the final (posterior) probabilistic projection (black curve cf. blue curve).

We cannot make a blanket assumption that this procedure will lead to the production of a credible result. For example, a basic assumption of our approach is that robust probabilities would be difficult to infer from small multi-model ensembles in isolation (see Section 3.1), and that perturbed physics ensembles

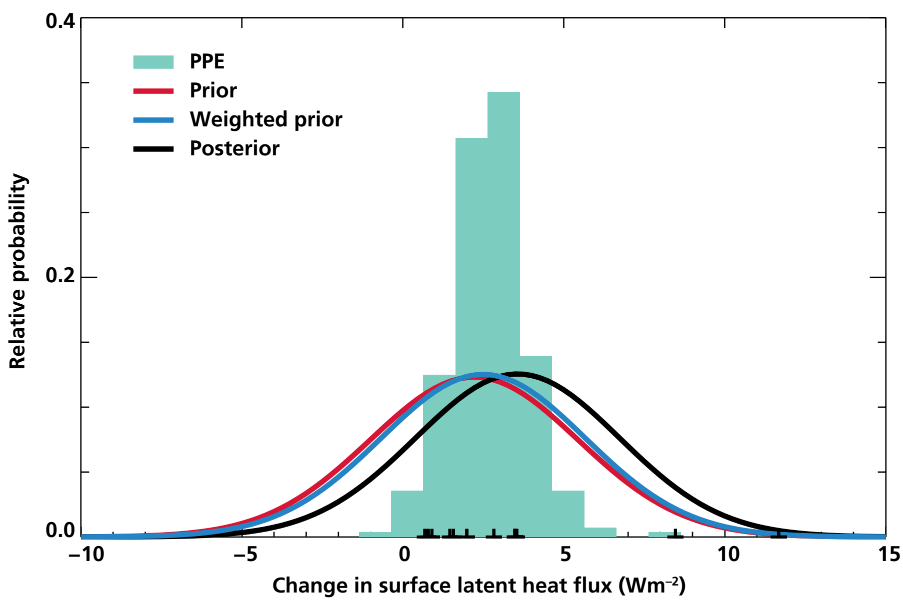


Figure 3.5: As Figure 3.4, for changes in surface latent heat flux (Wm^{-2}) over the HadSM3 grid box corresponding to Scotland, for September–November.

are therefore needed to supply a more systematic means of sampling key process uncertainties to first order. If this is the case, then we would expect the spread of changes simulated by the perturbed physics ensemble to encompass that described by the multi-model ensemble, as it does in Figure 3.4.

We checked all the UKCP09 variables according to this criterion, and generally found that the spread of MME responses did lie within that of the HadSM3 ensemble. For surface latent heat flux, however, two MME members were often found to give projections at or beyond an extreme of the range given by our HadSM3 ensemble (Figure 3.5 shows a typical example). This signals that for latent heat flux the simulated changes are strongly dependent on detailed choices made in the physics of different climate models, and cannot be assumed to be approximately independent of how our experimental design was constructed (for example our decision to base the perturbed physics ensemble on HadCM3/HadSM3, rather than on some other climate model). In Figure 3.5 the outlying MME responses lead to a large discprepancy variance, which substantially inflates the spread in the red, blue and black curves, leading in particular to the projection of a significant probability for negative change in latent heat flux. This is not supported by any of the underlying model simulations. We therefore conclude that the method cannot be used to provide robust probabilistic projections for latent heat flux.

Another issue concerns the magnitude of the shift in the final projections resulting from the mean of the discrepancy term (black cf. blue curve in Figure 3.4). If the perturbed physics ensemble is an effective means of sampling key uncertainties to first order, we would expect the mean value of discrepancy to exert a limited (albeit non-trivial) influence on the final results. This is indeed the case in Figure 3.4. Here, it is important to understand that the mean discrepancy can in theory be large, even when the multi-model and perturbed physics ensemble results cover similar ranges. This is because the procedure used to match MME members to their nearest perturbed physics ensemble analogues is conducted using information based on a wide range of historical and future climate information derived from global multivariate patterns. This is done to ensure that it will only be possible to find a perfect match (across all variables and regions) if the perturbed physics analogues truly replicate all aspects of the representations of physical processes simulated in their target MME members. Any remaining disparities (for some particular local variable like temperature change over Wales in March) will then be a consequence of true structural differences between HadSM3 and the MME members. Note that if we had attempted to calculate the discrepancy by conducting the matching exercise using a more limited choice of variables (say using only temperature changes over the UK), we would have risked finding misleadingly good matches over the chosen variables (through a convenient local compensation of errors effectively achieved via statistical overfitting), accompanied by unrealistically poor matches over other variables or regions not included in the matching process.

Figure 3.6 shows a histogram of the shifts in Tmean arising from the mean of the discrepancy, considering the 60 Tmean projections obtained by pooling monthly changes at all five UK land points in HadSM3. In most cases the mean discrepancy is within the range plus or minus 0.5ºC (as in Figure 3.4), and therefore provides a significant but not dominant contribution to the final projection, compared to the spread of responses simulated by the HadSM3 ensemble, or emulated across the full HadSM3 parameter space. In such cases, we typically find that the median of the posterior distribution lies somewhere between the medians of the HadSM3 and MME ensembles.

Occasionally, however, larger shifts are found. Figure 3.7 shows the biggest shift (between the posterior probabilistic projection and the underlying climate model simulations) found in our Tmean projections, over Scotland in March. In this particular case the median of the posterior distribution ends up towards the lower end of the distributions of both the HadSM3 and MME simulations, because all the effects described above (sampling the full parameter space, weighting, and discrepancy) conspire to shift it in the same direction. The largest component in the total shift comes from discrepancy. Detailed investigation reveals that this occurs because the HadSM3 ensemble members have a larger local snow albedo feedback in their response to doubled CO_2, compared to the MME members. This is due to a cold bias in their present day simulations over Scotland, which means that there is too much snow to melt when CO_2 is doubled in their climate change simulations. The discrepancy calculation captures the resulting bias in their simulated changes, reducing the estimated warming to account for the excessive contribution from reduced snow cover in HadSM3. If this was the only contribution to the total shift, then the median of the posterior distribution (black curve) would in this case lie close to the median of the MME results. However the effects of sampling the full HadSM3 parameter space (red curve cf. green histogram in Figure 3.7), and of weighting the projections with observations (blue curve cf. red curve), both add to the total shift, explaining why the posterior distribution shows a median warming smaller than that of either the HadSM3 or MME ensembles. The posterior distribution thus suggests a probability of about 15% for a warming smaller than those simulated by any of the climate model runs. We believe that the shifts arising from sampling parameter space and weighting are both credible, because these aspects of the method improve the sampling of uncertainties and give more emphasis to the better HadSM3 model variants. We also believe the direction of the shift arising from discrepancy is physically credible (see above). Despite this, the magnitude of the shift in this particular case is a cause for concern, as it must be regarded as uncertain (as explained in Section 3.2.8), and yet exerts a substantial influence on the final result. If Figure 3.7 was a typical example of the impact of discrepancy, it would be difficult to justify the production of probabilistic projections of Tmean.

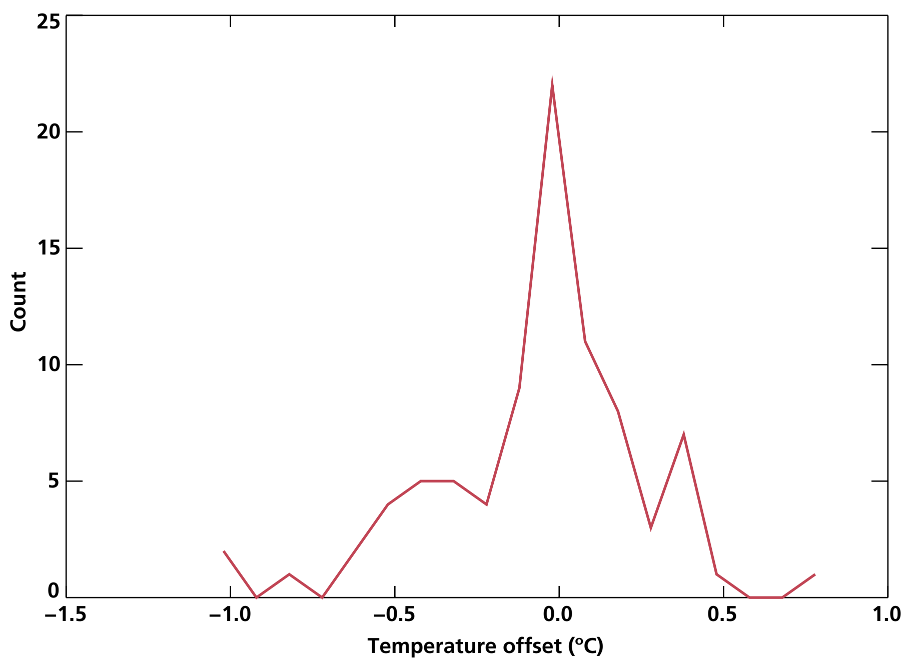


Figure 3.6: Histogram of values for the mean discrepancy for 20 yr mean changes in monthly surface air temperature (°C) in response to doubled CO_2, at UK grid points in HadSM3 (5 grid points x 12 months gives 60 values in all, distributed in bins of width 0.1°C).

However Figure 3.7 is actually an extreme example (see above discussion of Figure 3.6), so overall we judge the impact of discrepancy to be sufficiently modest to justify the production of probabilistic projections for Tmean.

We checked the impact of the shift due to the mean discrepancy in all UKCP09 variables. While isolated examples of significant shifts could be found for some variables (as in Figure 3.7 for Tmean), the typical impacts of such shifts were judged sufficiently modest to imply that the methodology could be considered a reasonable basis for the production of probabilistic projections. However, we note that surface latent heat flux was excluded (due to the mismatch between the MME and HadSM3 ensemble results discussed above). Also, it was not possible to produce probabilistic projections of snowfall or soil moisture content for other reasons, discussed in Section 3.3.

3.2.11 Downscaling for UKCP09

Regional climate model simulations

In order to provide climate projections at the fine spatial scales required for UKCP09 (see Figure 1.2(a), a downscaling method is required to derive such information from our global climate model simulations, run using a horizontal resolution of ~300 km. This was achieved by running simulations of a high resolution limited area regional climate model (RCM), configured from HadCM3 and run at 25 km horizontal resolution. A perturbed physics ensemble of 17 RCM variants was produced, eleven of which were eventually used in UKCP09 (as explained below). These simulations sampled uncertainties in the effects of varying regional physical processes on the simulation of fine scale detail. The simulations capture detailed regional effects of mountains, coastlines and variations in land surface properties, although they do not allow for variations of land surface types within a model grid box, in contrast to a more recent version (Essery *et al*. 2003) being used in additional work to provide a more sophisticated assessment of Urban Heat Island effects (see Annex 7).

Each ensemble member was driven from 1950 to 2100 by time series of lateral boundary conditions (atmospheric surface pressure, wind, temperature and moisture plus chemical species required for the calculation of sulphate aerosol

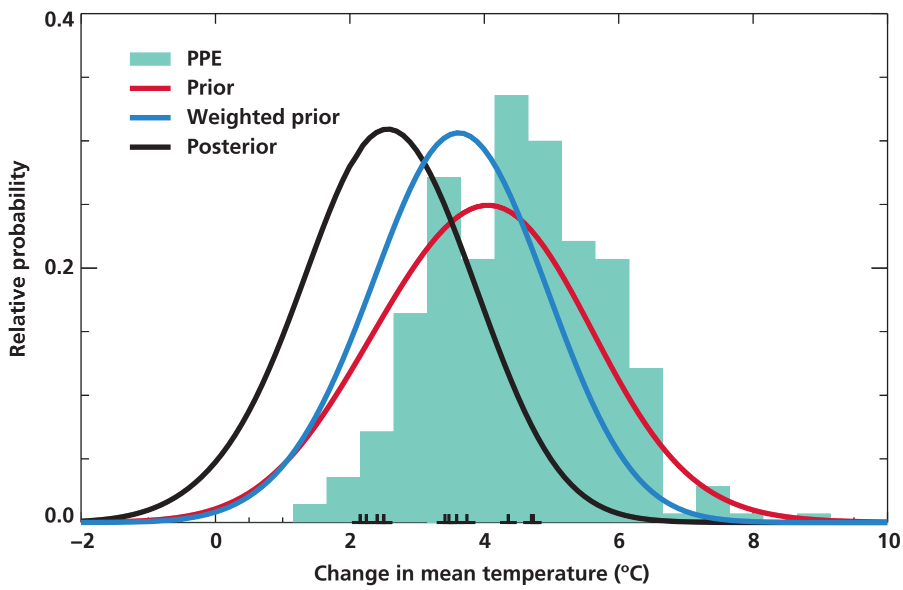


Figure 3.7: As Figure 3.4, for changes in Tmean over the HadSM3 grid box corresponding to Scotland, in March.

concentrations) and surface boundary conditions (sea surface temperatures and sea ice extents) saved from a member of the PPE_A1B ensemble of HadCM3 simulations (Section 3.2.4).* Parameter settings in each RCM ensemble member were chosen to be consistent with the settings used in the relevant HadCM3 simulation. For most parameters this was achieved simply by using the same values in both simulations, however in a few cases the parameters were adjusted to allow for known dependencies on horizontal resolution.

The RCM simulations used the domain shown in Figure 3.8, chosen so as to be large enough to avoid the risk that relaxation to GCM data at the lateral boundaries will damp the simulation of fine scale detail over interior regions of interest (e.g. Jones *et al*. 1995), yet small enough to minimise the risk that inconsistencies could develop between the simulations of large scale climate features in the driving GCM and nested RCM integrations (e.g. Jacob *et al*. 2007).

In eleven ensemble members this experimental design succeeded in producing simulations of detailed climate variability and change over the UK which were physically plausible, and consistent with the driving GCM simulations of

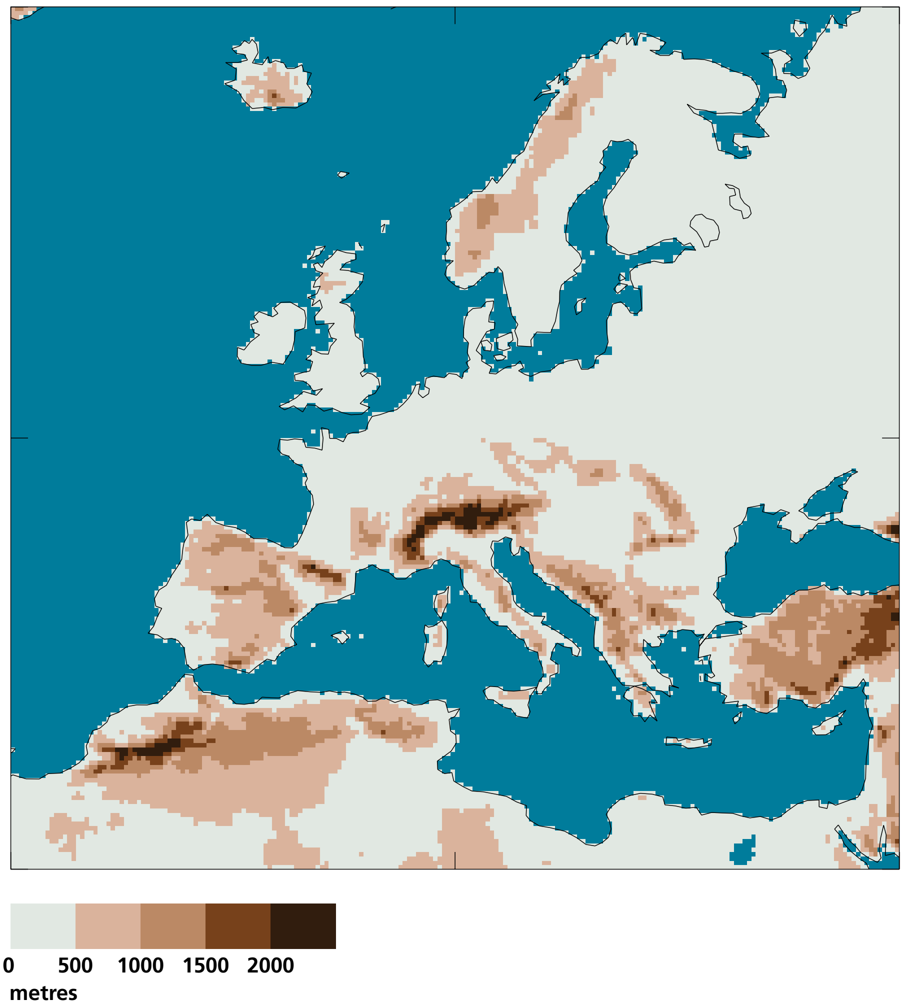


Figure 3.8: Domain used for the UKCP09 regional climate model simulations, excluding the exterior rim within which the model is relaxed to the boundary data supplied from the driving global model simulations. Orographic heights (in metres) are also shown.

* The RCM simulations in UKCP09 are a significant development from those done for UKCIP02 in terms of resolution (25 km cf. 50 km), ensemble design (eleven simulations sampling modelling uncertainties cf. three simulations sampling only initial state uncertainties), and length of simulation (covering 1951–2100 continuously, cf. two *time slices* of 1961–1990 and 2071–2100). These developments allow us to sample a spread of possible realisations of fine scale detail throughout the 21st century in UKCP09, thus avoiding the assumption in UKCIP02 that a single *master pattern* for the 2080s can be scaled back in time to earlier periods.

synoptic scale features (see Annex 3). In six ensemble members, however, the RCM simulations were found to be deficient in their simulations of storms and precipitation, exhibiting too little variability and too many dry days, especially in summer. This was traced to the impact of one of the parameter perturbations, involving a reduction in the order of the diffusive damping applied when calculating dynamical transport of heat, momentum and moisture. The GCM uses sixth order diffusion in its standard variant, whereas the RCM uses fourth order damping as standard (due to its finer grid). Some of our perturbed GCM simulations used fourth order diffusion (thus sampling the effect of increasing the spatial scale of the applied damping), leading to modest reductions in storminess and precipitation variability. An attempt was made to implement an equivalent perturbation in the relevant RCM simulations, moving from fourth to second order diffusion with accompanying changes to the diffusion coefficient to achieve a corresponding change in damping characteristics based on theoretical calculations. However, in practice the changes had a much larger impact than anticipated in the RCM simulations, rendering their time series of winds and precipitation inconsistent with those of the driving GCM runs. These six ensemble members were therefore not used in the calibration of our downscaling procedure, summarised in the following paragraph.

Downscaling to UKCP09 target regions

The downscaling was implemented by developing regression relationships between changes simulated by the RCM over regions for which projections are required by UKCP09 (individual 25 km grid boxes and a set of administrative and river-based regions over land (Figure 1.2), plus a set of marine regions (Figure 1.4)), and changes simulated at nearby grid points in the GCM. This task bears some similarities to a traditional statistical downscaling approach, in which a set of large-scale *predictor* variables is used to obtain values of localized *predictand* variables, using relationships trained on historical observations (e.g. Wilby *et al*. 2004). Such methods assume that historical relationships persist into the future, however such an assumption is avoided in our case, as the relationships are trained using future changes in the predictor and predictand variables simulated by the GCM and RCM, since their purpose is to allow us to infer fine-scale changes for parts of the model parameter space for which no RCM simulation is available.

We expressed the simulated change in a given RCM variable at a given grid point as a univariate linear regression (with slope but no intercept) against the change in the same variable simulated in the GCM at a single nearby grid point. Values for five non-overlapping 30-yr periods (1950–1979, 1980–2009, 2010–2039, 2040–2069, 2070–2099) were expressed as changes relative to the UKCP09 baseline period of 1961–1990, and changes for all five periods and all eleven ensemble members were pooled into a single dataset for the calculation of the regression coefficient (and its associated uncertainty), and the residual unexplained variance. The residual is assumed to be normally distributed with zero mean. Figure 3.9 shows an example, in which the red lines represent the regression relationship, with residual obtained from the scatter of the black crosses about the red lines, which arises from a combination of uncertainty in the relationship between changes in the global and regional models, and also from locally generated internal variability in the RCM runs. This simple approach was used in order to minimise the risk of obtaining unrealistic relationships through overfitting. For non-coastal RCM locations over the mainland UK, the GCM point used in the regression was selected from UK land boxes in HadCM3, selecting the nearest point to the target RCM location unless an adjacent HadCM3 box could be found which explained a significantly greater portion of the variance found in the RCM response. For marine regions, a similar approach was taken, using predictors chosen from marine HadCM3 boxes nearest or adjacent to the target region. When considering coastal RCM mainland points, or points representing small islands (Channel Islands, Hebrides, Orkney, Shetland, etc.), the predictor variables were selected from surrounding GCM land and sea points, to account for the possibility of a dominant maritime influence on climate at these locations.

Figure 3.9 shows close relationships between the global and regional model changes in winter. Figure 3.10 gives further examples, showing that strong relationships can also be found for summer changes, even for extreme variables subject to considerable internal variability, such as the 99th percentile of daily maximum temperature, Nevertheless, the strengths of the downscaling relationships do depend on which variable, season and region is being considered.

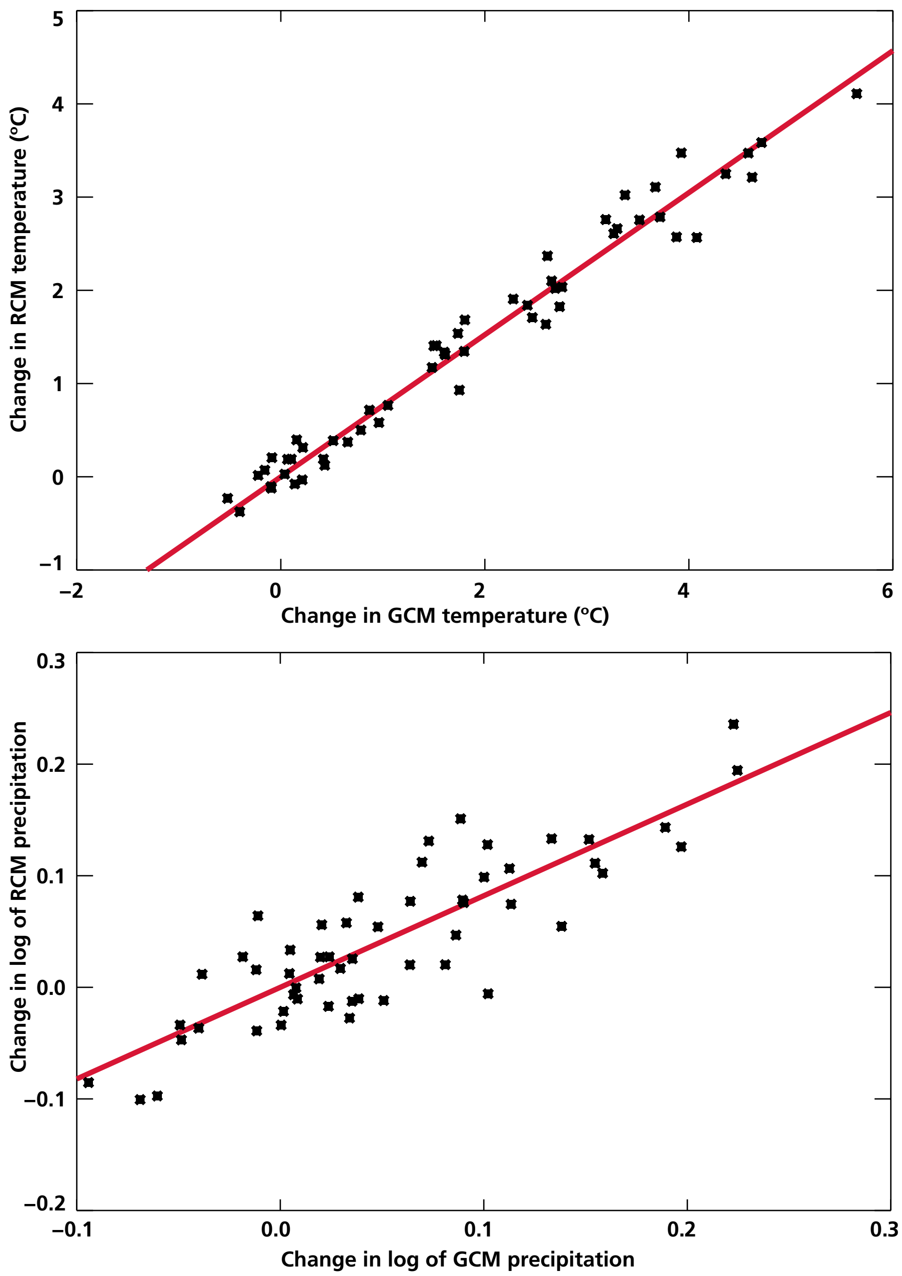
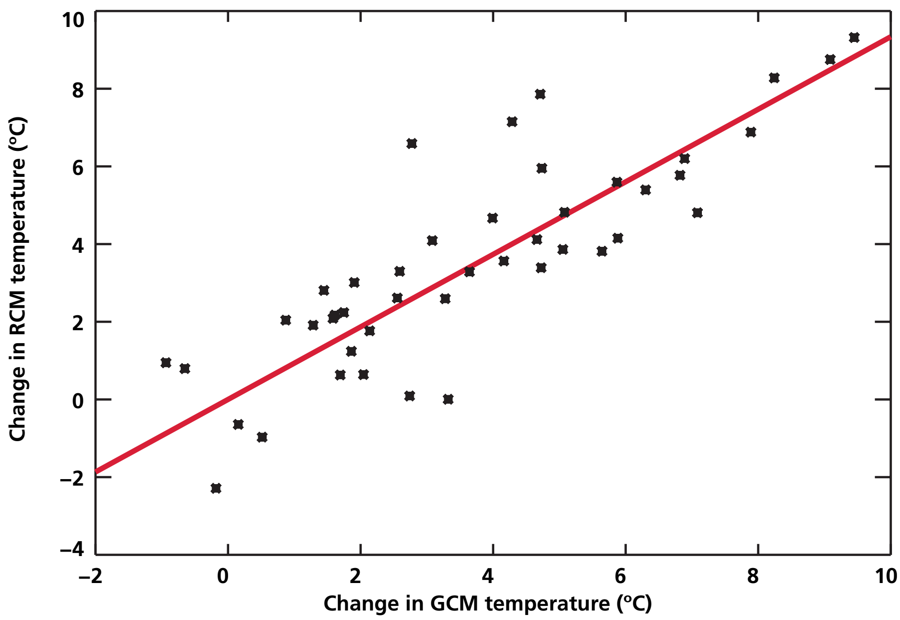


Figure 3.9: Plots of changes in winter surface temperature (°C, top) and in the natural logarithm of precipitation* (bottom), for the North Scotland administrative region, for five non-overlapping 30-yr periods relative to 1961–1990, simulated by 11 members of our regional climate model ensemble (RCM), compared with corresponding changes simulated by driving global climate model simulations (GCM) at a nearby grid point found to be most strongly related to the regional model changes (see text). The red lines show the linear regression relationships between the RCM and GCM changes derived from the data, and used in the downscaling procedure adopted for UKCP09. A zero intercept is imposed on the regression relationships, constraining the red line to pass through the origin and hence preventing the relationship from indicating a non-zero forced response in the RCM when there is no forced response in the GCM.

* Some of the UKCP09 statistical calculations were performed using a transformed variable (here the natural logarithm of precipitation), which is subsequently converted back into the variable provided to users (here percentage changes in precipitation). This is done for reasons explained in Section 3.2.3.



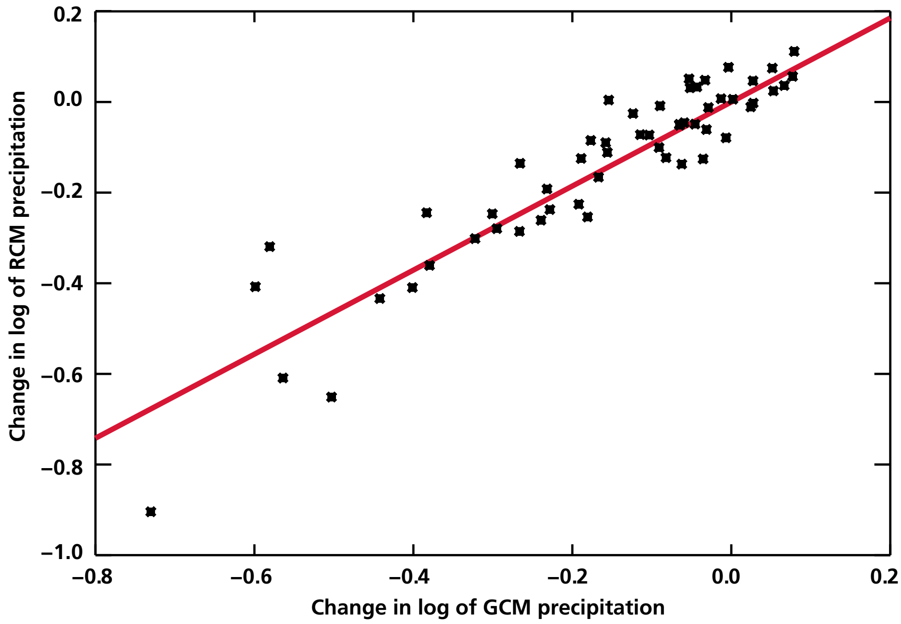
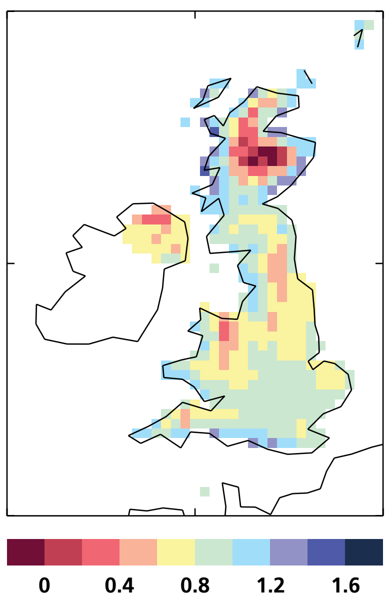


Figure 3.10: As Figure 3.9 for changes in the 99th percentile of daily maximum temperature (°C, top), and in the natural logarithm of precipitation (bottom), for South East England in summer.

Figure 3.11 (below): Plots of regression coefficients between changes in the natural logarithm of winter precipitation in regional and global climate model projections, for UKCP09 25 km grid squares.

Figure 3.11 plots the regression coefficients for changes in winter precipitation at 25 km grid squares around the UK. Significant regional variations are apparent: For example the coefficients exceed unity at many coastal locations, indicating enhanced responses in the RCMs compared with the corresponding GCM simulations, while smaller coefficients are found over parts of Wales, northern England and northern Scotland. Note that the occurrence of small regression coefficients does not necessarily indicate a failure of the downscaling method. For example, this can occur simply because: (i) the RCMs give systematically smaller changes than are found in the GCM simulations, perhaps due to the influence of regional surface topography in modifying changes found at larger scales; or (ii) because the responses in the RCM are dominated by locally generated internal variability. The region of small coefficients over central parts of northern Scotland, for example, occurs because the ratio of internal variability to forced changes is larger than in the driving GCM simulations. However, in some cases our reliance on a simple regression technique using only a single GCM *predictor* may limit the extent to which the relationship between forced changes in the RCM and GCM simulations is captured in the downscaling procedure.



Assumptions and limitations

Probabilistic projections for UKCP09 target regions were obtained by applying the calibrated downscaling relationships to probabilistic projections of 21st century climate change for the above-mentioned GCM grid boxes covering the UK and surrounding sea points, and hence obtaining estimates for the regions of Figure. 1.2 (see Section 3.2.12 for more details). In doing so, a number of limitations of our approach should be recognised. Firstly, we assume that the downscaling relationship (for a given target region and climate variable) is independent of the climate model parameter settings, and of the future period of interest. Secondly, we do not account for variations across parameter space in the skill in simulations of historical fine scale climate features found in our RCM simulations, hence the observational constraints applied to weight different parameter combinations in our Bayesian calculation (see Sections 3.2.7 and 3.2.9) are based purely on aspects of global model performance. Thirdly, we do not account for potential structural errors in our downscaling procedure, arising, for example, from our exclusive reliance on RCM variants configured from HadCM3, or (as noted above) from our neglect of more complex regression techniques based on multivariate GCM predictor variables. All of these limitations arise from the small size of our ensemble of RCM simulations: In particular, we do not possess enough simulations to emulate potential variations in fine scale characteristics of historical or future climate across parameter space. Further research in multivariate downscaling techniques and improvements in computing capacity may allow refined estimates of downscaling uncertainty to be produced in future.

3.2.12 Production of probabilistic projection data for UKCP09

Here we summarise the computational procedure used to generate probabilistic projections for UKCP09 for the SRES A1B scenario, from the elements described in the preceding sub-sections. Figure 3.12 gives a schematic overview of the main elements of the procedure, described in more detail below.

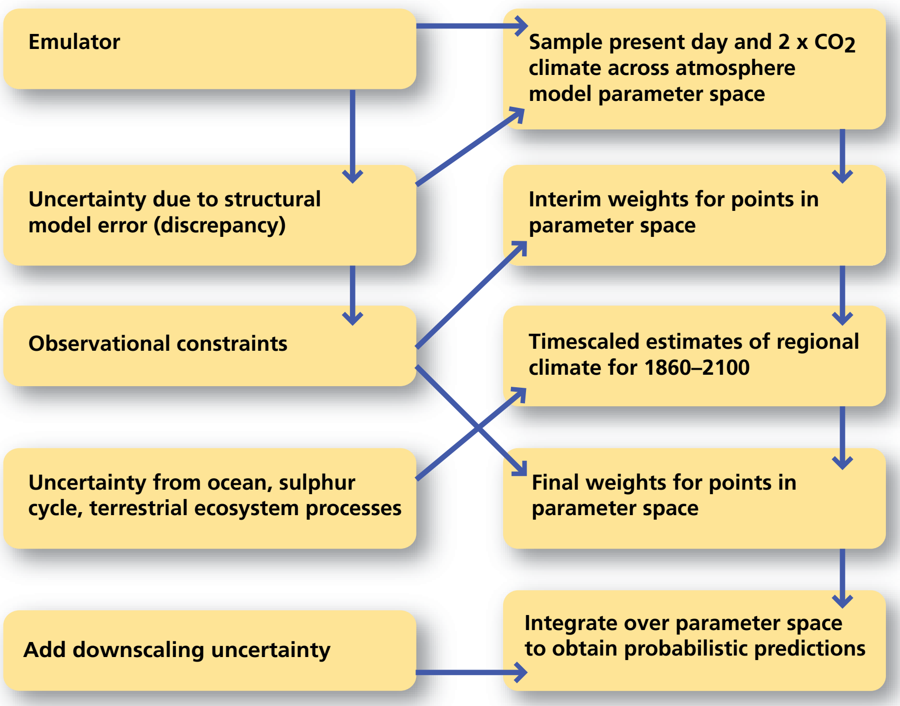


Figure 3.12: Schematic summary of the main elements involved in the derivation of probabilistic projections of climate change for UKCP09, obtained by applying the Bayesian framework of Sections 3.2.7–3.2.9 and the timescaling procedure of Sections 3.2.4 and 3.2.6 to the results of our climate model ensemble simulations. An interim weight, which quantifies the relative likelihood of different model variants based on time-averaged recent climate (see paragraph (i) below), is used to achieve efficient sampling of the atmosphere model parameter space in the timescaling of time-dependent climate changes. Following this final weights are calculated (paragraph (iii)), which account for observations of both recent time-averaged climate, and historical temperature trends.

i. Produce a large Monte Carlo sample (10^6 members) of the parameter space of surface and atmospheric processes in HadSM3, using our emulator (Section 3.2.3) to estimate multiannual mean global fields of the set of the recent climate variables identified as observational constraints in Section 3.2.9, and of the equilibrium response to doubled CO_2 for the set of variables for which future projections are required (Table 1.1), at UK land and marine points in our global climate model (downscaling is handled later in step (vi)). Uncertainties in emulated model output, observational errors and discrepancy are accounted for by sampling from their specified distributions, obtained respectively from calibration of the emulator against climate model simulations, estimates of observational errors statistics derived either from the use of alternative datasets or (where available) formal published estimates (Section 3.2.9), and the use of HadSM3 to predict the results of an ensemble of alternative climate models (see Section 3.2.8). At this stage, an interim weight is calculated for each Monte Carlo sample member, based on the recent climate observables but neglecting the Braganza *et al.* (2003) indices of historical temperature change.

ii. Sub-sample 25,000 of the 10^6 members. This is necessary because step (iii) below involves running a simple climate model, which places computational restrictions on the sample size. In selecting the 25,000 members, we use the interim weights from (i) to ensure that different parts of parameter space are sampled with a likelihood approximately consistent with their likely final contribution to the final probabilistic projections.

iii. Obtain realisations of time-dependent climate changes for the 21st century (such as those shown in Figure 3.2) by applying our timescaling technique to each of the 25,000 members from (ii). This is done by forcing our simple climate model from 1860 to 2100 with time series of historical and future forcing agents, using emulated values of regional equilibrium responses and land and ocean climate sensitivities (see Section 3.2.4), and sampling values of timescaling error, ocean heat uptake, carbon cycle feedback and sulphate aerosol forcing from the distributions described in Sections 3.2.4 and 3.2.6. Calculate the final weight to be assigned to each point in parameter space, given by the emulated values of present-day climate observables from step (i), plus the Braganza *et al*. (2003) indices measuring changes in surface temperature patterns for the period 1970–1999 relative to 1910–1939 (see Section 3.2.9).

iv. Sub-sample the 25,000 points according to the ratio of the final weights from (iii) to the interim weights from (i). This produces a final sample of 10,000 points which can be treated as a set of individual estimates of equal likelihood, based on the final weights. This further restriction of the sample size is done in order to provide a dataset which can be processed by users without placing an excessive burden on their data processing facilities.

v. Ideally, step (iv) would provide, for relevant GCM grid boxes, 10,000 samples of the joint variations between all the future variables of interest, at all times of the year (see Table 1.1), for all future periods of interest (Figure 1.3). However, such a large joint calculation is not computationally feasible, so the data are split into smaller batches. Each of the five GCM land boxes and nine marine boxes is treated separately, in two distinct batches containing different subsets of the required variables, making 28 batches in all. For a given grid box, the first batch includes all variables relating to temperature and precipitation in Table 1.1, and the additional variables required as input to the UKCP09 weather generator (with the exception of the correlation between successive daily precipitation amounts), for all times of the year and all future periods. The second batch covers the remaining variables. Within a given batch, the sampled values for different variables, months/seasons and future periods include a fully consistent treatment of covariances between both the best estimate values of the variables (driven by variations in the various climate and simple model parameters controlling the relevant physical and biogeochemical processes), and between their sampled errors. Many of these errors are actually assumed independent of one another (e.g. we assume no relationship between emulation errors, timescaling errors, observational errors or discrepancy values), however we do account for covariances between emulation errors for different variables, months (or seasons) and locations in parameter space, and between timescaling errors for different variables for a given month/season and future period. Data in different batches (e.g. projections of a given variable for a given month and future period, but at different GCM boxes), will account for physically-driven covariances between the variables, but not for the statistical error covariances identified above. The implications of handling variables from separate batches are discussed further in the UKCP09 User Guidance.

vi. Sampled climate changes for a given batch are then converted into 10,000 equiprobable Monte Carlo estimates for UKCP09 target locations (i.e. 25 km squares or aggregated regions, see Figure 1.2) using our downscaling relationships, sampling values for the regression coefficients and residuals assuming Gaussian distributions with means and variances determined from the fitting procedure described in Section 3.2.11. Joint probabilities can be estimated from these downscaled samples for changes in two or more variables in the same batch.

vii. Marginal posterior probabilities for individual climate variables for each UKCP09 target location and period are generated by a slightly different procedure. In this case, we start from probabilistic projections of the relevant variable from the appropriate GCM grid box, adjusting values associated with different probability levels of the cumulative distribution function (CDF) according to the slope and uncertainty in the appropriate downscaling relationship, and hence generating an updated CDF appropriate to the required 25 km grid box or administrative region. This procedure provides a robust numerical approximation to a full (but unfeasible) integration over the entire model parameter space.

viii. The sampled data were not considered robust either below the 1% probability level or above the 99% probability level, so we prevented the sampled data from going outside that range. That is, for a given combination of variable, location, time of year, future period and emission scenario, the values of sampled data below the 1% probability level are set to the value of the 1% probability level from the corresponding CDF, and values above the 99% probability level are set to the value of the 99% probability level. Three variables used by the weather generator (variance and skewness of daily precipitation and variance of daily temperature) are higher order statistics than the other variables, and were considered less robust; for these three variables we set the limits at the 5 and 95% probability levels.

3.2.13 Probabilistic projections for the SRES B1 and A1FI emissions scenarios

The ensemble simulations of Sections 3.2.4 and 3.2.5 are all driven by future emissions and/or concentrations of anthropogenic forcing agents consistent with the SRES A1B emissions scenario. In order to provide probabilistic projections for the B1 and A1FI scenarios, the 17 member PPE_A1B ensemble was re-run using appropriate time-dependent concentrations of greenhouse gases, and emissions of sulphate aerosol precursors. These ensembles were used to re-calibrate key timescaling statistics (specifically the correction and error terms) for the B1 and A1FI scenarios by comparing the HadCM3 simulations against timescaled estimates derived from corresponding HadSM3 simulations in conjunction with our simple climate model, as described in Section 3.2.4.

Probabilistic projections were then obtained by following the procedure of Section 3.2.12, specifying time series of forcing agents for B1 or A1FI in the simple climate model in step (iii). Apart from the timescaling aspects referred to above, all sources of uncertainty were all assumed to be the same as those specified for the A1B scenario. Some of these sources would clearly be independent of future emissions, such as emulation errors derived from our HadSM3 simulations, or the discrepancy attached to simulations of historical observables. The discrepancy for future projection variables is assumed independent of future emissions as a basic constraint of our experimental design. Further uncertainties could be specified separately for different emissions scenarios in principle, but were not in practice. These include global mean sulphate aerosol forcing, ocean heat uptake efficiency and carbon cycle feedback strengths, and regional downscaling relationships, for which resources to run additional ensemble simulations for B1 and A1FI were not available.

These assumptions are generally likely to be reasonable if global feedback strengths, and regional patterns of change per unit global warming (e.g. Mitchell, 2003), can be assumed independent of the chosen emissions scenario. Results from the latest IPCC assessment suggest that this is a reasonable assumption to leading order (e.g. Figure 10.9 of Meehl *et al*. 2007); however, our assumptions render the results for SRES B1 and A1FI somewhat less robust than those for A1B, particularly for projections in the latter decades of the 21st century, when the applied forcing and simulated response for different SRES scenarios diverges significantly (Figure 2.14).

3.3 Interpretation of UKCP09 probabilistic climate projections

UKCP09 provides a state-of-the-art basis for assessing the risk of different outcomes consistent with current climate modelling capability and understanding. However it is not yet possible to provide probabilistic projections for all variables of interest. As knowledge improves in future, the projections are liable to change.

In this chapter we have described our methodology for probabilistic projection in UKCP09, based on perturbed physics ensembles of climate model simulations specifically designed to sample uncertainties in key physical and biogeochemical processes. This is done by perturbing poorly constrained parameters in a number of configurations of one particular climate model (HadCM3), to which is added a strategy for the sampling of structural modelling uncertainties (discrepancy, explained in Section 3.2.8) by using results from one of our perturbed physics ensembles to predict the results of an alternative ensemble of climate change simulations from models developed at different climate research institutes.

Our ensemble projections are converted into probabilistic projections using a Bayesian statistical framework developed to support inference of future information about real systems from complex but imperfect models (Goldstein and Rougier, 2004; Rougier, 2007). This process allows our projections to be constrained by a set of observations of past climate (Section 3.2.9), and also involves the use of expert judgements, for example in specifying prior distributions for uncertain model parameters. The probabilities which emerge from this approach represent the relative credibility of a family of different possible outcomes, taking into account our understanding of physics, chemistry, biology, observational evidence, and expert judgement. Climate change probabilities cannot be verified in the same way as (say) probabilistic weather forecasts, because we do not have the opportunity to test our projections over many historical forecast cycles. Rather, they should be interpreted as an attempt to quantify the relative risk of different future outcomes, consistent with climate modelling technology, physical understanding and observational evidence currently available.

The credibility of the UKCP09 projections should be judged, therefore, on whether the underlying experimental design captures the leading known drivers of uncertainty, and on the extent to which the projections are robust to reasonable variations in the experimental choices and assumptions. These have been highlighted throughout the chapter, and Annex 2 contains a number of tests of key assumptions, including our expert prior distributions for model parameters, our method of estimating discrepancy, and our method of selecting the appropriate level of detail in the observational information used to constrain our projections (specifically the number of eigenvectors retained in our analysis, as explained in Section 3.2.9). This Annex also tests our results by comparing them against an approach based on a different philosophy, in which probabilities of future change are sought using a method designed to maximize the role of the constraining observations, and to be as independent as possible from the set of climate models used (e.g. Allen *et al*. 2000; Stott *et al*. 2006a).

Some of our experimental choices are not yet testable, and arise from unavoidable limitations imposed by limited scientific understanding or modelling capability. For example, while we believe that our experimental design caters for the leading known drivers of uncertainty in 21st century climate change (in particular physical atmospheric feedback processes, and carbon cycle feedbacks), there are other possible forcing agents (e.g. non-sulphate aerosol species), or feedbacks (e.g. through methane cycle processes) which are not included in UKCP09. We have no positive evidence that such factors would, if included, provide sources of uncertainty comparable with those included in UKCP09 (at least for projection time scales of a century or less), but this remains an issue for future research.

Further assumptions are imposed by limitations in computational resource. In particular, we sample uncertainties in surface and atmospheric physical processes more comprehensively than uncertainties in other earth system modules (ocean, sulphur cycle, carbon cycle), because it was not feasible to run the large ensembles of time-dependent climate change simulations which would be required. Thus we characterise uncertainties in these modules using simpler methods, applying the greater sophistication of our Bayesian calculations only to the treatment of surface and atmospheric uncertainties. In the case of the carbon cycle, however, we do make a simple attempt to account for variations in historical simulation skill between different ensemble members, and to account for structural modelling uncertainties by including results from a multi-model ensemble of projections (Friedlingstein *et al*. 2006), in addition to those from our perturbed physics ensemble.

We also assume that non-linear interactions between uncertainties in different components of the Earth System are important at the global scale, but not at the regional scale, because our finite computing resources were not able to support ensembles of climate projections with a comprehensive Earth System Model (ESM) in which uncertain processes in different components were simultaneously co-varied. Such an experiment is now in progress with HadCM3C, but UKCP09 relies on the assumption that regional interactions between earth system components are likely to be small compared with uncertainties arising when each component is sampled in isolation.

It is important that such caveats are clearly recognized. However, we believe that the UKCP09 methodology represents the most systematic and comprehensive attempt yet to provide climate projections which combine the effects of key sources of uncertainty, are constrained by a set of observational metrics representative of widely-accepted tests of climate model performance, and provide a state-of-the-art basis for the assessment of risk, within limits of feasibility imposed by current modelling capability and computing facilities.

Another key point is that we cannot make a universal assumption that probabilistic predictions can be provided for all variables that users might be interested in. As discussed in Section 3.2.10, our method is based on the assumption that robust probabilities cannot be inferred from small multi-model ensembles in isolation (see Section 3.1), and that larger perturbed physics ensembles can be used as an alternative means of sampling key process uncertainties to first order. If this is the case, then we would expect that: (a) the spread of changes simulated by the 12 member multi-model ensemble used in UKCP09 should lie more or less within that simulated by our corresponding perturbed physics ensemble; (b) even if (a) is satisfied, the discrepancy term calculated from the multi-model ensemble results should supply a modest (albeit non-trivial) component to the total uncertainty reflected in our probability distributions. With the exception of the latent heat flux variable (see Section 3.2.10), we find that criteria (a) and (b) are satisfied for the UKCP09 projection variables.

However, there were two further variables for which probabilities could not be provided, for different reasons. In the case of soil moisture content, the issue was that different models define this variable in slightly different ways, so it was not possible to calculate a discrepancy term by comparing the perturbed physics results against simulations of a consistently defined quantity in the multi-model ensemble. Secondly, it was not possible to provide probabilistic projections of fractional changes in snowfall. This is because the logarithmic transformation applied prior to our statistical calculations (in order to avoid the possibility of projecting reductions below the absolute bound of –100% — see Section 3.2.3) sometimes resulted in distributions with a highly skewed upper tail. This suggested a non-negligible probability for substantial increases in snowfall, not supported by the climate model results. This arose because the logarithm of snowfall varies rapidly at small snowfall values, and small values are often simulated in the climate model runs. This in turn means that statistical uncertainties (variances resulting from emulation error, downscaling error and timescaling error) calculated in the transformed variable tend to have large values. However our method does not account for changes in this variance as a function of the value of the projection variable, so these large variances are then assumed to apply to all projected values, leading to an unrealistic inflation of the upper tail of the attempted probabilistic projection. Changes in snowfall derived from our 11 member regional climate model ensemble projections are discussed in Chapter 4, noting that these simulations sample only a subset of the uncertainties considered in the fuller probabilistic analysis applied to other variables.

For users, an important question concerns how climate projections will change in future. Should planners make decisions now, based on estimates showing a wide range of possible changes, or should they delay in the hope that more precise information will be available in (say) 10 yr time? On the one hand, modellers have striven successfully to improve their models over the past decade or so (e.g. Reichler and Kim, 2008), yet the range of future global projections in the IPCC AR4 (Meehl *et al*. 2007) was not significantly narrower than in the previous IPCC assessment, and the range of projected changes over the UK has certainly not narrowed. On the other hand, some of the errors in climate models tend to be systematic across different models, partly due to shared features such as limited resolution. Examples, including a tendency to underestimate the frequency of blocking anticyclones over Europe in winter, are given in Annex 3. The presence of common errors gives rise to the possibility that ensemble climate projection exercises of the future might give different results to those deriving from the current generation of models, at least for some aspects of climate.

In practice, therefore, the prospects for better projections will depend on which variables or which future periods users are most interested in. For example, uncertainties in the UKCP09 projections are substantial even for a couple of decades ahead (Sections 4.4.2 and 4.5), due to the significant influence of internal variability at regional scales, and then grow larger through the 21st century due to the additional influence of uncertain climate change feedbacks (Box 2.1). Prospects for reducing uncertainties in near-term changes are likely to rest mainly on constraining projections of internal variability by initializing climate models with ocean observations (Smith *et al*. 2007; Keenlyside *et al*. 2008), and through improvements in the ability of models to simulate regional modes of variability. For example, increased horizontal or vertical resolution might lead to better simulation of features such as the North Atlantic storm track, or the coupling between sea surface temperature anomalies and atmospheric circulation anomalies. At longer lead times progress would also depend on improvements in our ability to represent thermodynamic climate feedbacks and carbon cycle processes, and their complex interactions. An active dialogue between users and climate research scientists will therefore be crucial, in order to ensure that adaptation decisions are taken on the basis of up-to-date information concerning the potential for emerging research to update projections currently available, such as UKCP09.

As mentioned above, improvements in climate models are one potential route to improved projections in future. By *improved*, we mean both more comprehensive sampling of climate feedbacks (through the use of comprehensive ESMs), and smaller uncertainties through the development of models with higher resolution and better representations of sub-grid scale processes. Initialisation of climate models with observations (also mentioned above) has potential to improve projections of near-term climate over the next decade or so, and possibly longer. Uncertainties could also be reduced by developments in experimental design, subject to available computing resources. For example, future exercises of this type could potentially be based entirely on simulations in which the atmosphere model is coupled to a full dynamical ocean component, rather than a simple mixed layer ocean (see Section 3.2.3). This would remove the need for scaling approaches to infer time-dependent climate changes from equilibrium changes, and hence narrow the probability distributions significantly, as our timescaling procedure is responsible for a significant component of the total uncertainty captured in our probabilities (see Annex 2). It would also allow a wider range of observational metrics to be used in constraining the projections.

In summary, the UKCP09 projections should be seen as a comprehensive summary of possible climate futures consistent with understanding, models and resources available at present, but users should be aware that the projections could change in future, as the basis for climate prediction evolves over time.

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