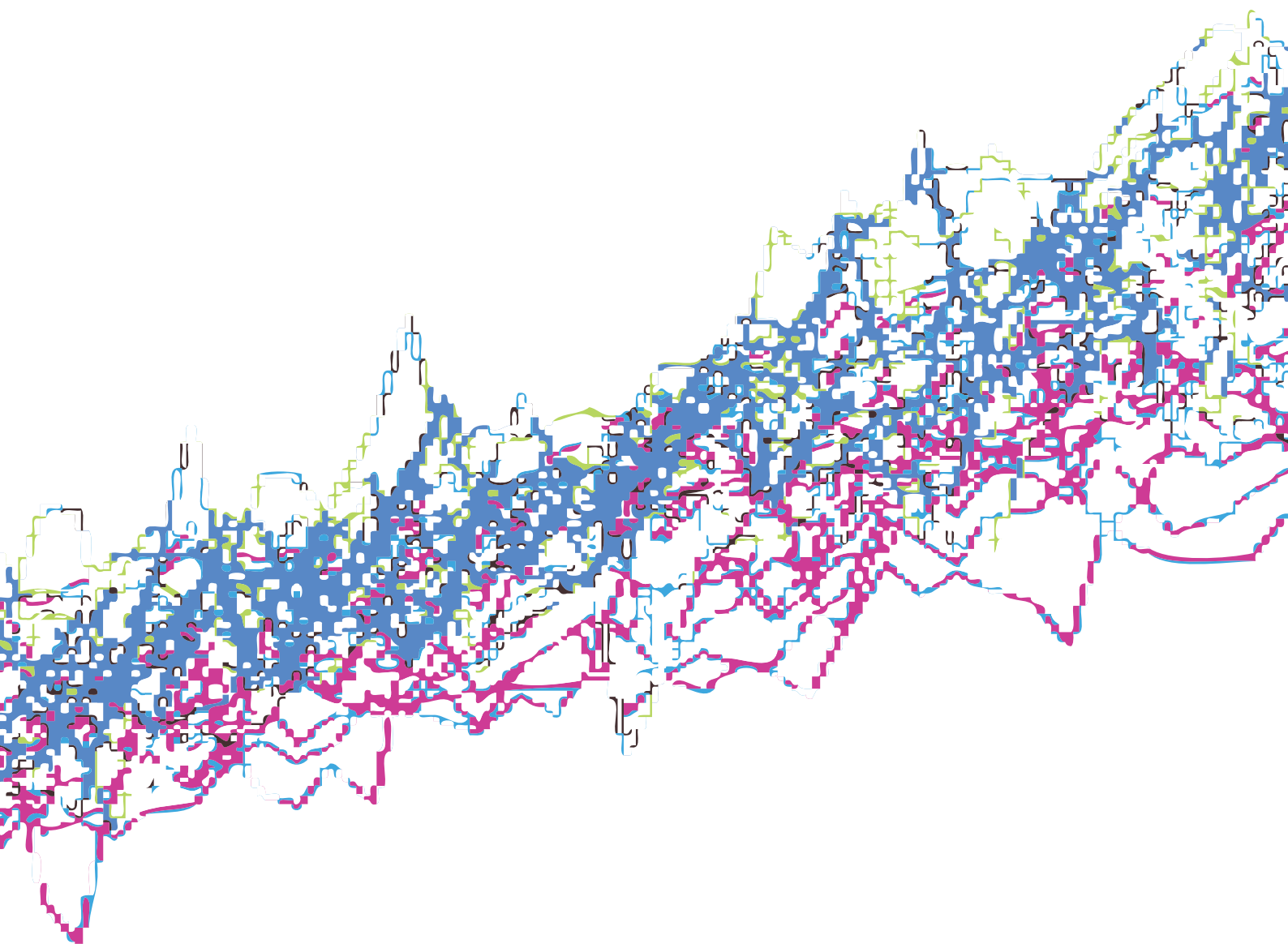


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UK Climate Projections science report: Climate change projections

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Contents

Summary	7
Purpose and design of UKCP09	7
Some examples of projected seasonal and annual changes	9
1 Introduction and overview	11
1.1 Why are climate change projections needed? Why new ones?	12
1.1.1 <i>What do we mean by probability in UKCP09?</i>	13
1.2 What information do the UKCP09 projections provide? A summary	15
1.2.1 <i>Climate change over land areas</i>	15
1.2.2 <i>Climate change over marine regions</i>	19
1.3 Uncertainty	19
1.4 Projections at a daily resolution over land	23
2 Why do we need probabilistic information? Uncertainties in climate change projections	23
2.1 Background	25
2.2 Natural variability	26
2.3 Uncertainty due to climate models	28
2.3.1 <i>Accounting for modelling uncertainty in UKCP09</i>	36
2.4 Uncertainty due to future emissions	41
2.5 Uncertainties in UKCP09 probabilistic projections and future prospects	43
2.6 References	45
3 Construction of probabilistic climate projections	47
3.1 Introduction	47
3.2 Methodology	49
3.2.1 <i>Overview</i>	49
3.2.2 <i>Process uncertainties</i>	50
3.2.3 <i>Sampling uncertainties in surface and atmospheric processes</i>	52
3.2.4 <i>Sampling uncertainties in transient climate change</i>	54
3.2.5 <i>Sampling uncertainties in additional Earth System processes</i>	58
3.2.6 <i>Combining uncertainties in different Earth System processes</i>	60
3.2.7 <i>Probabilistic projections of the equilibrium response to doubled CO₂</i>	62
3.2.8 <i>Structural model errors (discrepancy)</i>	63
3.2.9 <i>Use of climate variables to estimate discrepancy and weight projections</i>	66

continues overleaf

Contents *continued*

3.2.10	<i>Probabilistic projections of the equilibrium response to doubled carbon dioxide</i>	69
3.2.11	<i>Downscaling for UKCP09</i>	73
3.2.12	<i>Production of probabilistic projection data for UKCP09</i>	78
3.2.13	<i>Probabilistic projections for the SRES B1 and A1FI emissions scenarios</i>	81
3.3	Interpretation of UKCP09 probabilistic climate projections	81
3.4	References	86
4	Probabilistic projections of seasonal climate changes	90
4.1	Probabilistic projections as PDFs and CDFs	90
4.1.1	<i>The credibility of changes at extremes of the probability distributions</i>	92
4.1.2	<i>Consequences of having the baseline climate as 1961–1990</i>	92
4.2	Key findings	93
4.2.1	<i>National key findings</i>	93
4.2.2	<i>Regional key findings</i>	94
4.2.3	<i>Key findings for marine regions</i>	97
4.3	Maps of changes in seasonal climate	98
4.3.1	<i>Interpreting maps of probabilistic climate change</i>	98
4.3.2	<i>Projected changes to winter and summer seasonal mean temperature</i>	100
4.3.3	<i>Projections of future winter and summer seasonal mean temperature</i>	101
4.3.4	<i>Projected changes to seasonal mean temperature over marine regions</i>	102
4.3.5	<i>Projected changes to mean daily maximum temperature in summer</i>	103
4.3.6	<i>Projected changes to the warmest day of the summer</i>	103
4.3.7	<i>Projected changes to the winter and summer mean daily minimum temperature</i>	103
4.3.8	<i>Projected changes to annual-, winter- and summer-mean precipitation</i>	105
4.3.9	<i>Projected changes to the wettest day of the winter/summer by the 2080s</i>	108
4.3.10	<i>Other variables</i>	109
4.3.11	<i>Comparisons with UKCIP02</i>	109
4.4	What effect do user choices have on the probabilistic projections?	112
4.4.1	<i>How are PDFs affected by choice of emissions scenario?</i>	114
4.4.2	<i>How are PDFs affected by choice of future time period?</i>	115
4.4.3	<i>How are PDFs affected by choice of spatial averaging?</i>	115
4.4.4	<i>How are PDFs affected by choice of temporal averaging?</i>	116
4.4.5	<i>How are PDFs affected by choice of geographic location?</i>	116
4.4.6	<i>How are PDFs affected by choice of mean or extreme variables?</i>	117
4.4.7	<i>How are PDFs affected by choice of climate change or future climate?</i>	118
4.5	Probabilistic projections changing with time	119
4.6	The joint probability of the change in two variables	120
4.7	Corresponding changes in global-mean temperature	121
4.8	Variables for which probabilistic projections cannot be provided	121

Contents *continued*

5 Projections from the ensemble of regional climate models	124
5.1 Regional climate models	124
5.2 RCM experiments	126
5.3 Advantages and disadvantages of data from the RCM ensemble	126
5.4 Examples of data from the RCM ensemble	130
5.5 Some applications of RCM ensemble data	130
5.6 Reference	132
Annex 1 Emissions scenarios used in UKCP09	133
A1.1 Background	133
A1.2 Relevant work since the publication of SRES	135
A1.3 References	137
Annex 2 Sensitivity of UKCP09 projections to key assumptions	139
A2.1 Introduction	139
A2.2 Sensitivity studies	140
<i>A2.2.1 Sensitivity of results to plausible variations in the UKCP09 methodology</i>	<i>142</i>
A2.3 Comparison of UKCP09 methodology against alternative approaches	145
A2.4 Contributions to uncertainty in the UKCP09 projections	148
A2.5 Summary	153
A2.6 References	156
Annex 3 Strengths and weaknesses of climate models	157
A3.1 What are climate models?	157
A3.2 Some basic assumptions and common misconceptions in climate modelling	158
A3.3 Large-scale and small-scale processes and climate change	160
A3.4 The ability of models to represent modes of variability	164
<i>A3.4.1 The North Atlantic Oscillation</i>	<i>164</i>
<i>A3.4.2 Storm tracks and blocking</i>	<i>165</i>
A3.5 The effect of mean biases in models	168
A3.6 Discussion	169
A3.7 References	170
Annex 4 Probabilistic projection data	171
A4.1 Cumulative distribution functions	171
A4.2 Sampled data	171
Annex 5 Changes to the Atlantic Ocean circulation (Gulf Stream)	175
A5.1 How does the Atlantic Ocean circulation influence UK climate?	175
A5.2 Is the Atlantic Meridional Overturning Circulation changing?	176
A5.3 Projections of future changes in the Atlantic circulation	178
A5.4 References	180

continues overleaf

Contents *continued*

Annex 6 Future changes in storms and anticyclones affecting the UK	181
A6.1 Introduction	181
A6.2 Future changes in mid-latitude depressions	182
A6.3 Future changes in blocking	184
A6.4 Summary	185
A6.5 Reference	186
Annex 7 Urban heat island effects	187
A7.1 Causes of the Urban Heat Island and observations	187
A7.2 Future changes in the Urban Heat Island	188
A7.3 References	190

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 wind speed or 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 4.2°C (2.2 to 6.8°C)) and least in the Scottish islands (just over 2.5°C (1.2 to 4.1°C)).
- **Mean daily maximum temperatures** increase everywhere. Increases in the summer average are up to 5.4°C (2.2 to 9.5°C) in parts of southern England and 2.8°C (1 to 5°C) in parts of northern Britain. Increases in winter are 1.5°C (0.7 to 2.7°C) to 2.5°C (1.3 to 4.4°C) across the country.
- Changes in the **warmest day of summer** range from +2.4°C (–2.4 to +6.8°C) to +4.8°C (+0.2 to +12.3°C), depending on location, but with no simple geographical pattern.
- **Mean daily minimum temperature** increases on average in winter by about 2.1°C (0.6 to 3.7°C) to 3.5°C (1.5 to 5.9°C) depending on location. In summer it increases by 2.7°C (1.3 to 4.5°C) to 4.1°C (2.0 to 7.1°C), 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** and **wind speed**. 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. It projects changes in winter mean wind speed of a few percent over the UK (Chapter 4).
- 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

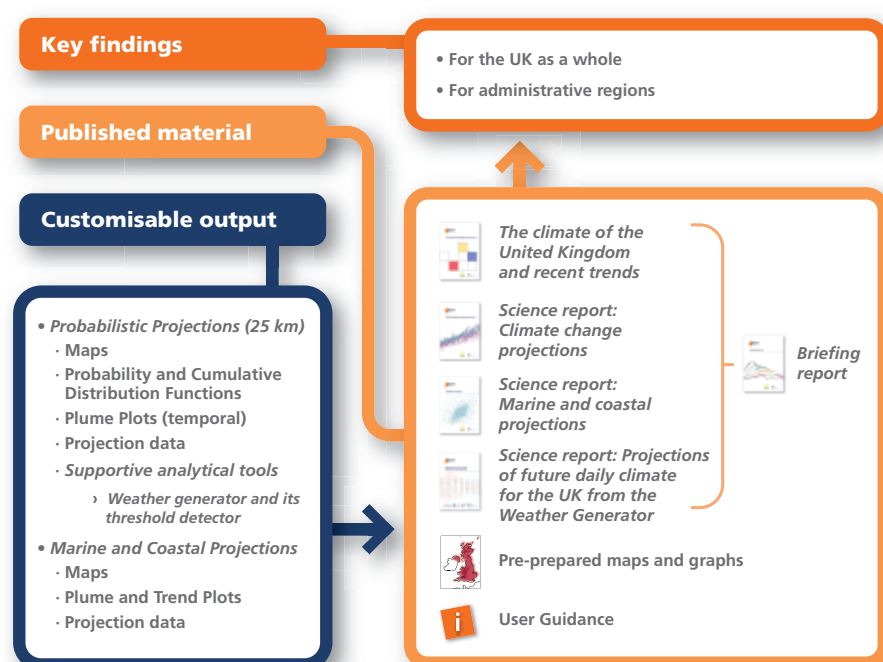


Figure 1.1: Information and publications supporting the UKCP09 projections.

* <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 minimum 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.

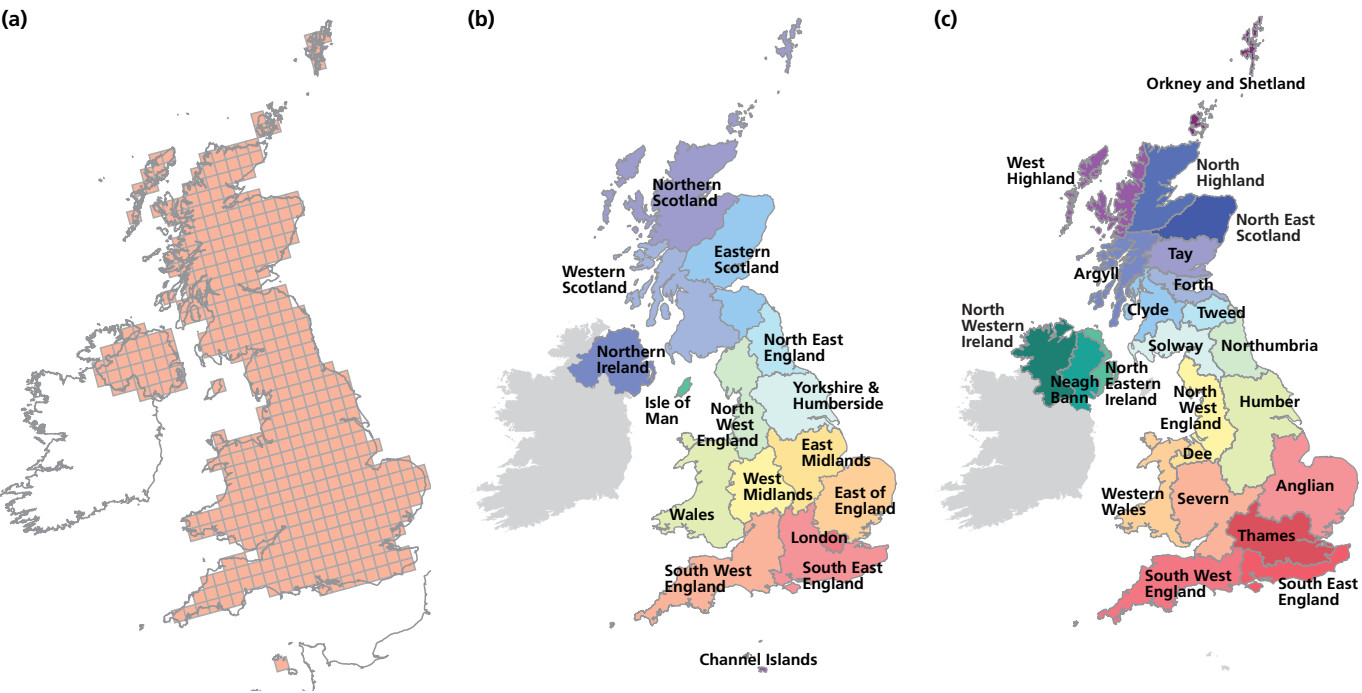


Figure 1.2: (a) Areas over which probabilistic projections are available: (a) the 25 km grid, (b) the 16 administrative regions and (c) 23 river-basin regions.

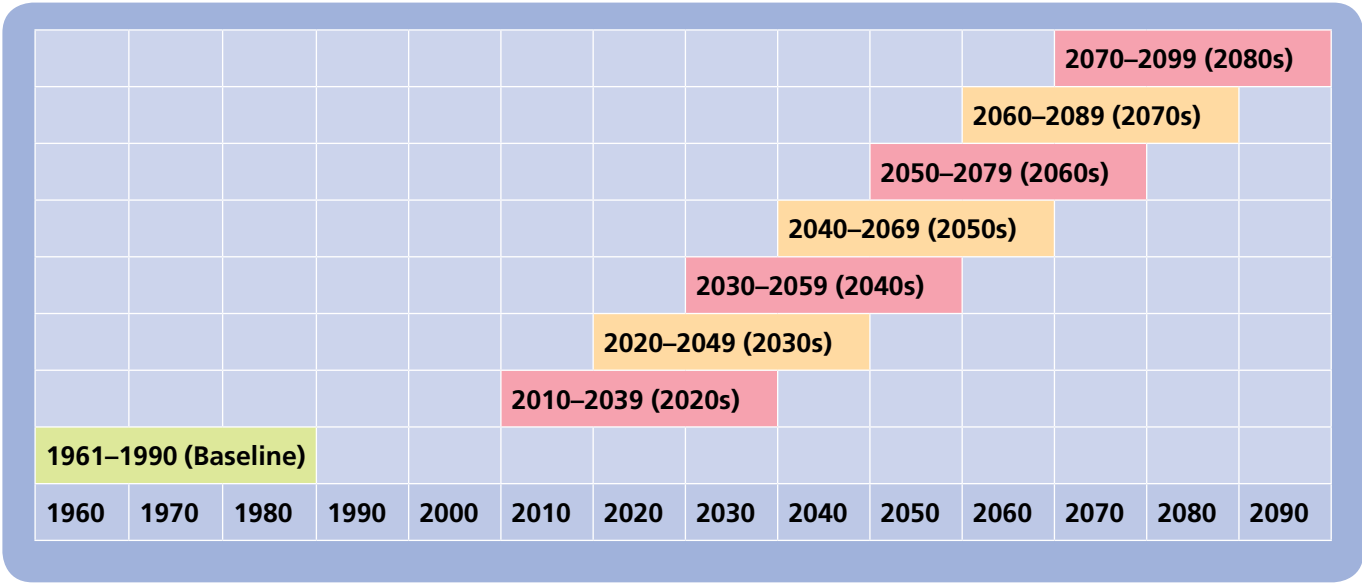


Figure 1.3: The seven 30-yr future time periods over which projections are averaged, relative to the baseline period.

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.

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

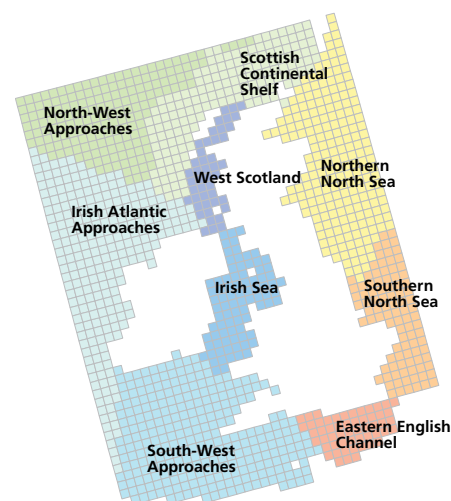


Figure 1.4 (above): The nine marine regions over which changes in climate variables have been projected. The names for these regions have been chosen specifically for the convenience of this report and hence may not be geographically or politically correct.

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 at 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.

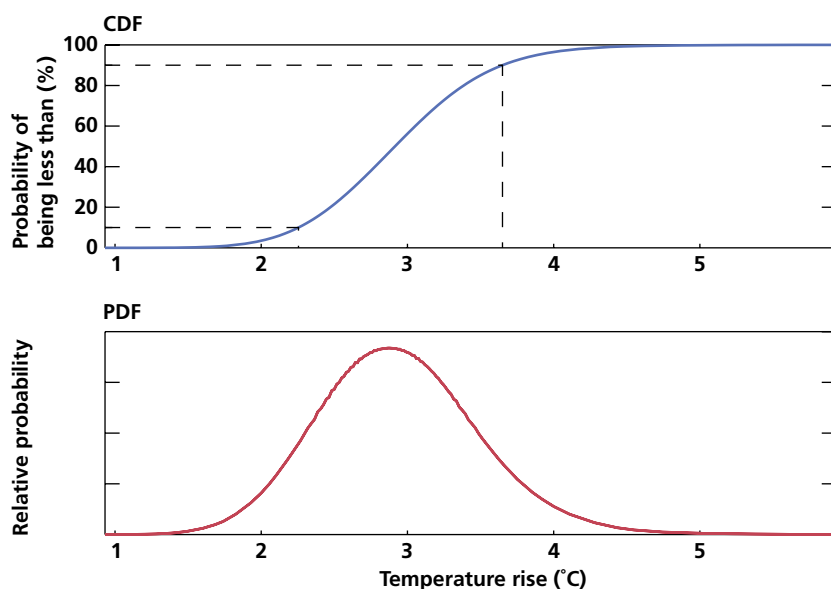


Figure 1.5: Top panel, Cumulative distribution function of temperature change for a hypothetical choice of emission scenario, location, time period and month. Bottom panel, Corresponding probability density function for this hypothetical case.

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.

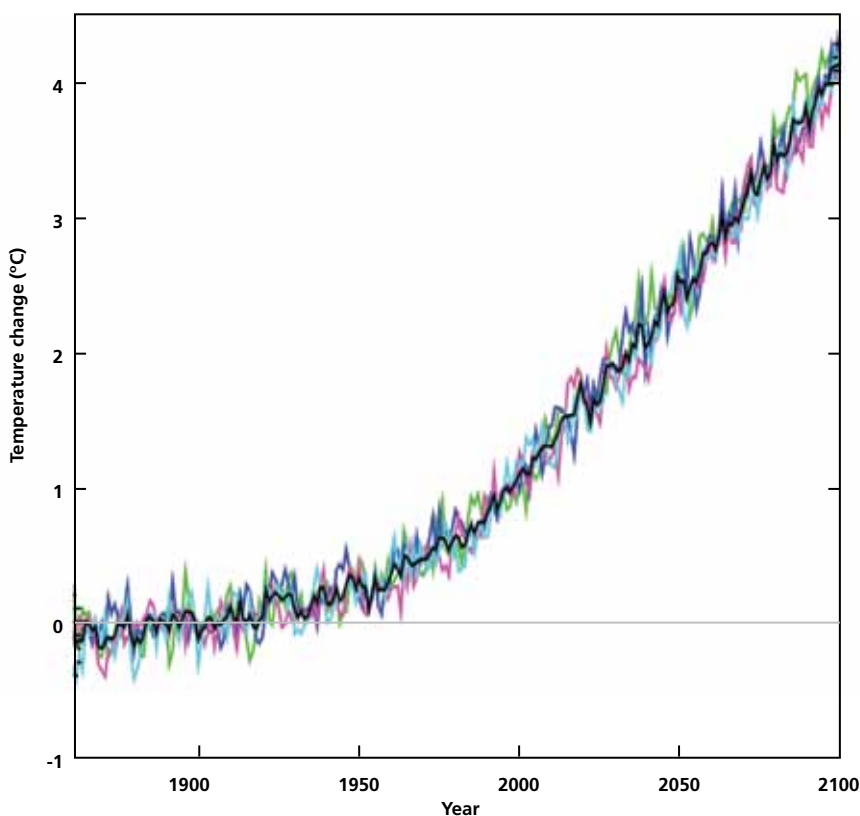


Figure 2.1: Simulations of change in global average temperature for the period 1860–2100 from three experiments with the HadCM3 climate model, shown in the three colours. Each experiment was driven with the UKCIP02 Medium High Emissions scenario but was started with different initial conditions. The 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.

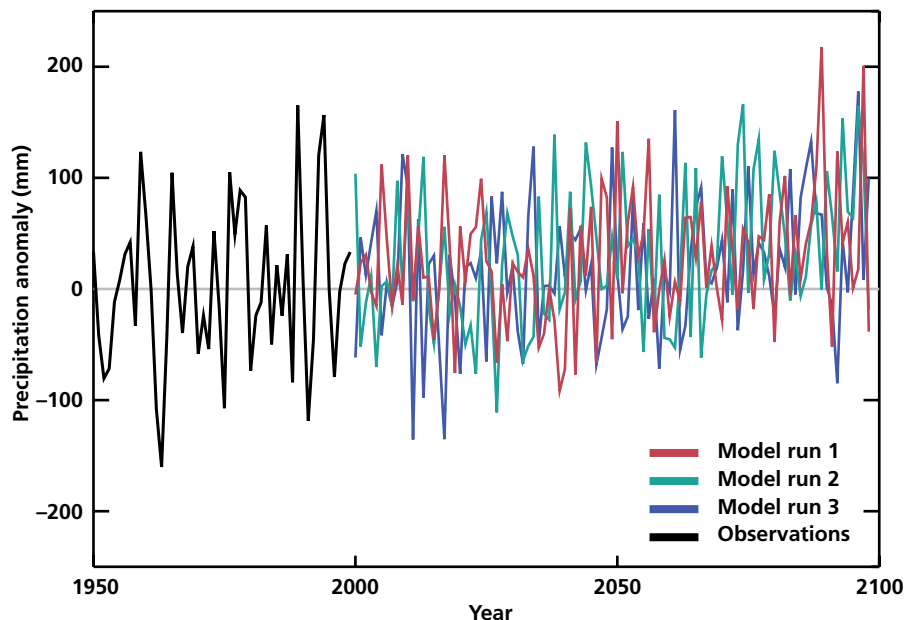


Figure 2.2: The back line shows the observed England and Wales winter precipitation anomaly from 1950–2000, relative to the 1961–1990 average. The three coloured lines show projections of the same variable, from three experiments using the HadCM3 global model. Each experiment was driven with the same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

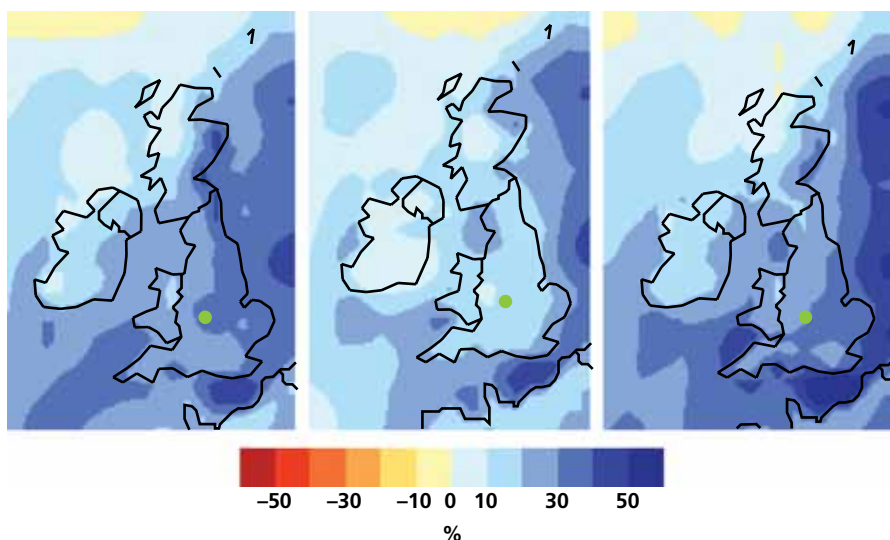


Figure 2.3: Maps of the change in winter precipitation averaged over the period 2071–2100, relative to 1961–1990, taken from the same three model experiments used in Figure 2.2 and described in the caption.

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 $\pm 0.5^\circ\text{C}$. (Gareth Jones, pers comm.)

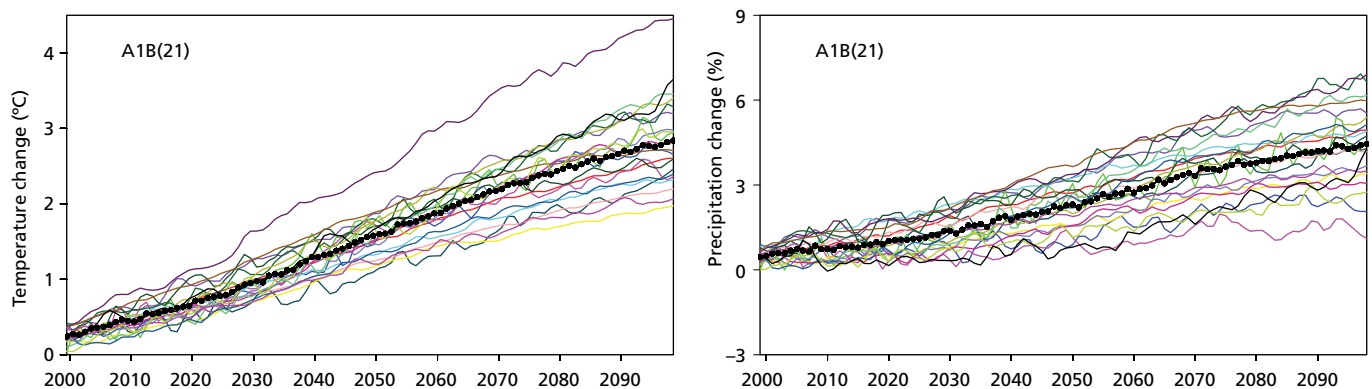
If volcanoes are energetic enough to inject gas into the stratosphere, then the resulting aerosol can remain there for a few years and gradually spread across the globe. Because solar radiation will be reflected back from this aerosol before it can warm the earth, it will have a cooling effect on climate 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.

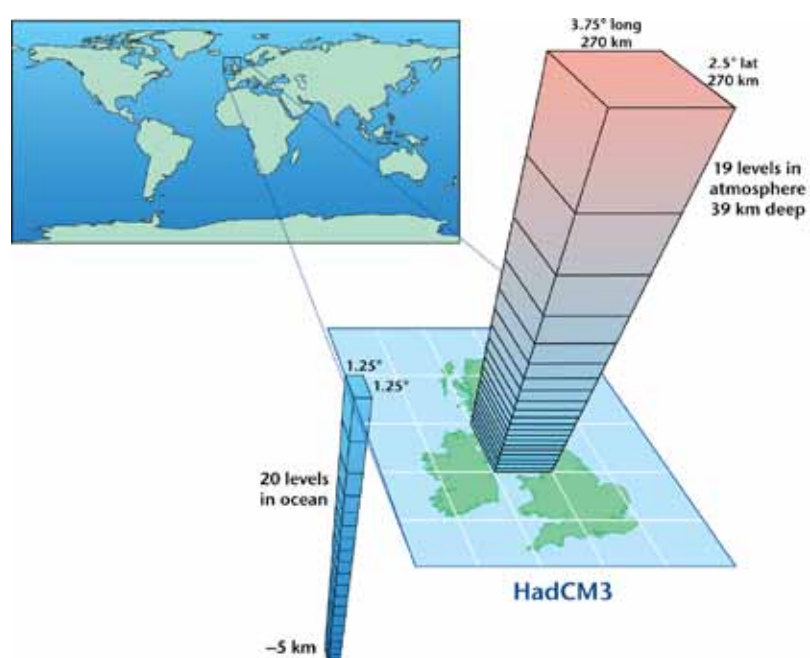


Figure 2.5: The horizontal and vertical structure of the HadCM3 climate model.

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 $\times$ 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 $\times$ 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 CO₂, 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

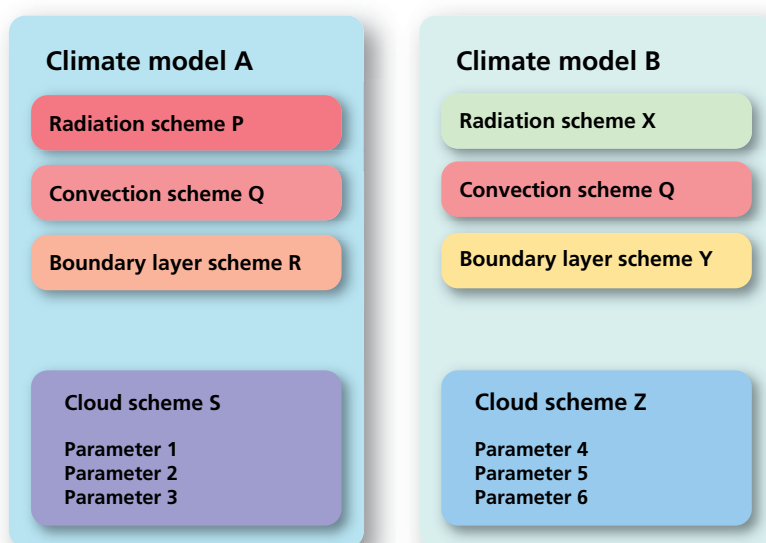


Figure 2.6: Schematic illustration of parametrisation schemes in two different climate models, and the parameter values within one scheme (that for cloud). Note that different models may share one or more parametrisation schemes; in the diagram this is denoted by the convection scheme.

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 CO₂ 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 CO₂ 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 CO₂ 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, CO₂ from the atmosphere. For example, as soils warm they increase their respiration of CO₂ back to the atmosphere and their ability to remove CO₂ 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 CO₂ 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, SF ₆	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.

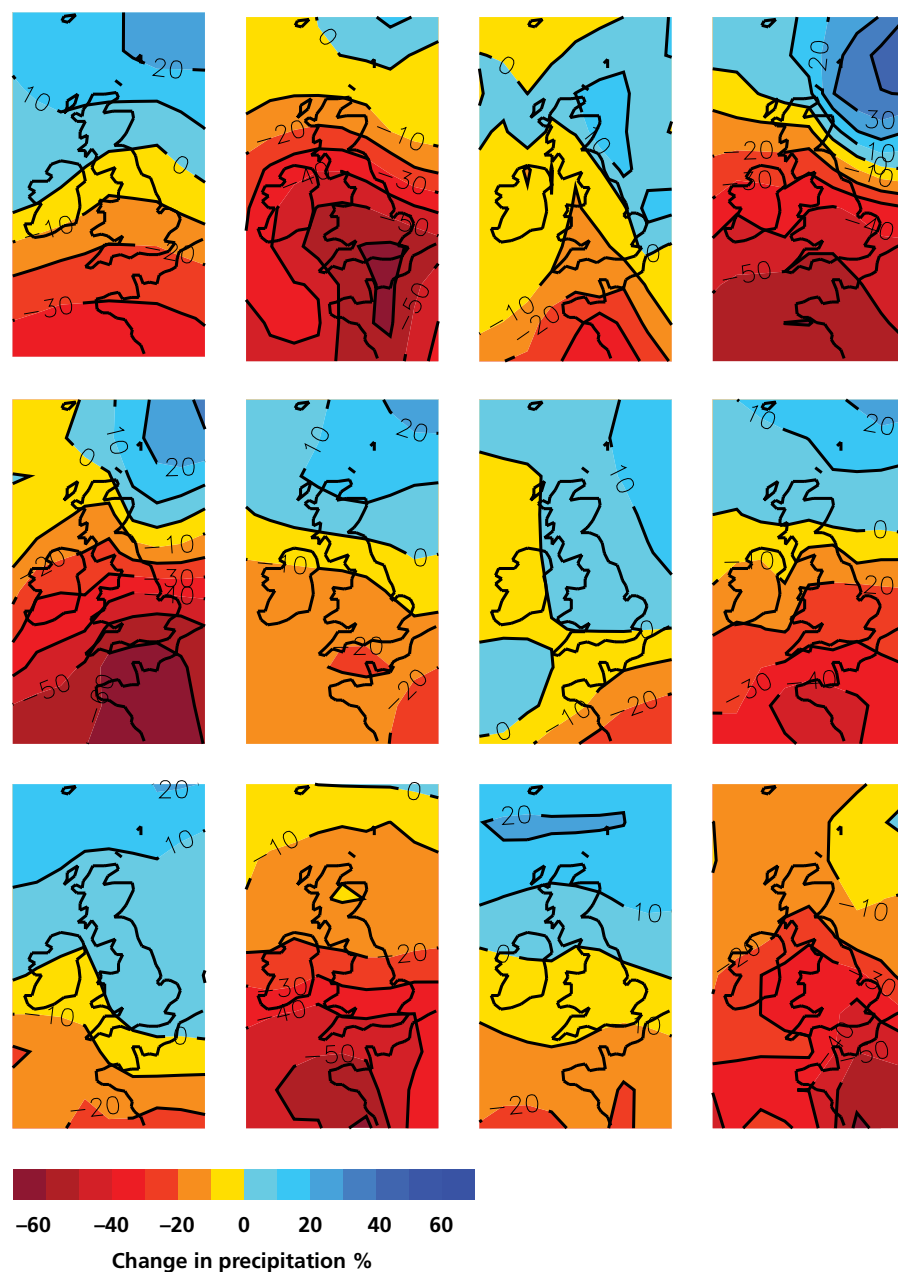


Figure 2.7: Changes (%) in summer (June–August) precipitation by the period 2071–2100 compared to 1961–1990, from 12 climate models, each of which took part in the IPCC AR4, all driven with the same SRES A2 emissions scenario.

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.

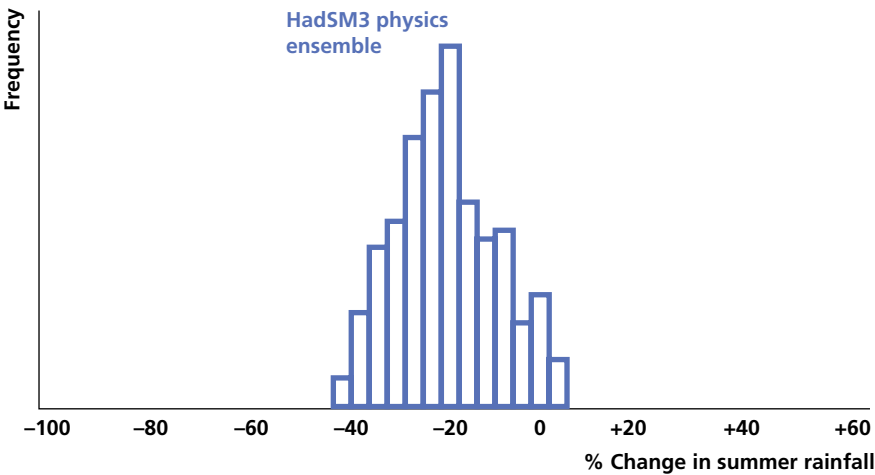


Figure 2.8: Hypothetical histogram showing the frequency of occurrence of different changes in summer rainfall from the 280-member perturbed physics ensemble of HadSM3.

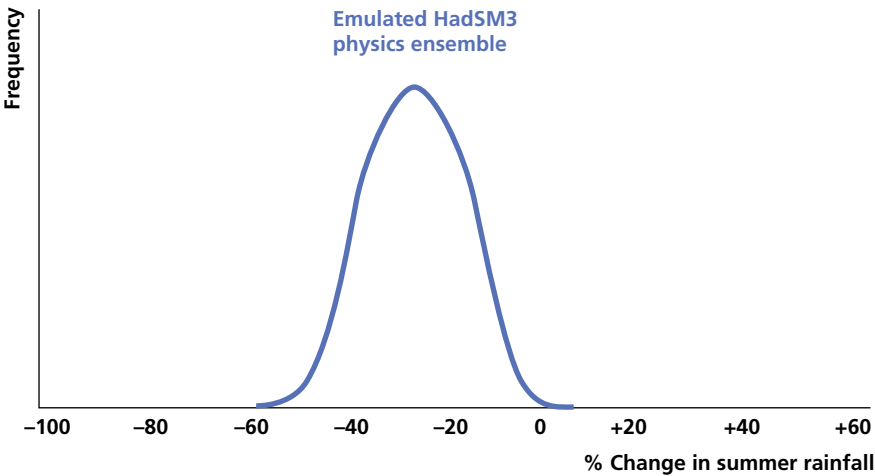


Figure 2.9: Hypothetical distribution showing the frequency of occurrence of different changes from the emulator.

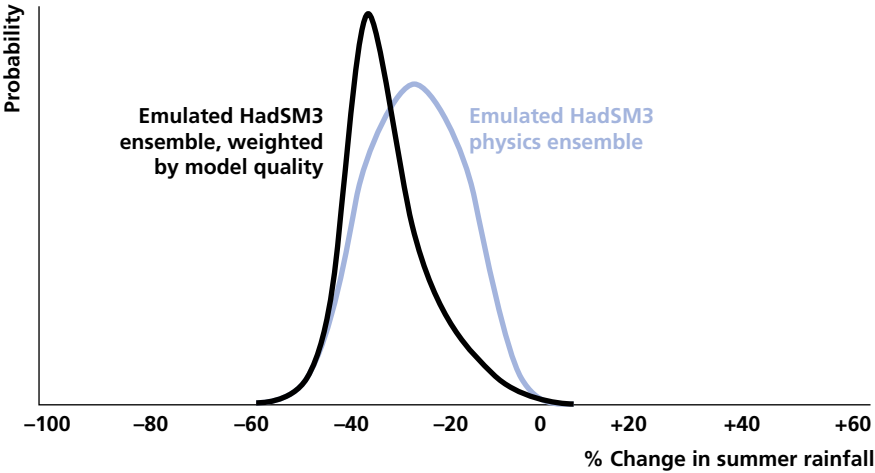


Figure 2.10: Hypothetical distribution showing the probability of different changes from the emulator, weighted according to model credibility based on observations (black curve).

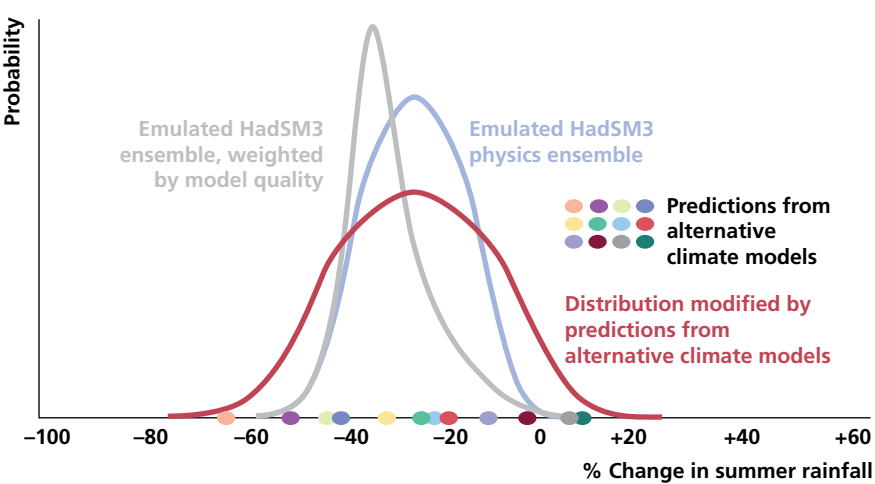


Figure 2.11: The hypothetical probability distribution function of change of summer rainfall (red curve), including projections from both the Met Office perturbed physics ensemble and from alternative international climate models.

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.

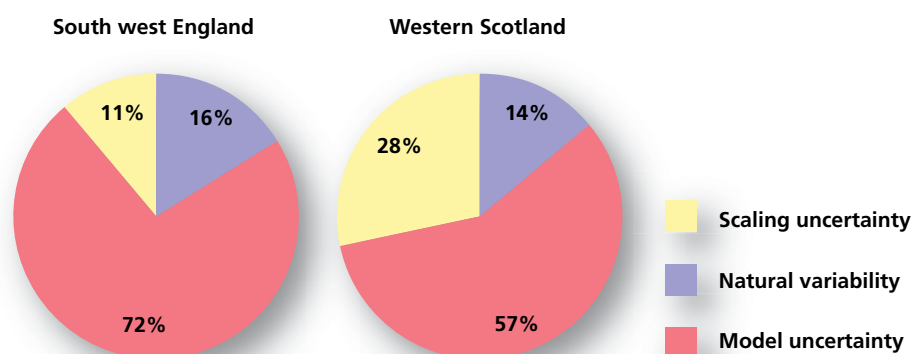


Figure 2.12: The relative contributions to overall uncertainty in change to winter-mean precipitation for 25 km squares in south west England (left) and west Scotland (right) by the 2080s under the Medium emissions scenario, from natural variability, modelling uncertainty and scaling uncertainty. (Contributions 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 (CO₂, 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 CO₂ 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 CO₂ 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.

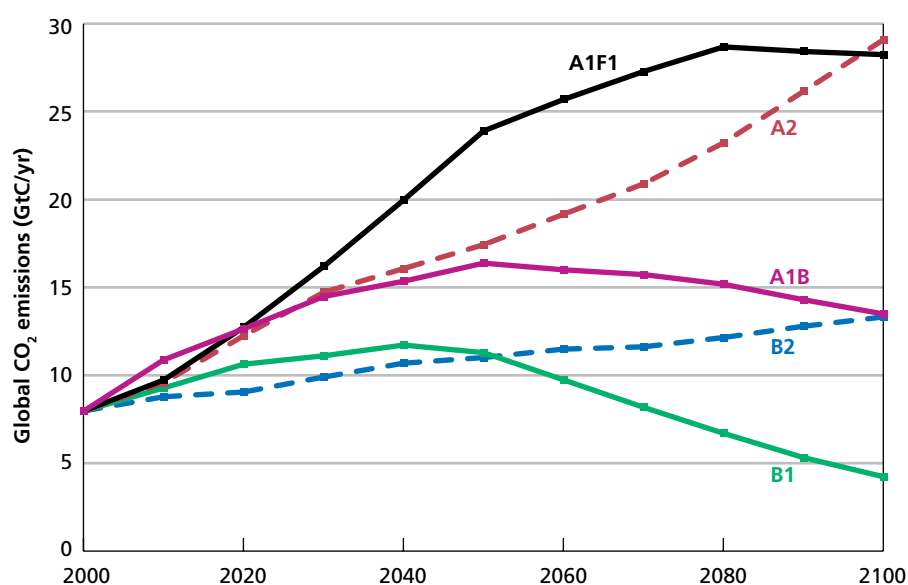


Figure 2.13: Global annual CO₂ emissions (expressed as gigatonnes of carbon) under the three IPCC SRES *marker scenarios* used in UKCP09: A1FI (black: High emissions), A1B (purple: Medium emissions) and B1 (green: Low emissions). Also shown dotted are two SRES emissions scenarios used in UKCIP02 but 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 CO₂ and the thermal inertia of the climate system, but also partly due to the offsetting effects of warming

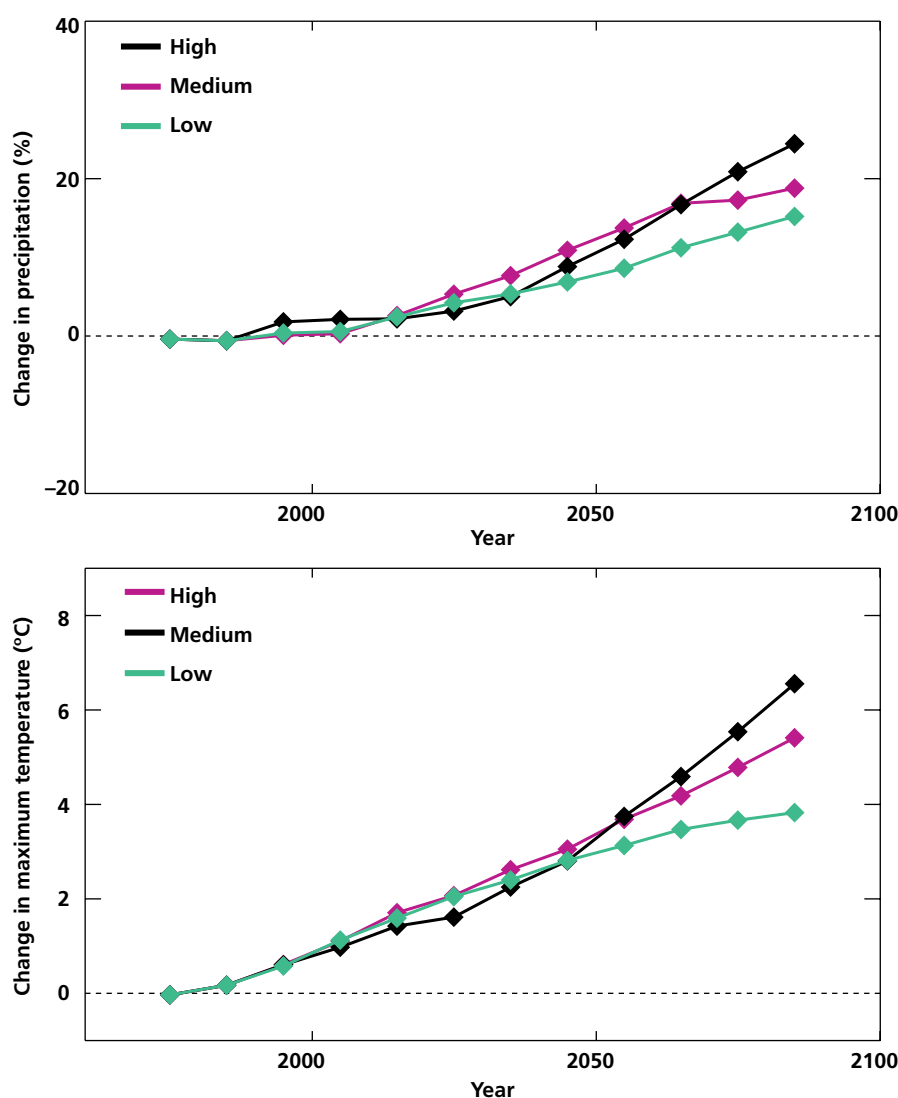


Figure 2.14 Changes in winter-mean precipitation (upper panel), and summer mean daily maximum temperature (lower panel) over Wales, averaged from 17 variants of the HadCM3 global model, for each of three different future emissions scenarios. (Because the purpose here is to show the relative insensitivity of climate change over the next few decades to emissions, the graphs do not reflect the uncertainties in future CO₂ 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, multimodel 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 km² 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.

Sampling uncertainties with perturbed physics ensembles

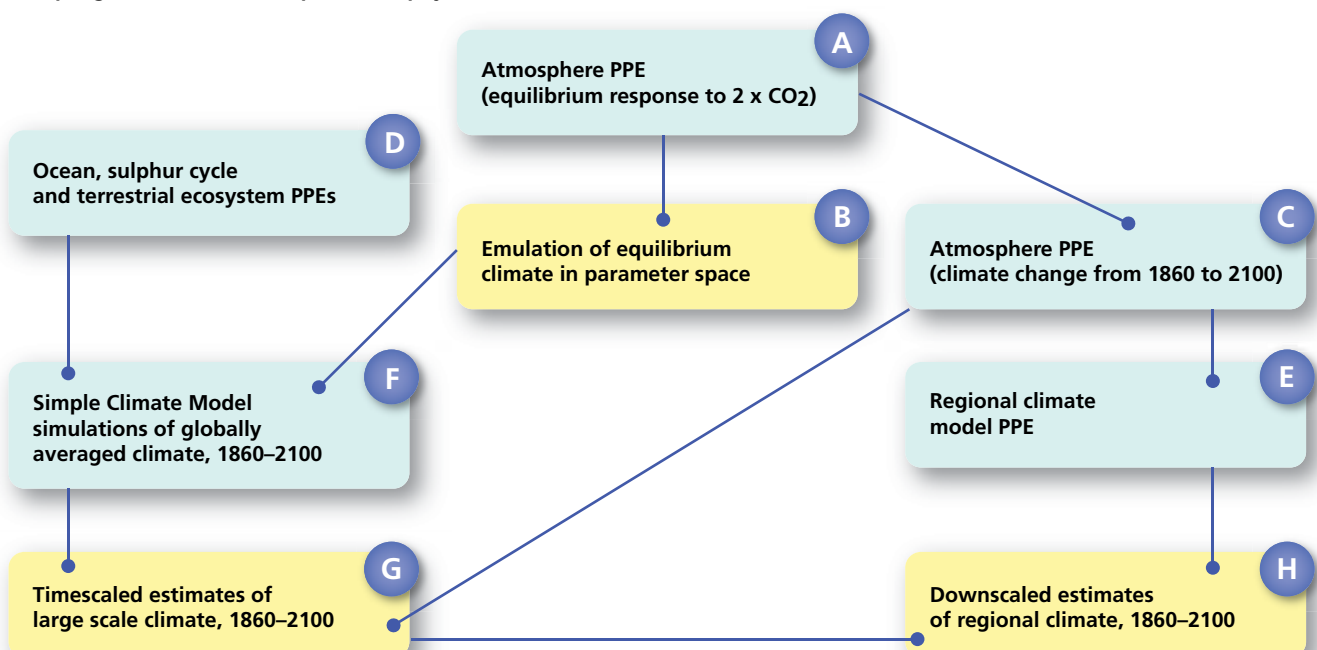


Figure 3.1 gives a schematic summary of the major components of our strategy for sampling modelling uncertainties, through the combination of a number of ensemble climate projection experiments. These experiments use several model configurations derived from HadCM3 to sample uncertainties in climate 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 CO₂

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 CO₂

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

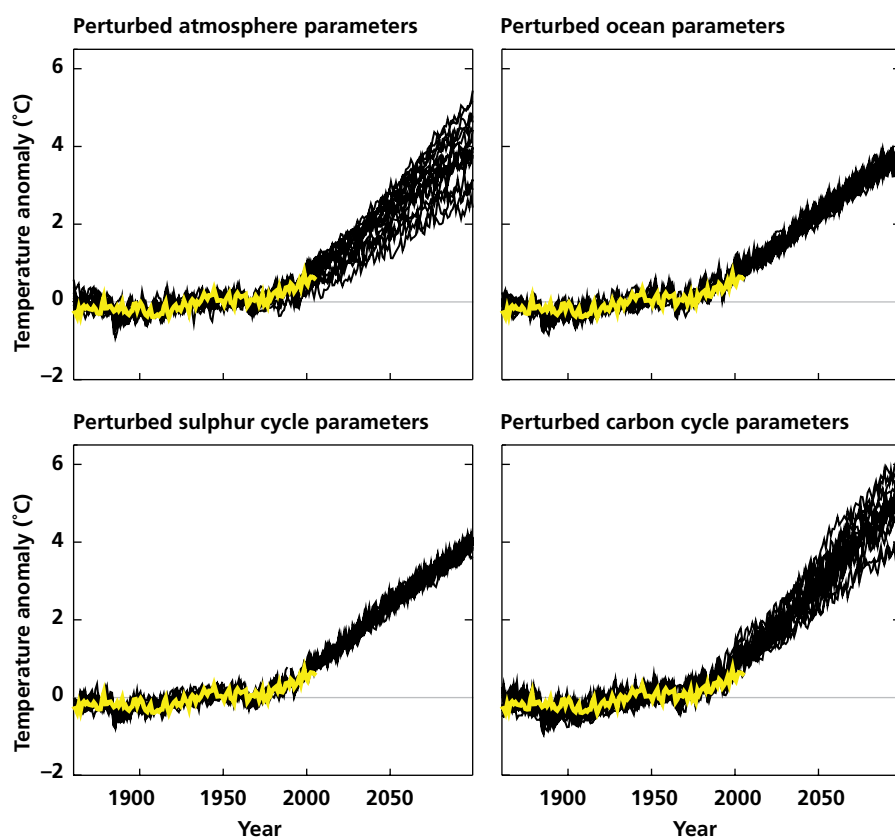


Figure 3.2: Global, annual mean 1.5 m temperature anomalies (°C) from different perturbed physics ensembles of time-dependent climate change under SRES A1B emissions, from 1860 to 2100. Anomalies are expressed with respect to the 1860–2000 mean. Each plot shows observations in yellow, with ensemble projections 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

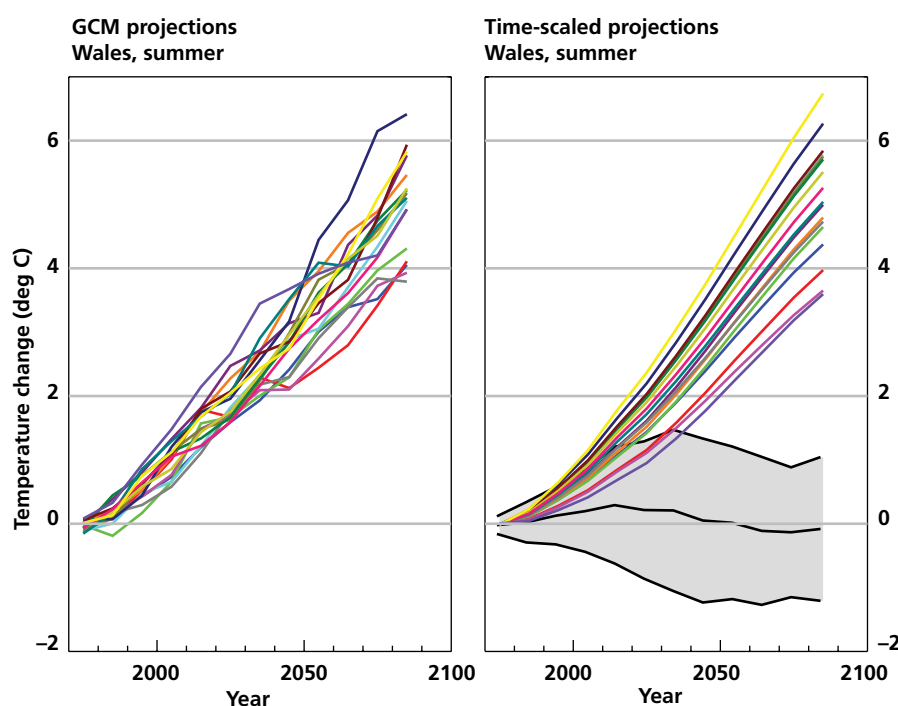


Figure 3.3(a): Left panel shows projected changes in 30-yr averages of surface temperature ($^{\circ}\text{C}$) relative to 1961–1990 over the global climate model grid box corresponding to Wales, in summer, for the 17 members of the PPE_A1B ensemble of perturbed HadCM3 variants. Right panel shows estimates 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

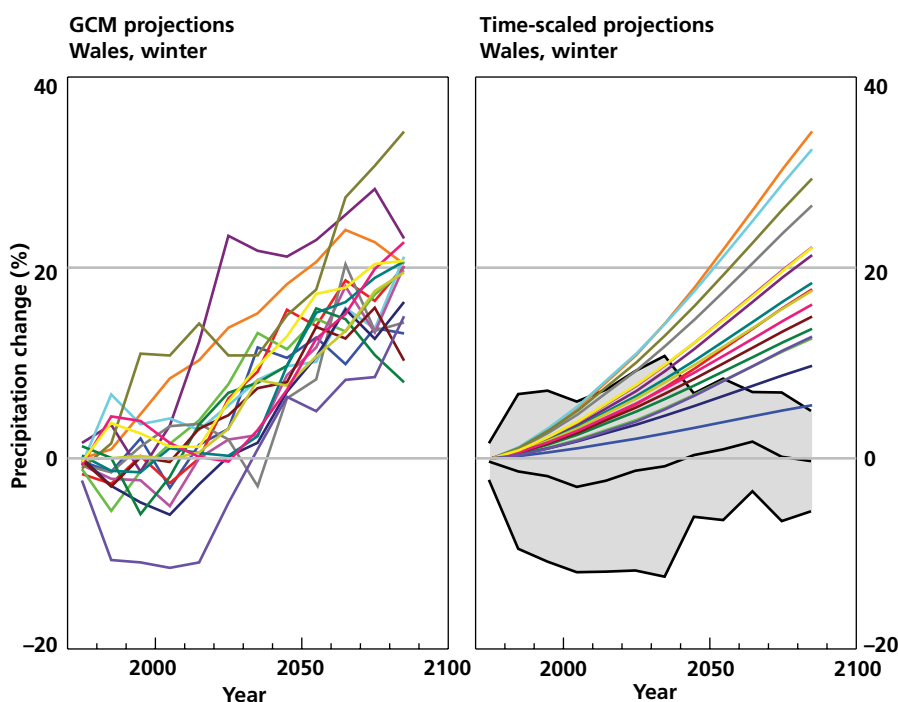


Figure 3.3(b): As Figure 3.3(a), but for precipitation changes (%) over Wales in winter.

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 (SO₂), 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 SO₂, 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. CO₂ 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 CO₂ 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 CO₂ 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 CO₂ 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 (C⁴MIP) by Friedlingstein *et al.* (2006). The C⁴MIP 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 CO₂ 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 CO₂ 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 processes 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 C⁴MIP 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 CO₂ increase, estimates of total emissions (fossil fuel plus land use emissions) and the oceanic uptake of anthropogenic CO₂ (Sabine *et al.* 2004). Two of the perturbed physics simulations and one of the C⁴MIP 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 C⁴MIP, as this model is strongly related to that used for our perturbed physics simulations. This left 9 members of the C⁴MIP 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 CO₂

In Sections 3.2.7–3.2.9 we describe how we obtain probabilistic projections for the equilibrium response to doubled CO₂ 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 km²). 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 CO₂ 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 CO₂ 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 CO₂ 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 CO₂. 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 CO₂ 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 (T_{mean}) 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 CO₂ (see Section 3.2.9). Once the four HadSM3 analogues have been found, discrepancy values can be calculated

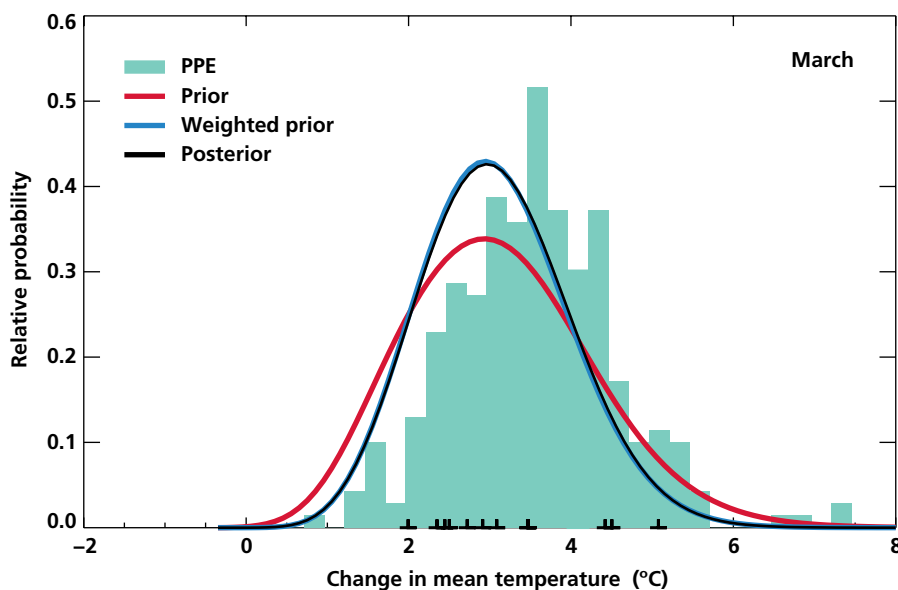


Figure 3.4: Changes in 20 yr-mean surface air temperature (T_{mean}, °C) over the HadSM3 grid box corresponding to Wales, in March, in response to doubled CO₂. Green histogram shows 280 perturbed physics simulations of HadSM3. Black ticks show corresponding changes simulated by 12 multi-model ensemble 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

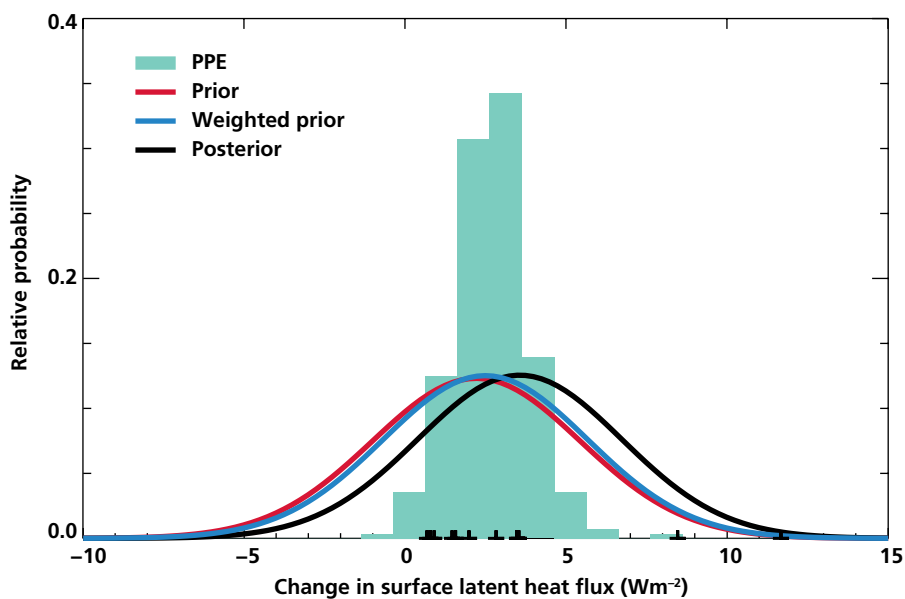


Figure 3.5: As Figure 3.4, for changes in surface latent heat flux (Wm^{-2}) over the HadSM3 grid box corresponding to Scotland, for September–November.

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 discrepancy 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 0.5°C (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 CO₂, 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 CO₂ 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.

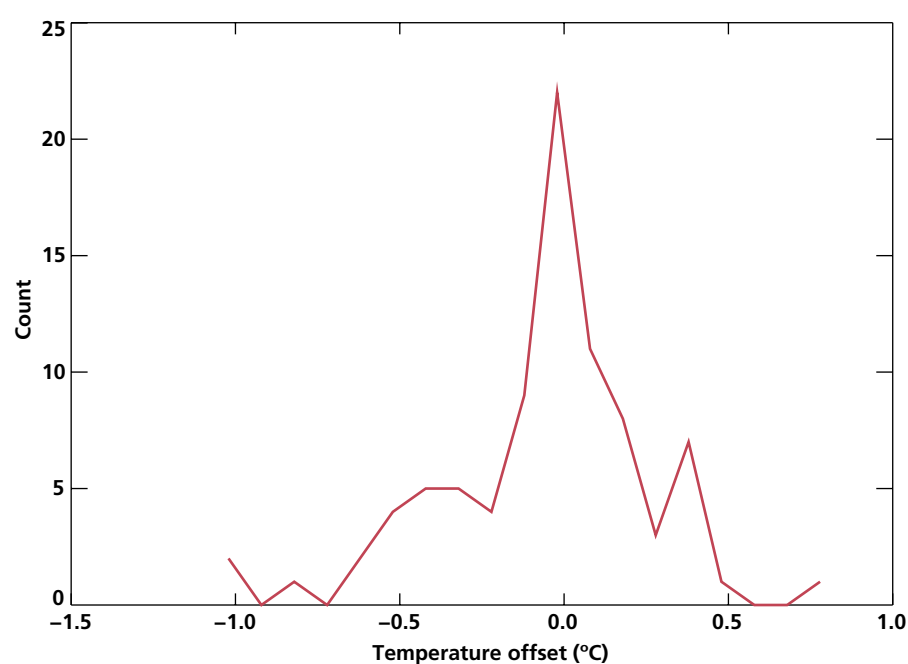


Figure 3.6: Histogram of values for the mean discrepancy for 20 yr mean changes in monthly surface air temperature (°C) in response to doubled CO₂, at UK grid points in HadSM3 (5 grid points x 12 months gives 60 values in all, distributed in bins of width 0.1°C).

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, surface wind speed 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

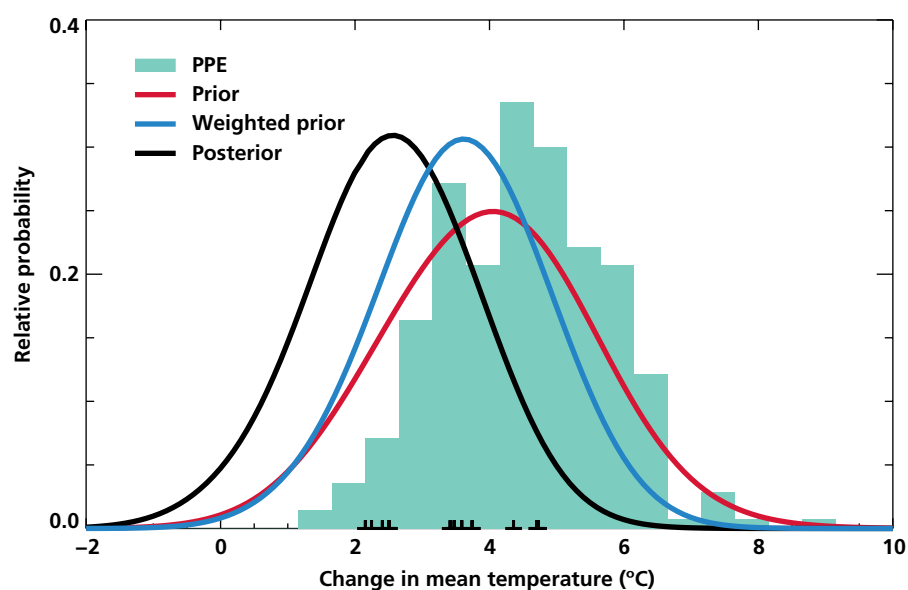


Figure 3.7: As Figure 3.4, for changes in Tmean over the HadSM3 grid box corresponding to Scotland, in March.

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.

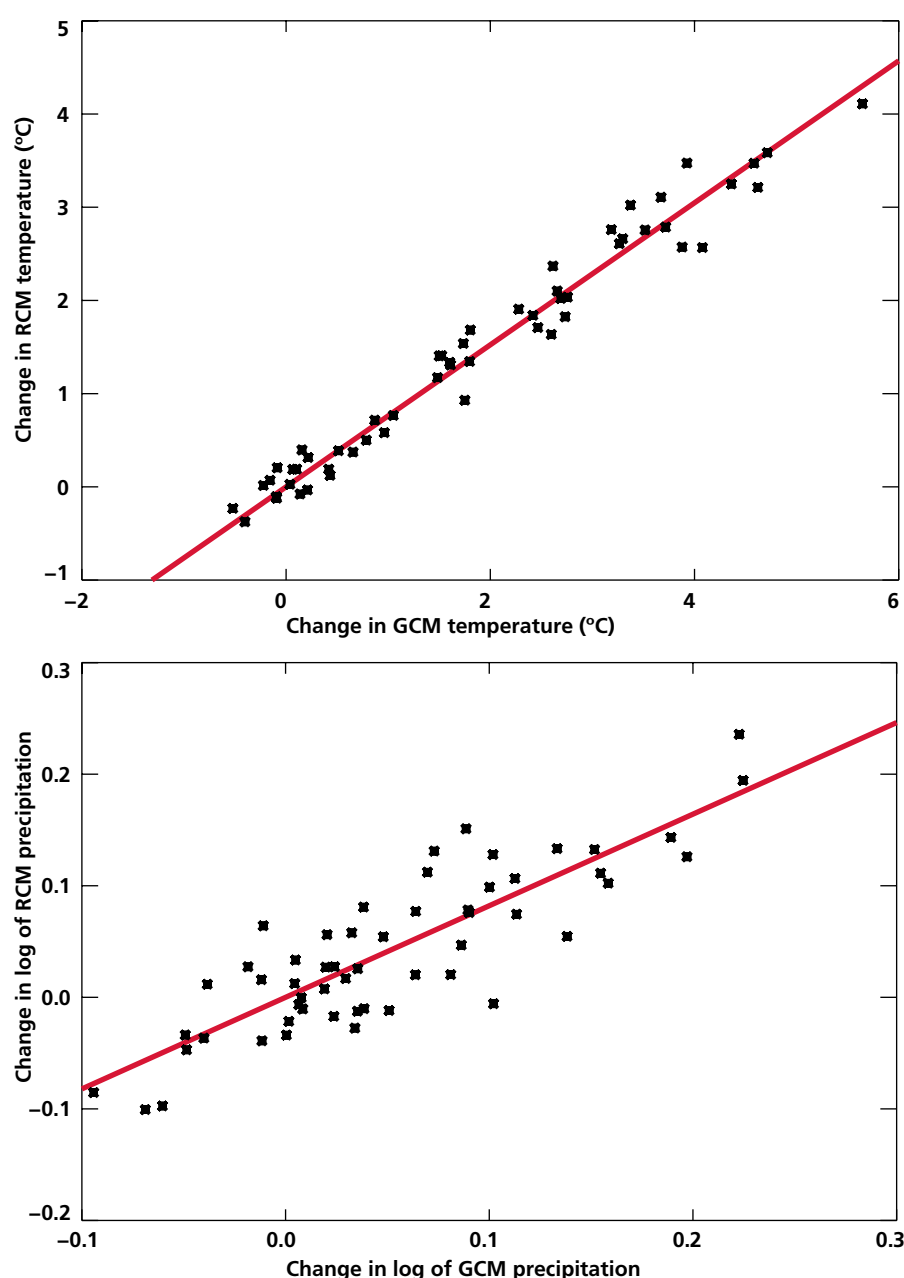


Figure 3.9: Plots of changes in winter surface temperature ($^{\circ}\text{C}$, top) and in the natural logarithm of precipitation* (bottom), for the North Scotland administrative region, for five non-overlapping 30-yr periods relative to 1961–1990, simulated by 11 members of our regional climate model 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.

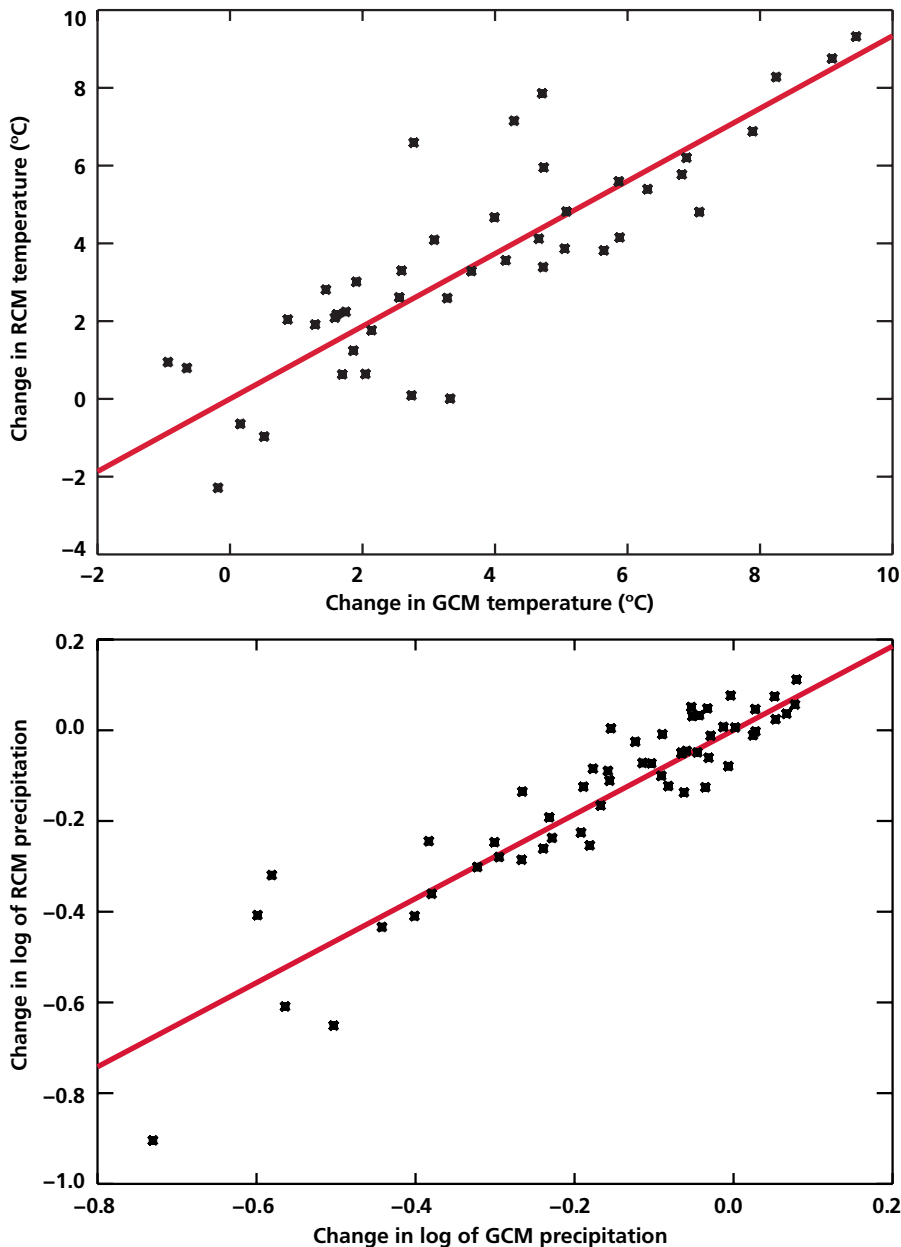
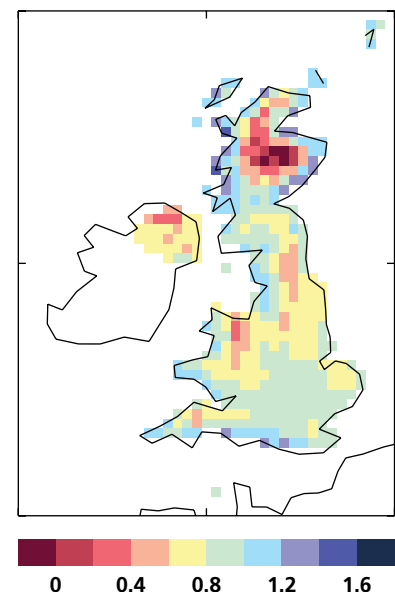


Figure 3.10: As Figure 3.9 for changes in the 99th percentile of daily maximum temperature (°C, top), and in the natural logarithm of precipitation (bottom), for South East England in summer.

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.

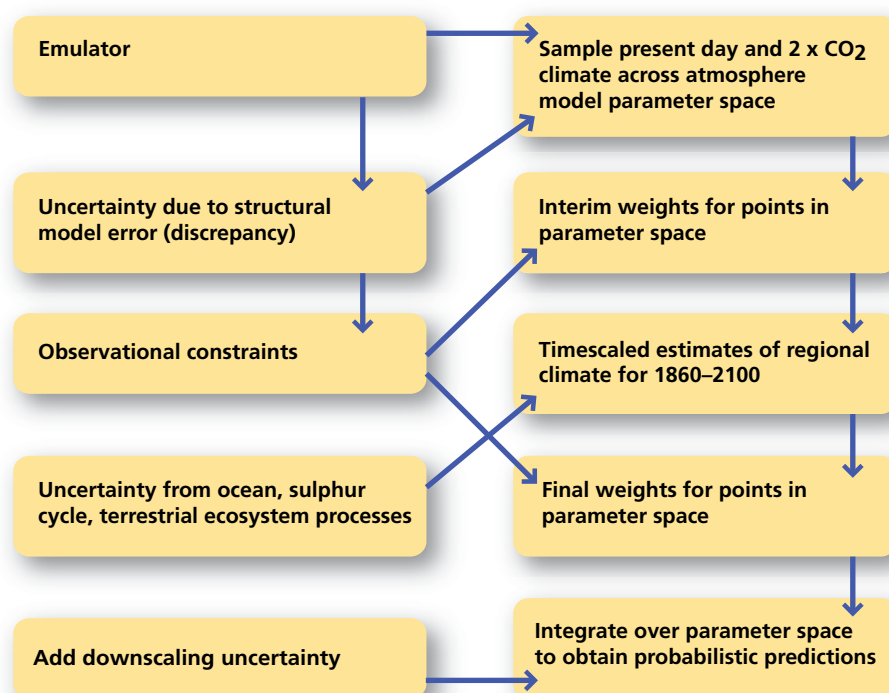


Figure 3.12: Schematic summary of the main elements involved in the derivation of probabilistic projections of climate change for UKCP09, obtained by applying the Bayesian framework of Sections 3.2.7–3.2.9 and the timescaling procedure of Sections 3.2.4 and 3.2.6 to the results of our climate model ensemble 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 three 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. In the case of near-surface wind speed, the archive of multi-model results did not contain values accumulated from simulated values at each model timestep (in contrast to the perturbed physics simulations), so it was not possible to compare values of time averaged wind speed calculated in a consistent manner from both ensembles. Finally, 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 wind speed and 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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4 Probabilistic projections of seasonal climate changes

This chapter has three purposes. Firstly, it gives some key findings of seasonal changes to climate, at national level and for each of the administrative regions, for the most widely used variables.

Secondly, it shows examples of the probabilistic projections of change which can be obtained from the User Interface. For many users, the maps and diagrams in the UKCIP02 Science Report acted as their main access to the scenarios, and provided them with all they needed. In UKCP09 the amount of information available, and its complexity, is substantially greater. For this reason, a comprehensive set of *pre-prepared* maps and graphs can be seen on the UKCP09 website, which provides many more illustrations of UKCP09 results than can be shown in a report — for example, maps for other future time periods and emissions scenarios. However, because pre-prepared graphics are not always sufficient, a User Interface has been developed which will create additional graphics and data to user specifications. This chapter will show some examples of the various maps which can be generated by the User Interface, focussing mainly on projected changes in seasonal means of some temperature and precipitation variables.

Thirdly, it compares various PDFs of change to show how they differ for different future time periods, emissions scenarios, and spatial and temporal averaging choices, using temperature and precipitation variables as examples. These comparisons, which are listed in Table 4.3, are designed to help users in deciding which choices to make from the possibilities that the User Interface presents. Understanding them is fundamental to their proper use.

As discussed in Chapter 3, it has not been possible to derive probabilistic projections of changes in wind speed, latent heat flux, snowfall rate and soil moisture; these variables are discussed at the end of this chapter.

4.1 Probabilistic projections as PDFs and CDFs

In Chapter 1 we discussed the presentation of the probabilistic projections in two ways: the probability density function (PDF) and the cumulative distribution function (CDF), using hypothetical cases. In Figure 4.1, we illustrate changes using UKCP09 projections for a 25 km square over the East of England. The information contained in the two plots is identical, and hence we present only the PDF form later in this chapter. The PDF form is useful to get an appreciation of the uncertainties in the change, but the CDF may be the form used in assessments

and impacts studies, particularly when thresholds are important; this is discussed in the UKCP09 User Guidance.

As explained in Annex 4, the UKCP09 User Interface allows the user to download probabilistic data and create PDF plots of their own offline. The User Interface dataset stores probability values down to very low levels, but when it creates plots the curves are trimmed at both ends to suppress long *tails* where the probability is changing only very slowly.

In UKCP09, following IPCC, we use the descriptors *very likely to be less than* or *very unlikely to be greater than* to describe projections with a cumulative probability of 90%. We use *very likely to be greater than* or *very unlikely to be less than* for a cumulative probability of 10%. We use the term *central estimate* to describe the projections having 50% cumulative probability (properly known as the median of the distribution). For convenience, we use the term *probability* rather than *cumulative probability* in the rest of the chapter.

Hence, the CDF in the example in Figure 4.1 tells us that, for the particular location, time period, emissions scenario:

- The projected warming is very unlikely to be less than (or, alternatively, very likely to be more than) about 3.7°C (red lines)
- The central estimate for the warming is about 7°C (green lines)
- The projected warming is very likely to be less than (or, alternatively, very unlikely to be more than) 11°C (blue lines).

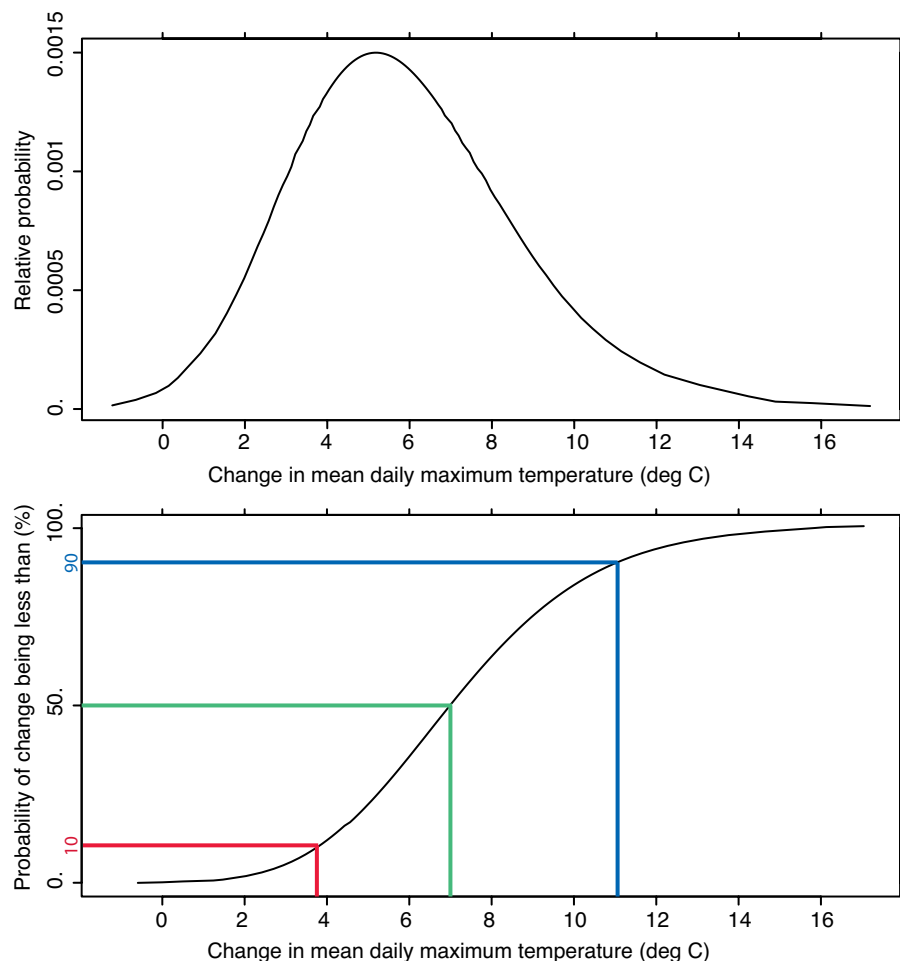


Figure 4.1: PDF (top) and CDF (bottom) of change in summer mean daily maximum temperature (°C) over a particular 25 km square by the 2080s under the High emissions scenario. Both these figures are from the User Interface, but the coloured lines on the CDF have been added later; they cannot be added by the User Interface.

Note that, as with all climate change projections (for example those in IPCC AR4), probabilities given are conditional on the methodology used. So when we say a particular projected change is *very likely* to be less than a given value of temperature change, we mean *very likely according to probabilities derived using the UKCP09 methodology*.

4.1.1 The credibility of changes at extremes of the probability distributions

The UKCP09 probabilistic projections allow us in principle to look at changes near the upper and lower extremes of the projected probability distributions; we advise against this. Probabilistic projections, although they are designed to quantify uncertainty, require us to make a number of assumptions in their development, and hence they are themselves uncertain. Annex 2 describes some of the sensitivities of the projections to choices and assumptions in our methodology. This uncertainty applies to the whole of the PDF or CDF, but increases as we go towards the extremes (tails) of the distribution, and for this reason the confidence in our results is much smaller here. We have different levels of confidence in different variables so, for example, data at a given probability level (say 95%) may be relatively robust for one variable (for example, seasonal mean temperature) but less robust in the case of another (for example, the wettest day of the season). In addition, what may be an unacceptable uncertainty for one user may be quite acceptable for another application. However, as a general guideline we suggest that users should be able to use the distribution from the 10% to the 90% probability levels, but not outside this range, although data covering the full range is available. For some variables the limits may be more stringent than this.

4.1.2 Consequences of having the baseline climate as 1961–1990

User consultations and surveys carried out by UKCIP showed support for retaining the same baseline (or reference) period as was used in UKCIP02, namely 1961–1990 (strictly Dec 1960–Nov 1990). Hence all changes shown or described in this report are changes with respect to that baseline. Users will recognise, however, that the current climate has already changed significantly since the baseline period, and so changes should not be described as “compared to today’s climate”. This is obviously more important for the earliest projected time period of the 2020s (2010–2039) and less important, but certainly not negligible, for the most distant one. For example, the central year of the baseline time period is 1975–1976; that of the first future time period is 2024–2025, 49 yr later. However, this report is published in 2009, 33 yr after the central year of the baseline period and hence already about two-thirds of the way to the central year of the first time period of the projections. Similarly, we are already about 40% of the way to the central year of the 2050s time period (2040–2069), and even about 30% of the way towards the last projected period of 2070–2099. If users wish to estimate the change in any variable relative to today’s climate, the UKCP09 report *The climate of the UK and recent trends* and data sources quoted in this, may help. However, users should note that (a) recent change may not be linear, and (b) due to natural variability, the actual climate change over the last 33 yr, based on observations, may not be the same as that simulated by models. For users who may wish to relate future changes to a pre-industrial baseline, some data (for example, the Central England Temperature) on longer term trends is available from the MOHC website (<http://hadobs.metoffice.com/hadcet/>).

4.2 Key findings

In this section we present key findings from the probabilistic projections at a national level and for each of the 16 administrative regions.

4.2.1 National key findings

National key findings are given in the form of tables (4.1 to 4.3) of the winter and summer seasonal average changes in a number of variables (plus the change in the annual average in the case of precipitation). The tables contain the values of change (relative to 1961–1990) in the 25 km grid squares which show both the highest and lowest changes anywhere in the UK, for each UKCP09 emissions scenario, for the 2080s time period and for the 10, 50 and 90% probability levels. To explain this further, we take the example, in Table 4.1, of the *highest change* of winter mean temperature shown in the *10% probability* box, by the 2080s, under the High emissions scenario — the top right box. This has a value of 2.2°C. This means that, for the grid square in the UK showing the highest change (for that time period, emissions scenario and probability level), the UKCP09 methodology estimates that it is very unlikely (10% probability) that the winter mean temperature change will be less than 2.2°C or, in other words, the warming is very likely to be greater than 2.2°C. The three probability levels shown in the tables (10, 50 and 90%) have been chosen to show the widest range which we consider to be robust within the methodology (see 4.1.1). The definitions of *highest* and *lowest* take into account the sign of change; for example a change of –10% is considered to be lower than one of +5%. Note that for a given emissions

Table 4.1: Highest and lowest changes in mean daily temperature, mean daily maximum temperature and mean daily minimum temperature (°C) in winter and summer, by the 2080s, relative to 1961–1990.

Variable		Mean temperature, winter			Mean temperature, summer			Mean daily maximum temperature, winter			Mean daily maximum temperature, summer			Mean daily minimum temperature, winter			Mean daily minimum temperature, summer		
Probability level		10%	50%	90%	10%	50%	90%	10%	50%	90%	10%	50%	90%	10%	50%	90%	10%	50%	90%
High emissions	Highest change in UK	2.2	3.8	5.8	2.9	5.3	8.4	1.6	3.4	6.1	3.0	6.8	11.7	2.0	4.2	7.0	2.8	5.3	8.8
	Lowest change in UK	1.0	2.1	3.5	1.6	3.1	5.0	1.1	2.3	3.9	1.2	3.5	6.3	0.8	2.4	4.3	1.7	3.3	5.6
Medium emissions	Highest change in UK	1.7	3.1	4.8	2.2	4.2	6.8	1.3	2.9	5.1	2.2	5.4	9.5	1.5	3.5	5.9	2.0	4.1	7.1
	Lowest change in UK	0.8	1.8	3.1	1.2	2.5	4.1	0.8	2.0	3.4	1.1	2.8	5.0	0.6	2.1	3.7	1.3	2.7	4.5
Low emissions	Highest change in UK	1.5	2.7	4.1	1.4	3.1	5.3	1.3	2.6	4.3	1.4	4.1	7.5	1.4	2.9	4.8	1.4	3.2	5.6
	Lowest change in UK	0.8	1.7	2.7	0.8	1.9	3.2	0.9	1.8	3.0	0.7	2.1	3.9	0.7	2.0	3.3	0.9	2.1	3.5

Variable		Mean precipitation, annual			Mean precipitation, winter			Mean precipitation, summer			Precipitation on wettest day of the winter			Precipitation on wettest day of the summer		
Probability level		10%	50%	90%	10%	50%	90%	10%	50%	90%	10%	50%	90%	10%	50%	90%
High emissions	Highest change in UK	-3	+3	+20	+18	+47	+97	-8	0	+10	+11	+35	+77	-1	+14	+64
	Lowest change in UK	-21	+6	+3	-12	-3	+6	-74	-49	-10	-12	0	+13	-46	-18	+6
Medium emissions	Highest change in UK	-3	+2	+14	+9	+33	+70	-8	+1	+10	+7	+25	+56	-1	+12	+51
	Lowest change in UK	-16	-3	+3	-11	-2	+7	-65	-40	-6	-12	0	+13	-38	-12	+9
Low emissions	Highest change in UK	-2	+3	+14	+8	+30	+59	-8	+1	+16	+4	+22	+47	-2	+10	+49
	Lowest change in UK	-12	-1	+3	-11	-2	+7	-55	-30	+1	-12	0	+13	-29	-7	+10

Table 4.2: Highest and lowest changes in annual-, winter- and summer-mean daily precipitation, and in precipitation on the wettest day of the season (%) in winter and summer, by the 2080s, relative to 1961–1990.

Variable		Total cloud, winter			Total cloud, summer			Relative humidity, winter			Relative humidity, summer		
Probability level		10%	50%	90%	10%	50%	90%	10%	50%	90%	10%	50%	90%
High emissions	Highest change in UK	-1	+2	+8	+1	+7	13	+2	+4	+6	+1	+2	+4
	Lowest change in UK	-10	-4	+1	-39	-23	-4	-3	0	0	-24	-11	0
Medium emissions	Highest change in UK	-1	+1	+6	0	+5	+11	+1	+3	+5	+1	+2	+3
	Lowest change in UK	-9	-4	+1	-33	-18	-2	-3	0	0	-20	-9	0
Low emissions	Highest change in UK	-1	+1	+5	-1	+3	+7	0	+2	+4	0	+1	+3
	Lowest change in UK	-8	-3	+1	-26	-12	0	-2	0	0	-16	-6	0

Table 4.3 Highest and lowest changes in cloud amount (%) and mean relative humidity (% of %) in winter and summer, relative to 1961–1990.

scenario, the grid square with the highest change at the 10% probability level may not be the same grid square that shows the highest change at the 50 or 90% probability levels.

4.2.2 Regional key findings

Regional key findings are based on changes averaged over administrative regions (shown as Figure 4.2), given in Tables 4.4 and 4.5. They show summer- and winter-mean changes for a number of key variables, at the 10, 50 and 90% probability level, by the 2050s under the Medium emissions scenario. In addition, the tables show a *wider range of uncertainty* for the 2050s, defined here as the lowest and the highest values seen in all three emissions scenarios and all three (10, 50 and 90%) probability levels. In the case of precipitation, change in the annual mean is also shown.

Variable	Mean temperature, winter °C					Mean temperature, summer °C					Mean daily maximum temperature, summer °C					Mean daily minimum temperature, summer °C				
Probability level	10%	50%	90%	Wider range		10%	50%	90%	Wider range		10%	50%	90%	Wider range		10%	50%	90%	Wider range	
North Scotland	0.6	1.7	2.8	0.6	3.0	0.9	2.0	3.4	0.9	3.9	0.8	2.5	4.5	0.9	5.3	0.9	2.3	3.9	0.9	4.4
East Scotland	0.7	1.7	2.9	0.6	3.1	1.1	2.3	3.9	1.0	4.5	1.0	3.0	5.4	1.0	6.3	1.1	2.5	4.3	1.0	4.9
West Scotland	1.0	1.9	3.0	0.8	3.3	1.1	2.4	3.8	1.0	4.4	0.9	3.0	5.2	0.9	5.9	0.9	2.4	4.2	0.9	4.7
N Ireland	0.9	1.7	2.7	0.6	2.9	1.0	2.2	3.5	0.8	4.0	0.9	2.7	4.8	0.8	5.4	1.0	2.4	4.2	0.9	4.6
Isle of Man	0.9	1.8	2.7	0.7	3.0	1.1	2.3	3.7	1.0	4.2	0.9	2.9	5.1	0.8	5.7	0.9	2.2	3.9	0.8	4.4
NE England	1.0	2.0	3.1	0.8	3.4	1.2	2.5	4.1	1.1	4.7	1.0	3.2	5.7	0.9	6.4	1.0	2.5	4.4	0.9	4.9
NW England	1.0	2.0	3.0	0.8	3.3	1.2	2.6	4.1	1.1	4.7	1.0	3.3	5.8	1.0	6.5	1.0	2.5	4.4	0.9	4.9
Yorkshire & Humber	1.1	2.1	3.3	0.9	3.7	1.1	2.3	3.9	0.9	4.4	1.2	3.1	5.4	1.0	6.1	1.1	2.6	4.4	1.0	5.0
East Midlands	1.1	2.2	3.4	0.9	3.8	1.2	2.5	4.2	1.0	4.7	1.3	3.3	5.9	1.1	6.6	1.2	2.7	4.6	1.1	5.2
West Midlands	1.2	2.1	3.2	0.9	3.5	1.2	2.6	4.4	1.0	4.8	1.3	3.6	6.5	1.1	7.2	1.1	2.7	4.8	1.0	5.3
Wales	1.1	2.0	3.1	0.8	3.4	1.2	2.5	4.1	1.0	4.6	1.3	3.4	6.1	1.0	6.8	1.1	2.6	4.6	0.9	5.1
East England	1.1	2.2	3.4	0.9	3.8	1.2	2.5	4.3	1.0	4.8	1.3	3.4	6.0	1.1	6.8	1.2	2.7	4.7	1.1	5.3
London	1.2	2.2	3.5	0.9	3.8	1.3	2.7	4.6	1.1	5.2	1.4	3.7	6.5	1.2	7.3	1.3	2.9	5.0	1.2	5.6
SE England	1.1	2.2	3.4	0.9	3.8	1.3	2.7	4.6	1.1	5.2	1.4	3.7	6.5	1.2	7.3	1.3	2.9	5.1	1.2	5.7
SW England	1.1	2.1	3.2	0.8	3.5	1.3	2.7	4.6	1.1	5.1	1.4	3.8	6.8	1.2	7.6	1.2	2.9	5.0	1.0	5.5
Channel Isles	1.1	2.0	3.1	0.8	3.4	1.2	2.5	4.2	1.0	4.7	1.3	3.4	6.2	1.0	6.9	1.1	2.8	4.8	0.9	5.3

Table 4.4: Changes in daily mean (summer and winter averages), and summer-mean daily maximum and minimum temperatures, averaged over administrative regions, by the 2050s under the Medium emissions scenario. *Wider range* is defined as the range from the lowest to highest value of change for all emissions scenarios and all three (10, 50 and 90%) probability levels by the 2050s. Note that values from the User Interface may differ by a percent from those above due to rounding.

These tabular findings can also be presented as written statements, using the term *very unlikely to be less than* to refer to the 10% probability level, *very unlikely to be greater than* to refer to the 90% probability level and *central estimate* to refer to the 50% probability level. We give below written key regional findings for Wales for some temperature and precipitation quantities as examples; statements for other administrative regions can be generated from Tables 4.4 and 4.5. On the UKCP09 website, users will be able to view pre-prepared maps and graphs and written key findings for all regions.

Figure 4.2: Administrative regions over which changes are averaged in the regional key findings.



Variable	Annual mean precipitation %					Winter mean precipitation %					Summer mean precipitation %				
Probability level	10%	50%	90%	Wider range		10%	50%	90%	Wider range		10%	50%	90%	Wider range	
North Scotland	-6	0	+5	-7	+6	+3	+13	+24	0	+26	-23	-10	+2	-23	+6
East Scotland	-4	0	+5	-5	+6	+2	+10	+20	-1	+21	-26	-12	+1	-27	+6
West Scotland	-6	0	+5	-7	+6	+5	+15	+28	0	+30	-26	-12	+1	-27	+6
Northern Ireland	-3	0	+3	-3	+3	+2	+9	+19	0	+19	-26	-12	+3	-27	+8
Isle of Man	-5	0	+4	-6	+5	+2	+16	+35	-1	+36	-31	-15	+1	-32	+8
North East England	-4	0	+5	-5	+5	+1	+11	+24	0	+26	-29	-14	+1	-30	+7
North West England	-5	0	+6	-6	+7	+3	+13	+26	0	+27	-34	-17	+1	-36	+8
Yorkshire & Humber	-3	0	+4	-4	+5	+2	+11	+24	0	+27	-35	-17	+1	-37	+9
East Midlands	-4	0	+6	-5	+6	+2	+14	+29	+1	+33	-35	-15	+6	-37	+13
West Midland	-4	0	+6	-5	+6	+2	+13	+28	+1	+31	-36	-16	+6	-38	+13
Wales	-4	0	+5	-5	+6	+2	+14	+30	0	+31	-36	-16	+6	-38	+13
East England	-4	0	+5	-4	+6	+3	+14	+31	+1	+35	-37	-16	+6	-39	+14
London	-4	0	+5	-4	+5	+2	+15	+33	0	+37	-39	-18	+7	-41	+16
South East England	-4	0	+6	-5	+6	+2	+16	+36	+1	+40	-40	-18	+7	-42	+16
South West England	-4	0	+6	-5	+6	+4	+17	+38	0	+41	-41	-19	+7	-43	+16
Channel Islands	-4	0	+3	-4	+4	+2	+15	+34	0	+38	-47	-22	+9	-49	+20

Table 4.5: Changes in annual-, winter- and summer-mean precipitation, averaged over administrative regions, by the 2050s under the Medium emissions scenario. *Wider range* is defined as the lowest and the highest values of change seen in all three emissions scenarios and all three (10, 50 and 90%) probability levels. Note that values from the User Interface may differ by a percent from those above due to rounding.

Key findings for Wales, changes by the 2050s

- Under Medium emissions, the central estimate of increase in winter mean temperature is 2.0°C; it is very unlikely to be less than 1.1°C and is very unlikely to be more than 3.1°C. A wider range of uncertainty is from 0.8 to 3.4°C.
- Under Medium emissions, the central estimate of increase in summer mean temperature is 2.5°C; it is very unlikely to be less than 1.2°C and is very unlikely to be more than 4.2°C. A wider range of uncertainty is from 1.0 to 4.6°C.
- Under Medium emissions, the central estimate of increase in summer mean daily maximum temperature is 3.4°C; it is very unlikely to be less than 1.3°C and is very unlikely to be more than 6.1°C. A wider range of uncertainty is from 1.0 to 6.8°C.

- Under Medium emissions, the central estimate of increase in summer mean daily minimum temperature is 2.6°C; it is very unlikely to be less than 1.1°C and is very unlikely to be more than 4.6°C. A wider range of uncertainty is from 0.9 to 5.1°C.
- Under Medium emissions, the central estimate of change in annual mean precipitation is 0%; it is very unlikely to be less than –4% and is very unlikely to be more than +5%. A wider range of uncertainty is from –5% to +6%.
- Under Medium emissions, the central estimate of change in winter mean precipitation is +14%; it is very unlikely to be less than +2% and is very unlikely to be more than +30%. A wider range of uncertainty is from 0% to +31%.
- Under Medium emissions, the central estimate of change in summer mean precipitation is –16%; it is very unlikely to be less than –36% and is very unlikely to be more than +6%. A wider range of uncertainty is from –38% to +13%.

4.2.3 Key findings for marine regions

Variable	Mean temp winter °C					Mean temp summer °C					Precipitation winter %					Precipitation summer %				
	10%	50%	90%	Wider range		10%	50%	90%	Wider range		10%	50%	90%	Wider range		10%	50%	90%	Wider range	
Scottish Continental shelf	0.3	1.2	2.2	0.3	2.5	0.1	1.1	2.3	0.1	2.6	–5	0	+4	–8	+5	–8	–1	+6	–8	+8
Northwest approaches	–0.2	0.9	2.1	–0.2	2.3	–0.3	0.8	2.2	–0.3	2.5	–4	+4	+15	–4	+15	–7	–1	+6	–7	+6
West Scotland	0.3	1.1	2.2	0.3	2.5	0.1	1.2	2.5	0.1	2.8	–4	+1	+6	–9	+7	–8	–1	+7	–8	+8
Irish Atlantic approaches	0.7	1.4	2.4	0.6	2.7	0.6	1.5	2.5	0.6	2.8	–5	+5	+19	–5	+19	–18	–9	+1	–18	+3
Northern North Sea	1.0	1.8	2.9	0.9	3.1	0.9	1.8	2.8	0.9	3.1	+1	+9	+18	–2	+19	–9	–2	+6	–9	+7
Southern North Sea	1.4	2.2	3.3	1.2	3.7	1.2	2.1	3.2	1.2	3.6	+3	+11	+21	+1	+24	–32	–17	0	–33	+6
Irish Sea	0.6	1.4	2.3	0.6	2.6	0.3	1.5	2.9	0.3	3.3	–1	+6	+14	–2	+15	–25	–12	0	–25	+4
Southwest approaches	1.2	1.9	2.9	1.0	3.1	1.3	2.2	3.2	1.2	3.5	0	+11	+28	–3	+30	–43	–23	–2	–44	+7
Eastern English Channel	1.2	2.1	3.3	1.0	3.6	1.4	2.3	3.4	1.2	3.9	+1	+14	+31	–2	+34	–49	–27	0	–50	+10

Table 4.6: Changes in winter- and summer-mean temperature and precipitation, averaged over marine regions, by the 2050s under the Medium emissions scenario. *Wider range* is defined as the lowest and the highest values of change seen in all three emissions scenarios and all three (10, 50 and 90%) probability levels.

4.3 Maps of changes in seasonal climate

The purpose of this section is to display a number of maps (mainly of projected summer- and winter-mean changes by the 2080s under the Medium emissions scenario) of some of the more frequently used temperature and precipitation variables. We show in each case changes at 10, 50 and 90% probability levels. Most maps are at 25 km resolution but we also show a single set of maps of change averaged over administrative regions, river basins and marine regions.

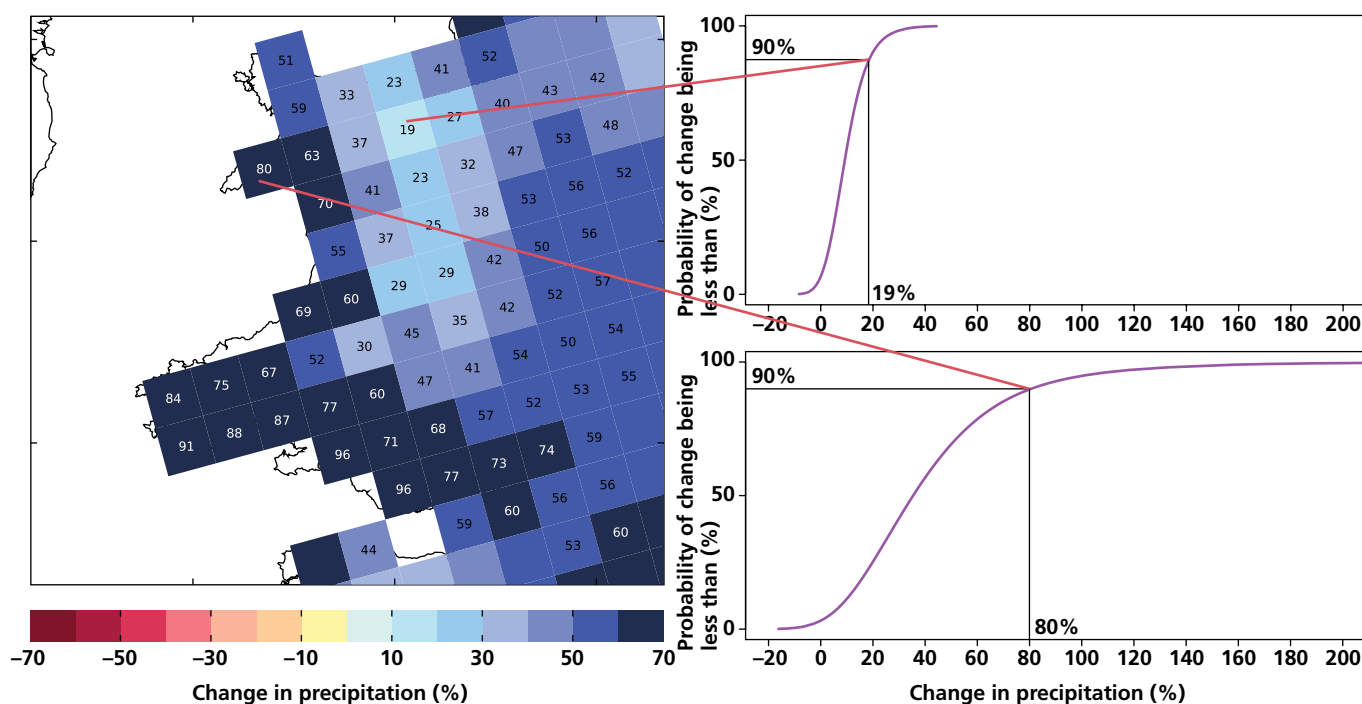
As mentioned earlier, this is not meant to be a comprehensive source of information, but simply to show examples of some of the likely most-requested products available from UKCP09. In the pdf and html versions of this report, users can click on a map of interest to be taken to the same map within the User Interface; they can then use the accompanying control panel to create similar maps for a different variable, future time period, temporal averaging period or emissions scenario.

Geographical patterns can be most easily seen from the maps. Nevertheless a short summary of any significant pattern is given for changes at the 50% probability level by the 2080s under the Medium emissions scenario. Other time periods and emissions scenarios, and particularly probability levels, may have very different patterns.

4.3.1 Interpreting maps of probabilistic climate change

Many users of the UKCIP02 projections will have become used to looking at maps which show a *snapshot* of the distribution of changes in climate over the UK, for example those showing change in summer precipitation by the 2080s, for a High emissions scenario, at a resolution of 50 km. The UKCP09 maps which are shown in this chapter have the same sort of appearance as those in UKCIP02, apart from the increased resolution of 25 km, but the nature of their content is quite different.

Figure 4.3: Relating a map of changes, at 90% probability level, to mean winter precipitation over Wales by the 2080s under High emissions, to the CDFs of change at two of the 25 km squares.



The maps in this section show changes at the 10, 50 and 90% probability level, taken from the cumulative distribution functions, CDF, at each 25 km square. Figure 4.3 shows a map generated by the User Interface, of projected changes in mean winter precipitation at the 90% probability level, over Wales. Values of percentage change are overprinted on each 25 km square; there is a 90% probability of the precipitation change being below this value. Shown alongside are the CDFs for two of the individual squares in that region, showing correspondence between the 90% probability level on the CDF and the value given on the map. So, for example, the upper CDF for an inland square shows that the projected change is very unlikely to be greater than 19% or, alternatively, very likely to be less than 19%. The lower CDF shows the very different change, 80%, at the same probability level, at a coastal grid square. The same principle will, of course, apply to maps showing projected changes at 10 and 50% probability levels.

The values of change at a particular probability level (for example, 90%) for a number of grid squares cannot be averaged together; for this reason projections in UKCP09 are also given over two sets of larger areas (administrative regions and river basins). In addition, values of change at a particular probability level (for example, 90%) for two different variables (for example, mean temperature and precipitation) at a particular grid square, cannot be combined; this is the reason that joint probability values are made available (see Section 4.6).

The maps shown in this chapter have been produced directly by the User Interface, although they have been grouped together offline. In addition, the User Interface allows users to zoom in on particular regions of the UK (as in Figure 4.3 above) where each 25 km square can be overprinted with the value of change for that square.

4.3.2 Projected changes to winter and summer seasonal mean temperature

Figure 4.4 shows that, in winter, the central estimates of change are projected to be generally between 2 and 3°C across most of the country, with slightly larger changes in the south east, and slightly smaller in the north west, of Britain. In summer a south to north gradient exists with changes in some parts of southern England being just over 4°C and in parts of northern Scotland about 2.5°C. This general north–south spatial gradient of change was also seen in UKCIP02, reflects the large scale difference between areas closer to continents (where warming is projected to be relatively more rapid) and those more influenced by oceans (where it is slower).

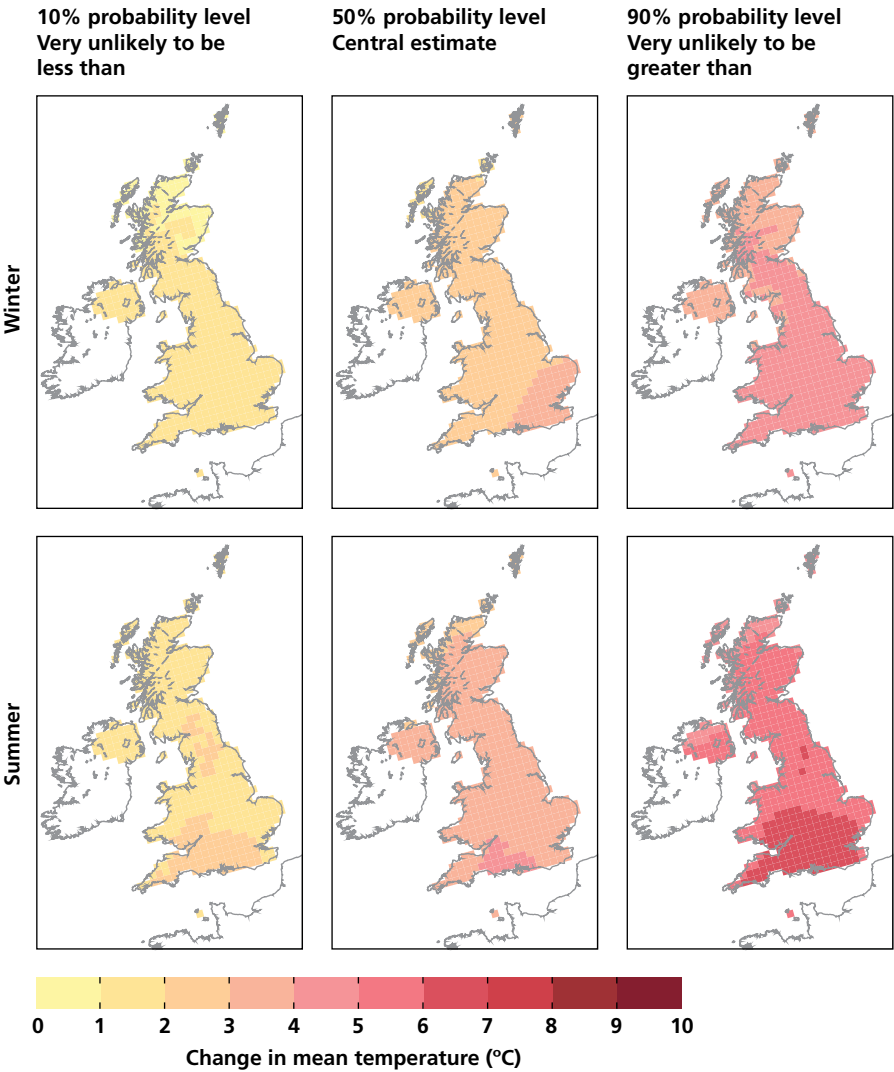


Figure 4.4: 10, 50 and 90% probability levels of changes to the average daily mean temperature (°C) of the winter (upper) and summer (lower) by the 2080s, under Medium emissions scenario. (Note that individual maps are from the User Interface, but this does not allow maps to be grouped as shown here).

4.3.3 Projections of future winter and summer seasonal mean temperature

In addition to maps of climate change, the User Interface will also supply maps of projected future climate over land regions, for a few of the variables (see Chapter 1, paragraph 1.3.1). These are generated by applying the projections of climate change applied to the 1961–1990 baseline observed climate. An example, for summer and winter mean temperature, is shown in Figure 4.5, where the projections of change shown in Figure 4.4 have been added to observations. For variables (such as precipitation) where change is expressed as percentages, the future climate is generated by increasing (or decreasing) the 1961–1990 baseline observations by the percentage change factor.

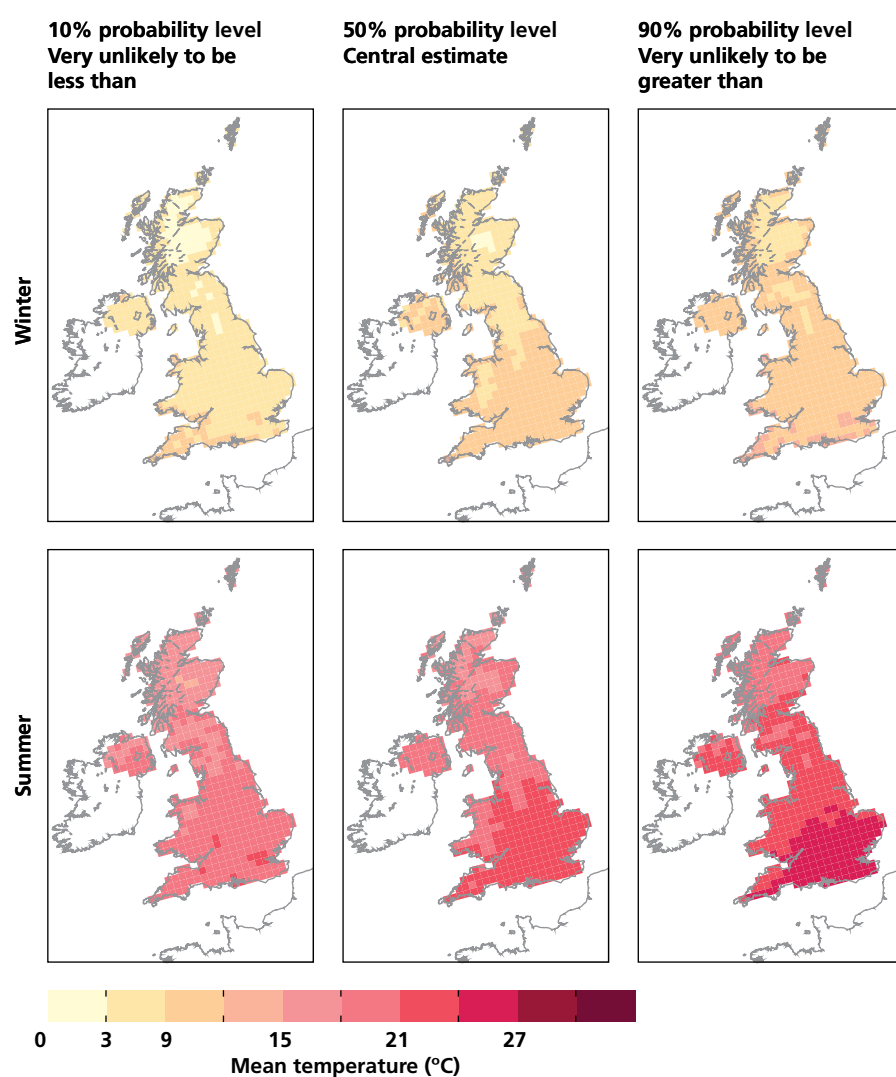


Figure 4.5: As Figure 4.4, but showing projected summer and winter seasonal mean temperature by the period of the 2080s under the Medium emissions scenario.

4.3.4 Projected changes to seasonal mean temperature over marine regions

Probabilistic projections of changes to winter- and summer-mean air temperature over the seas surrounding the UK, averaged over the nine marine regions, are shown in Figure 4.6.

Changes in air temperature in all cases are larger in the south and smaller in the north; this reflects the degree to which the marine regions are affected by proximity to continents or open oceans. As climate changes, land is projected to warm faster than oceans. Hence the marine regions closer to continental regions (for example, the Eastern English Channel) will warm faster because they are influenced by the nearby continent. More northern marine regions (for example, the Atlantic NW Approaches) will warm at a slower rate because they are influenced more by nearby ocean regions.

Note that, even by the 2080s, the 10% probability level shows small reductions in surface air temperature in the Atlantic NW Approaches in both seasons. This reflects the effect on temperatures of the large natural internal variability of climate. At the 10% probability level, this natural variability can more than offset the rather modest warming from human activities in these regions.

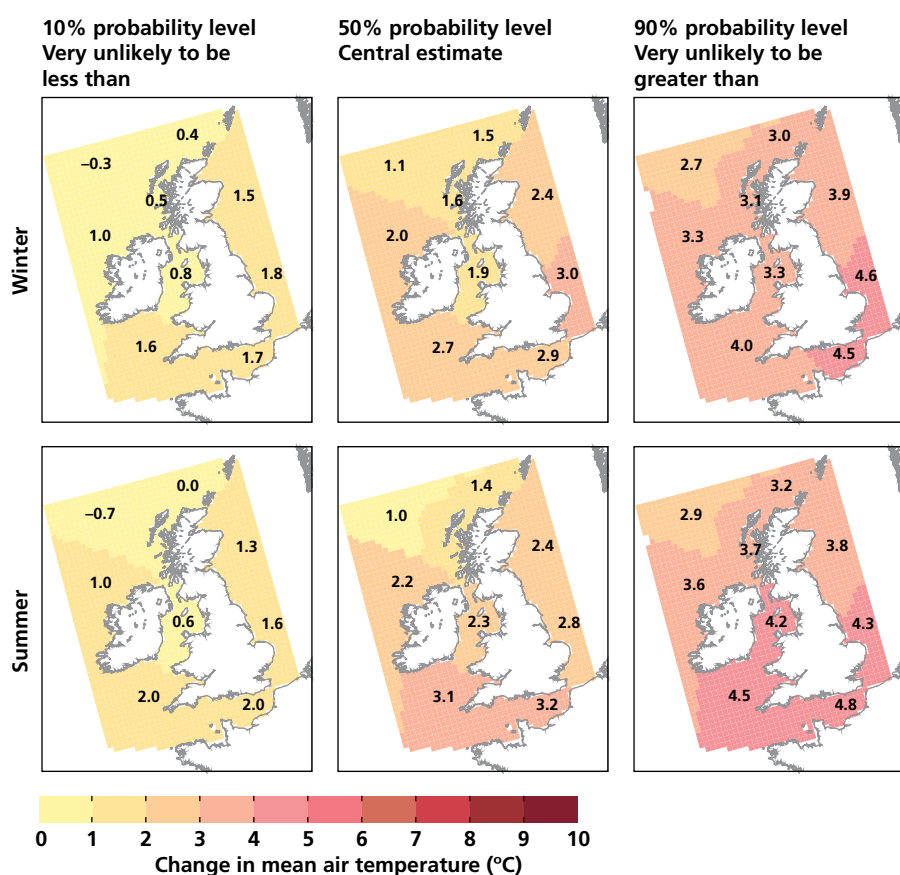


Figure 4.6: 10, 50 and 90% probability levels of changes to winter-mean (top) and summer-mean (bottom) mean air temperature under Medium emissions by the 2080s.

4.3.5 Projected changes to mean daily maximum temperature in summer

Figure 4.7 shows that, in summer, central estimates of changes to mean daily maximum temperature show a gradient between parts of southern England, where they can be 5°C or more, and northern Scotland, where they can be somewhat less than 3°C. Although not shown here, in winter the change is between 2 and 3°C across the whole of the UK.

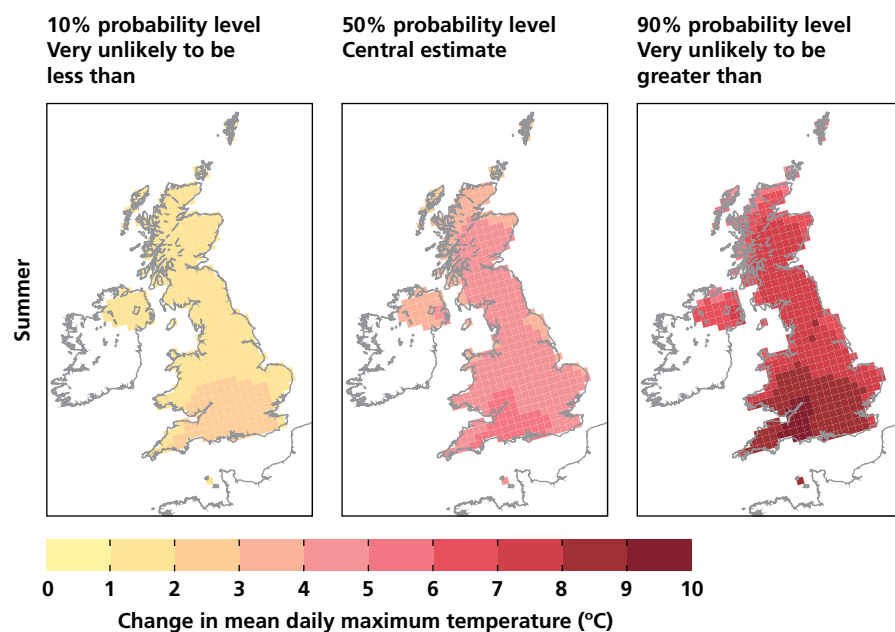


Figure 4.7: 10, 50 and 90% probability levels of changes to mean daily maximum temperature (°C) in summer, by the 2080s, under the Medium emissions scenario.

4.3.6 Projected changes to the warmest day of the summer.

Changes in extremes of temperatures are also available in UKCP09, and we illustrate one such change, that in the 99th percentile of daily maximum temperature, for the summer season, in Figure 4.8 (overleaf). This variable is calculated by taking the 99th percentile of the daily distribution of daily maximum temperature, over a complete 30-yr period (that is, about 2700 days). However, because a season has roughly 100 days, changes in the 99th percentile of the distribution can be thought of as roughly equivalent to changes in the extreme value of the season, giving a more user-friendly (albeit less accurate) 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 is referred to as such in this report. Change in this variable is projected to be between 2.5 and 4°C in the southern half of the UK, and between 4 and 5°C over most of the northern half.

4.3.7 Projected changes to the winter and summer mean daily minimum temperature

As can be seen from Figure 4.9 (overleaf), central estimates of change in mean daily minimum temperature in winter are 3–3.5°C in the south of the UK and 2–3°C in the north. In summer, changes are between 3 and 4°C across the vast majority of the UK; slightly lower in the far north and slightly higher in some southern parts.

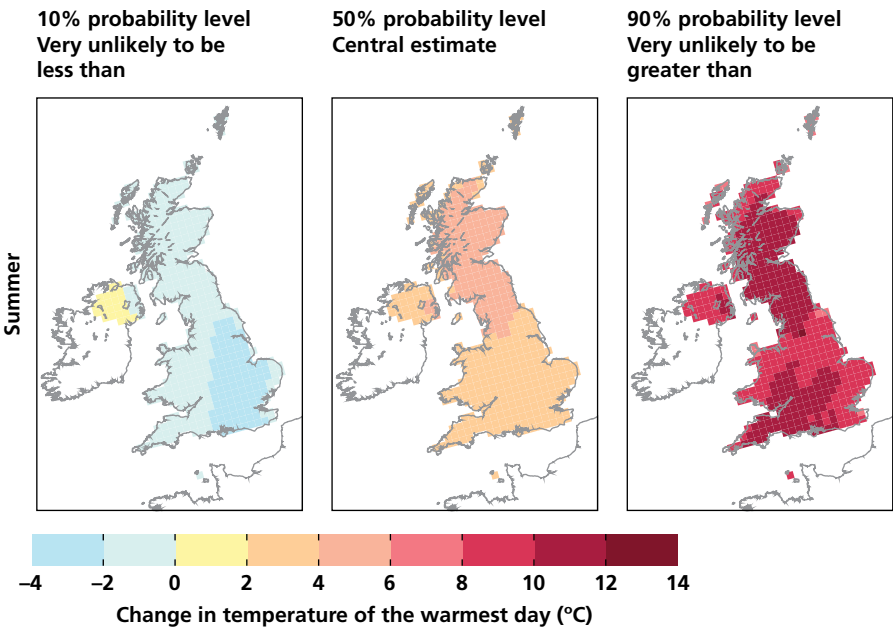


Figure 4.8: 10, 50 and 90% probability levels of changes to the temperature of the warmest day of the summer, by the 2080s, under the Medium emissions scenarios.

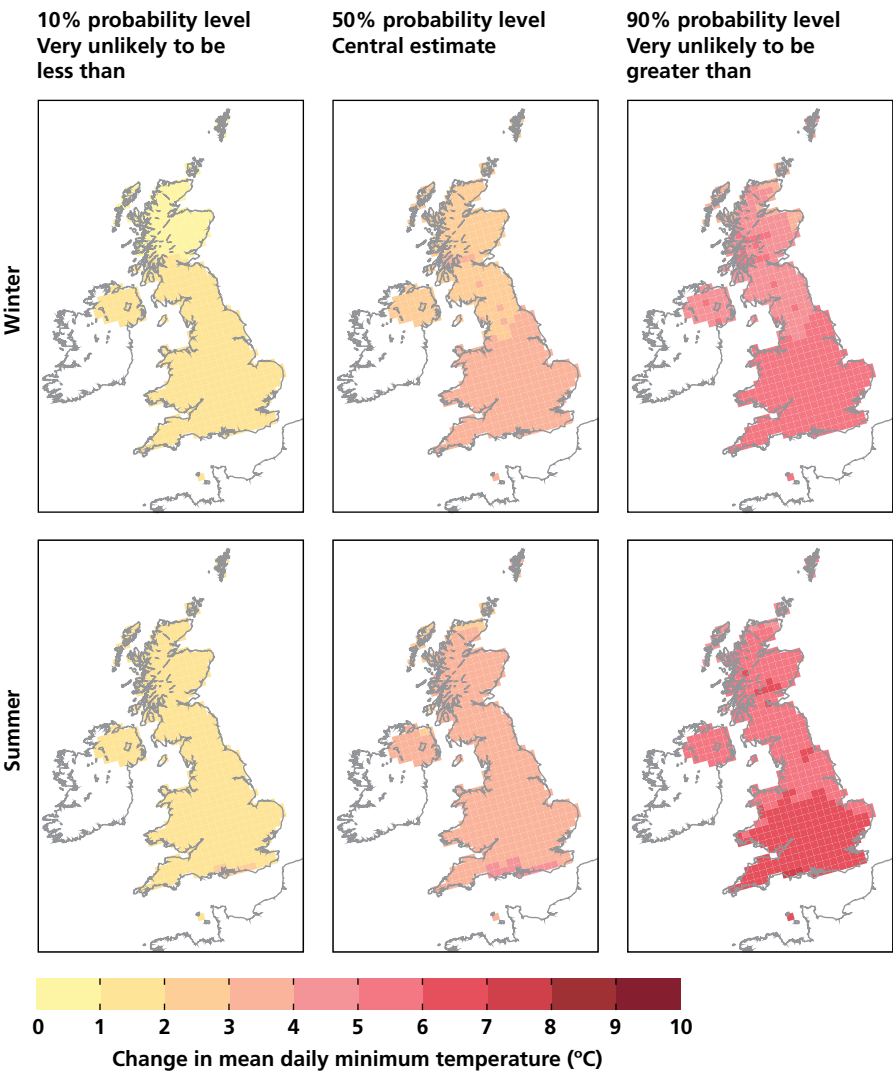


Figure 4.9: 10, 50 and 90% probability levels of changes to the mean daily minimum temperature in winter (top) and summer (bottom), by the 2080s, under the Medium emissions scenario.

4.3.8 Projected changes to annual-, winter- and summer-mean precipitation

The central estimate of changes in annual mean precipitation (Figure 4.10) are within a few percent of zero everywhere. In winter, precipitation increases are in the range +10 to +30% over the majority of the country. Increases are smaller than this in some parts of the country, generally on higher ground, where there can even be slight decreases. In summer, there is a general south to north gradient, from decreases of almost –40% in SW England to almost no change in Shetland.

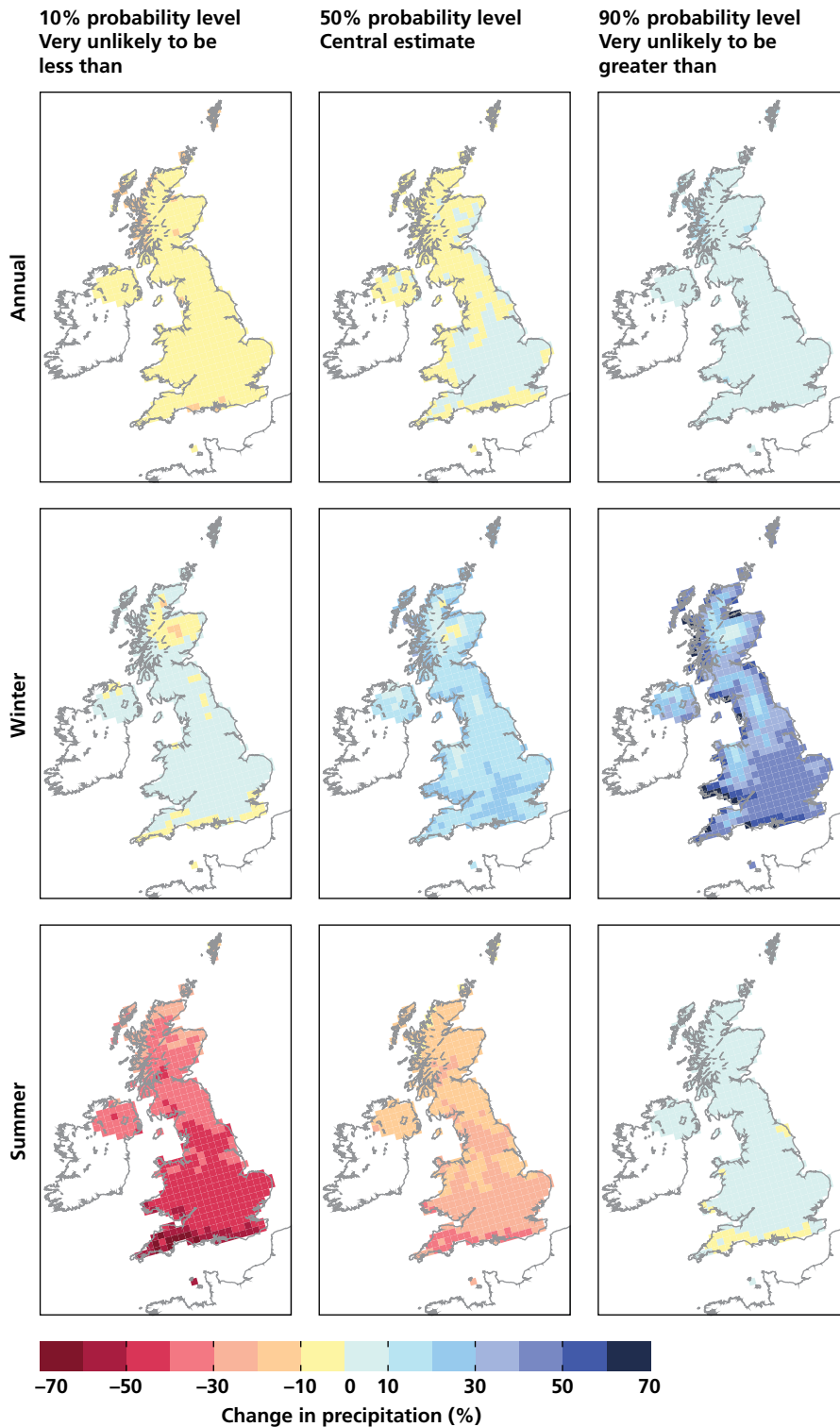


Figure 4.10: Changes in annual (top), winter (middle) and summer (bottom) mean precipitation (%) at the 10, 50 and 90% probability levels, for the 2080s under the Medium emissions scenario.

Note that the changes at 10, 50 and 90% probability levels not only have different magnitudes, but can also be in different directions (that is, can become wetter or drier). Thus summer precipitation (the lowest three maps in Figure 4.10) is projected to decrease almost everywhere in the UK at the 10 and 50% probability levels, but increase almost everywhere at the 90% probability level. In other words, using a specific area as an example, it is very unlikely that Northern Ireland in summer will dry by more than 30–40%, and very unlikely that it will be more than 0–10% wetter, with a central estimate of 10–20% drier.

The maps in Figure 4.11 show changes in precipitation for each administrative region, and those in Figure 4.12 show changes for river basins. The calculation of the change for the administrative region uses fractions of 25 km grid squares to approximate as closely as possible the true value for the administrative region;

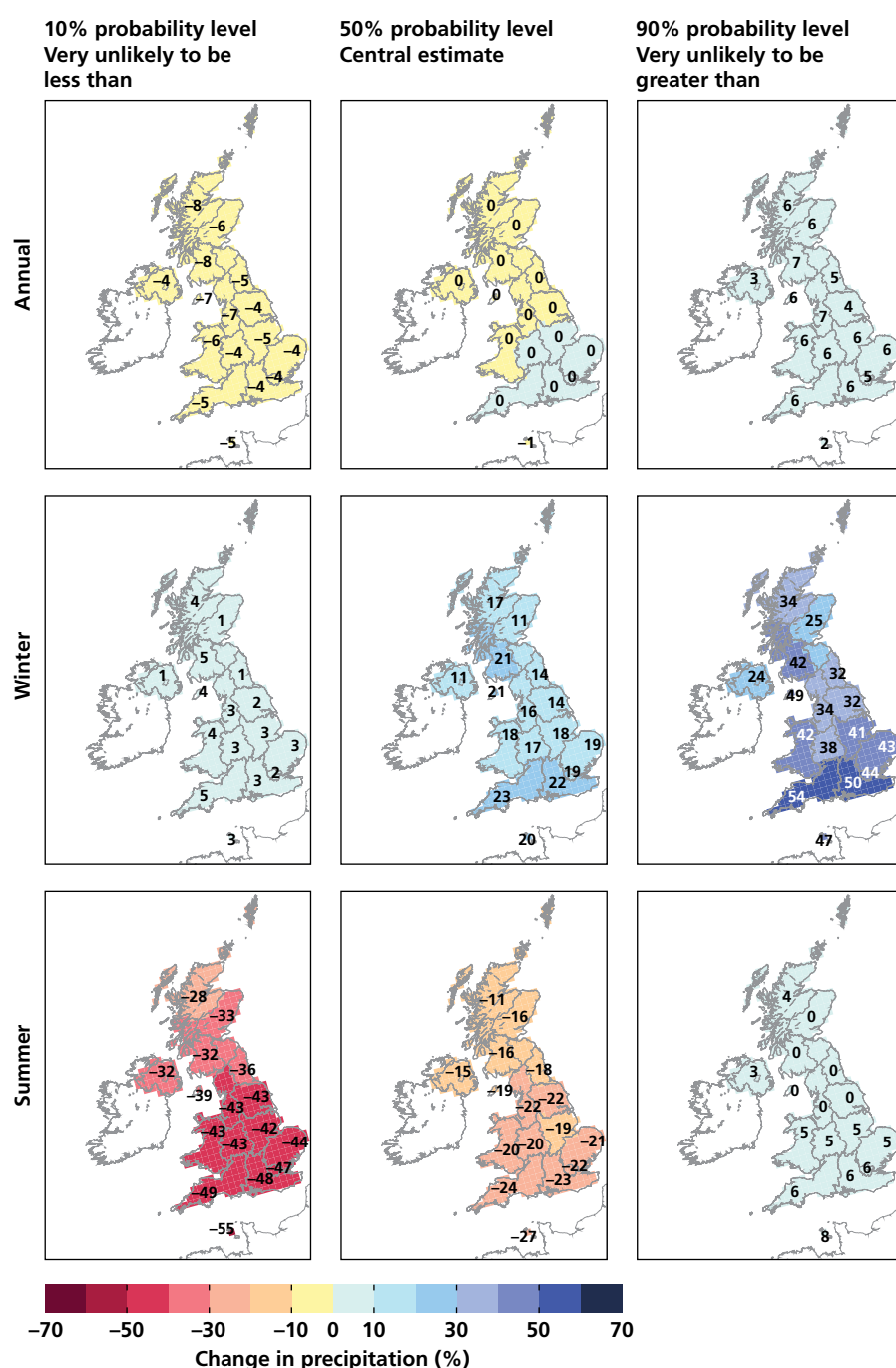


Figure 4.11: Changes to annual (upper panels), winter (middle) and summer (lower) seasonal mean precipitation (%) at the 10, 50 and 90% probability levels, by the 2080s under Medium emissions, for administrative regions. Values of change are shown over each region.

these are the values given in Table 4.5. The User Interface plots the same colour for the whole administrative region, of course, but the resolution in this case is that of the 25 km squares. Hence some small parts of administrative regions will appear from the User Interface map to be plotted in the *wrong* administrative region, but the value calculated, and shown on the region, is correct. The same comment applies also to river basins in Figure 4.12.

Figure 4.13 shows changes to seasonal mean precipitation over marine regions. Winter-mean precipitation at the 50% probability level by the 2080s under Medium emissions is projected to change by +17% over the Eastern English

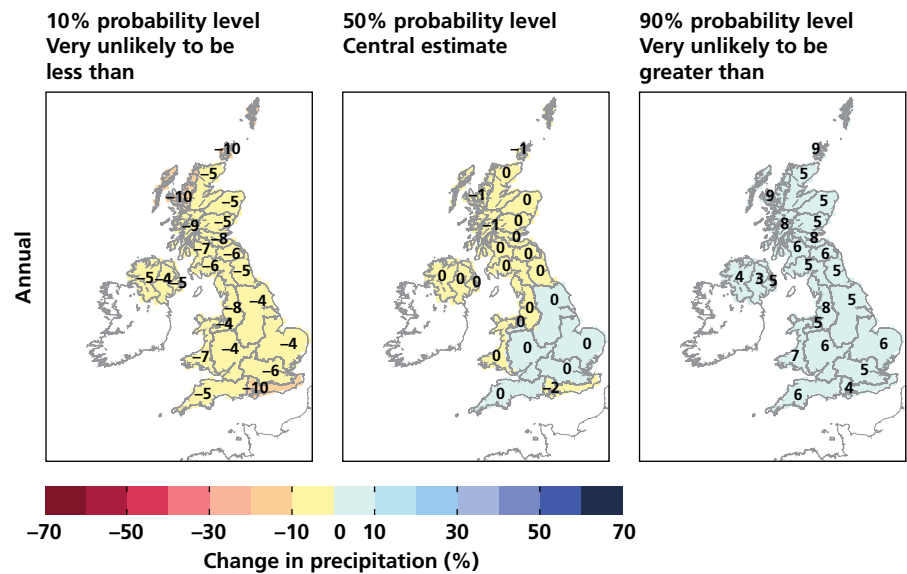


Figure 4.12: Changes to annual mean precipitation (%) at the 10, 50 and 90% probability levels, by the 2080s under Medium emissions, for river basins. Values of change are shown over each region.

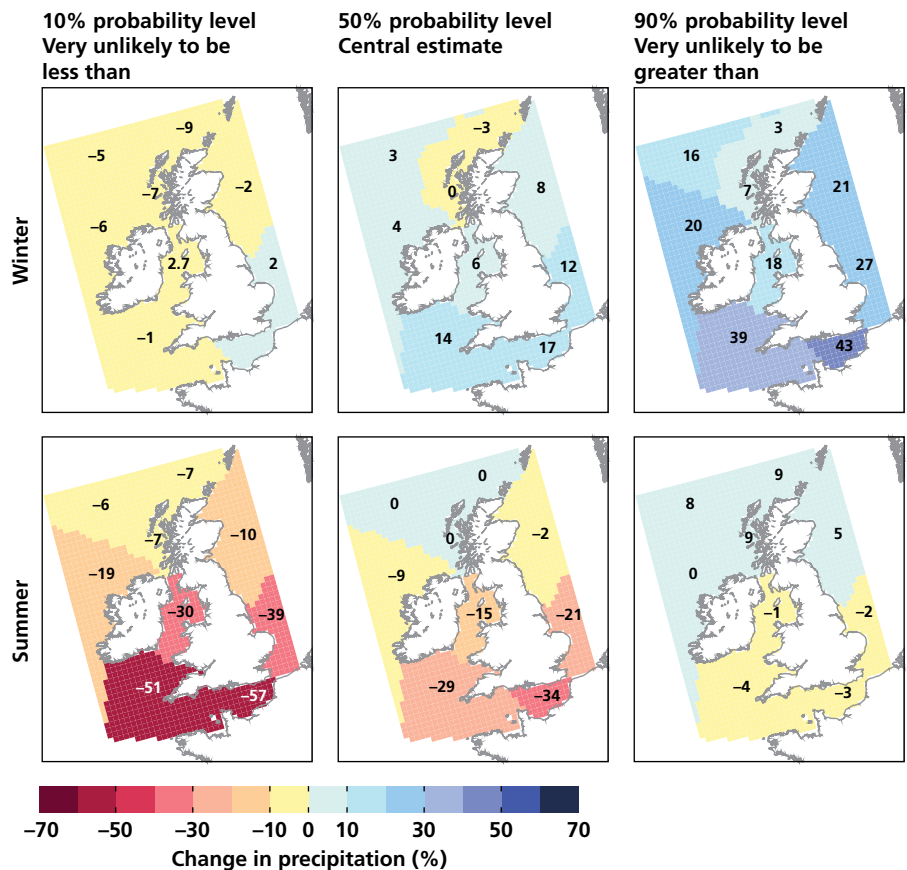


Figure 4.13: Change in winter-mean (top) and summer-mean (bottom) precipitation for marine regions by the 2080s under Medium emissions.

Channel to -3% over the Scottish Continental Shelf. There is also a south-north gradient in summertime, with changes ranging from -34% over the Eastern English Channel to essentially no change over the most northerly marine regions. Changes in the annual mean (not shown) at the 50% probability level are only a few percent everywhere.

4.3.9 Projected changes to the wettest day of the winter/summer by the 2080s

The change in the 99th percentile of daily precipitation in a season is roughly equivalent to change in the wettest day in that season. At the 50% probability level, Figure 4.14 shows increases in precipitation falling on the wettest day of winter of up to 25% in a few small areas of southern England, with a shallow gradient to zero change in the parts of the highlands of Scotland. In summer, there are reductions of 10% or so over parts of southern England, grading gradually to increases of around 10% in parts of north west Scotland.

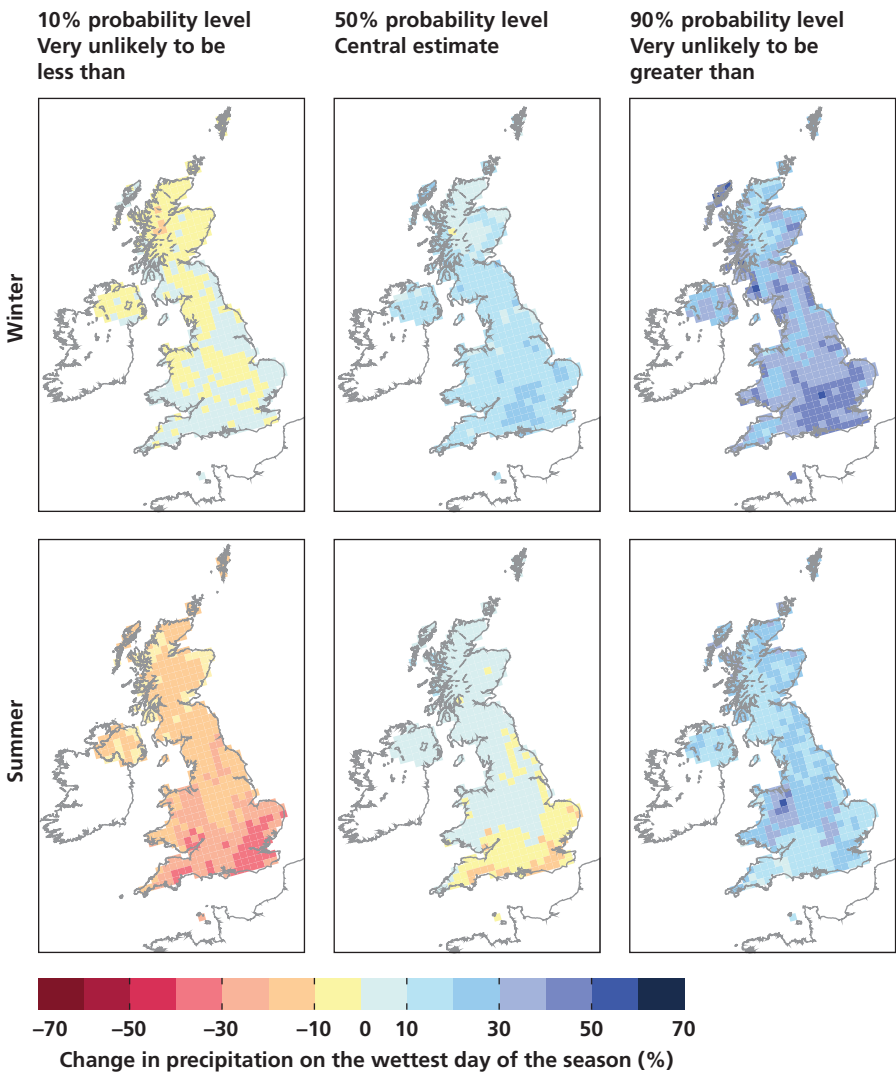


Figure 4.14: Changes to precipitation on the wettest day of the winter (top) and of the summer (bottom) at the 10, 50 and 90% probability levels, for the 2080s under the Medium emissions scenario.

4.3.10 Other variables

In addition to the temperature and precipitation variables discussed above, UKCP09 gives changes in a number of other variables. We summarise here changes in four of the most commonly used of these, by the 2080s under Medium emissions; projections are for the 50% probability level, followed in brackets by changes at the 10 and 90% probability levels.

- **Downward shortwave radiation** at the surface shows changes of only a few percent in winter. In summer it increases by up to 20 Wm^{-2} (0 to 45 Wm^{-2}) in parts of southwest England and Wales, but changes by only a few percent (0 to -25 Wm^{-2}) in parts of northern Scotland.
- **Total cloud amount** changes by only a few percent (-9% to $+6\%$) in winter. It decreases, by up to -18% (-33% to -2%), in parts of southern England, with smaller changes further north.
- **Relative humidity** decreases in summer in southern England, by up to about -10% (-20% to zero); changes are smaller further north. In winter, changes are $\pm$ a few percent only across the UK.

Note that, for cloud and relative humidity, the results refer to percentage changes relative to baseline values which are themselves expressed in units of percentages. Thus if the baseline value of relative humidity is (say) 80% , and the projected change is 10% , this implies a future value of 88% , not 90% .

4.3.11 Comparisons with UKCIP02

It is instructive to compare the UKCP09 projections with corresponding ones in UKCIP02. Figure 4.15 shows an example of a UKCP09 CDF of projected change in temperature, together with the single projection (for the same time period and emissions scenario, and at the closest location) from UKCIP02. It can be seen that, in this example, the UKCIP02 projection represents a probability of about 56%, that is, in the UKCP09 projections it is 56% probable that the change in temperature will not exceed the UKCIP02 value. This sort of comparison may be useful to those who have previously used UKCIP02 in research and to inform policy, as they can see where within the new distribution the previous value lies. The graph also shows that the change projected by UKCIP02 lies within the wide range of possible outcomes projected by UKCP09, illustrating the need to account for uncertainties in planning and decision-making. This comparison may give very different results for other locations, variables, time periods, etc.

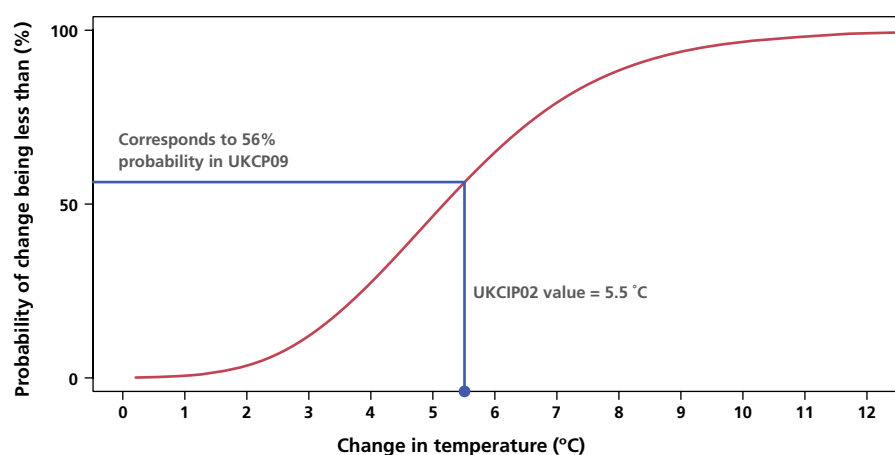


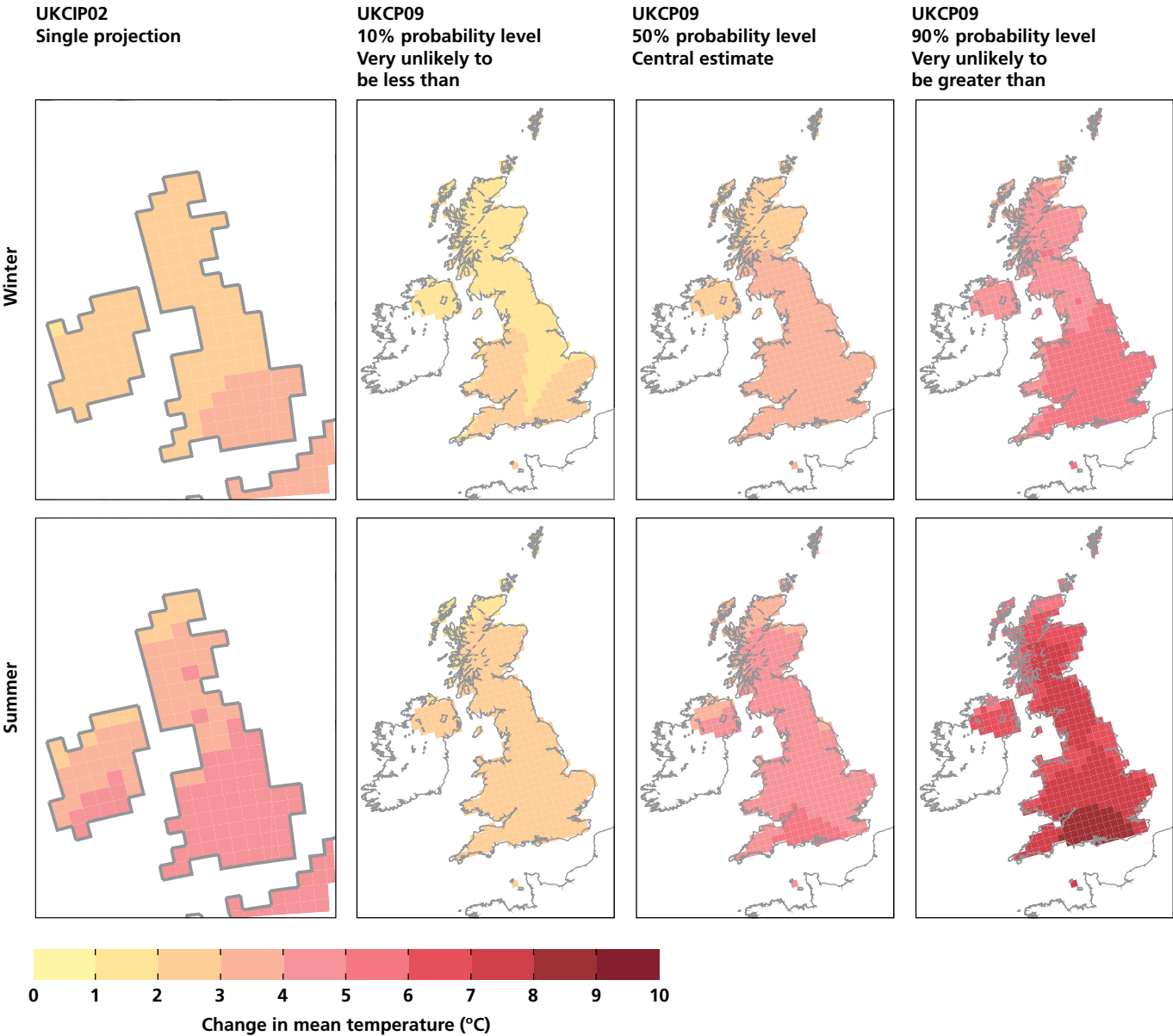
Figure 4.15: The CDF of temperature change for a 25 km square in Dorset, by the 2080s under High emissions. The blue dot shows the corresponding value from the nearest 50 km square in the UKCIP02 scenarios, and the blue lines show that this represents a probability in UKCP09 of about 56%.

Comparisons between the two sets of projections can also be illustrated using maps of changes; those below are in seasonal mean temperature (Figure 4.16) and precipitation (Figure 4.17), for summer and winter, for the 2080s under the High emissions scenario (which is identically the same scenario in the two sets of projections). We show the single result from UKCIP02 alongside the 10, 50 and 90% probability levels in UKCP09.

Having stressed the need for users to consider the full range of uncertainty given in UKCP09, it is nonetheless instructive to compare the central estimate (50% probability level) of the projected changes with the single projections (for the same, High, emissions scenario) in UKCIP02. This allows us to make the following qualitative comments:

- In the case of mean temperature, projected changes in UKCP09 are generally somewhat greater than those in UKCIP02.

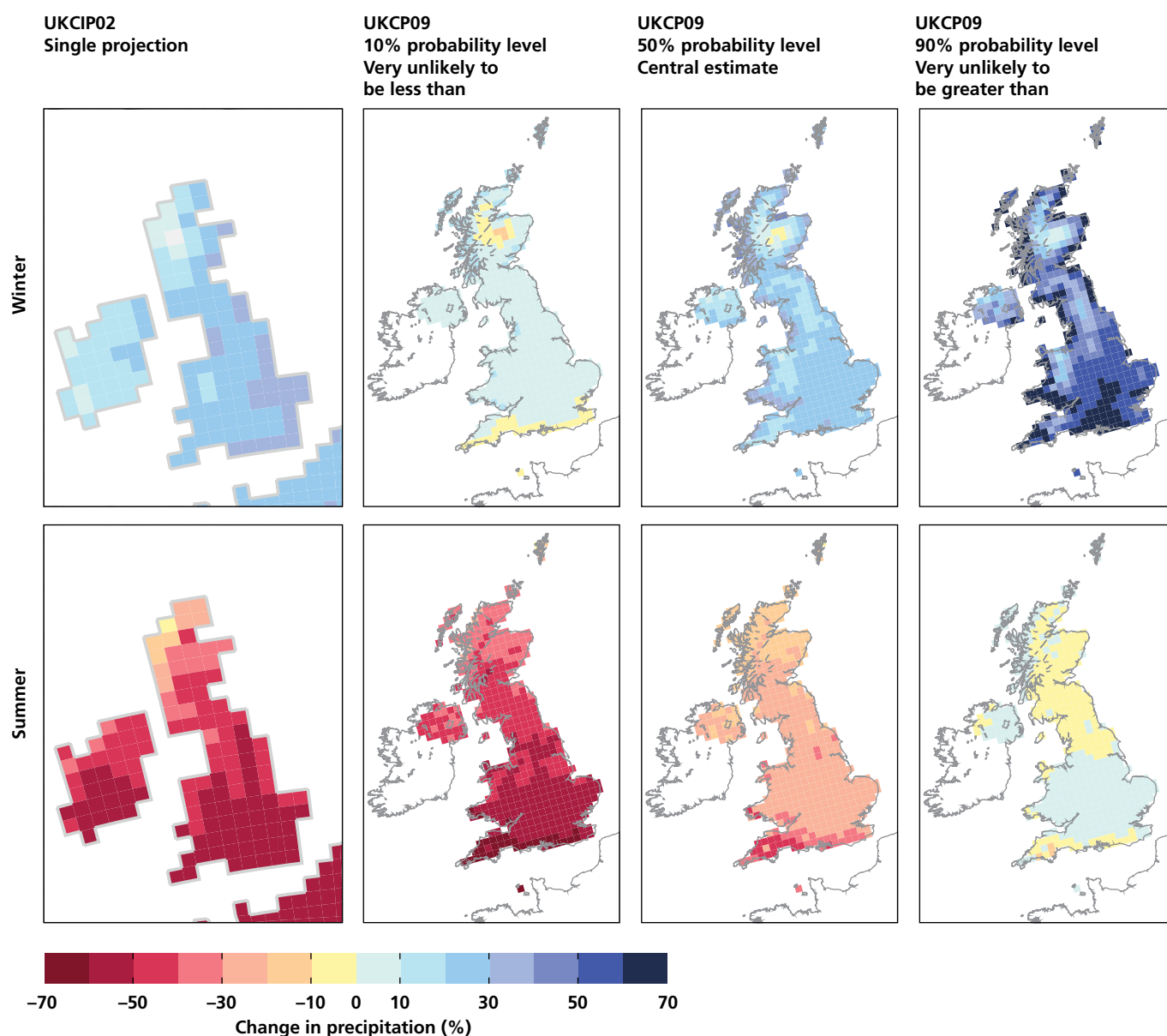
Figure 4.16: Comparison of changes in seasonal mean temperature, summer and winter, by the 2080s under High emissions scenarios, from the UKCIP02 report (far left panels) and as projected in UKCP09 (10, 50 and 90% probability level).



- The summer reduction in rainfall in UKCP09 is not as great as that projected in UKCIP02.
- The range of increases in rainfall in winter seen in UKCP09 are very broadly similar to those in UKCIP02, although with a different geographical pattern. A few grid squares UK are projected to dry in winter in UKCP09; in UKCIP02 all areas were projected to be wetter.
- Small changes in cloud (not shown here) are projected in winter, as in UKCIP02. Projections of summer decreases in cloud are similar to those in UKCIP02.

For brevity, comparisons above are made only with the central estimate in UKCP09; however, users are advised to use the projections over the full robust range (that is, 10–90%) of probabilities in adaptation decisions or when considering the need to update previous decisions based on UKCIP02.

Figure 4.17: As Figure 4.13 but for seasonal mean precipitation.



The reasons for the differences between the two sets of projections lie in the completely different model results and methodologies which were used to derive them. UKCP09 projections include:

- the explicit effects of land and ocean carbon cycle feedbacks, and the uncertainty in land carbon cycle feedback;
- uncertainty due to natural variability;
- modelling uncertainty: UKCIP02 was derived using one variant of one (Met Office) model, whereas UKCP09 is derived from ensembles of variants of Met Office models, together with smaller ensembles of other international models;
- uncertainties associated with the statistical processing required to convert results from model ensembles into probabilistic projections;

None of these factors were able to be included in the UKCIP02 projections.

Hence specific differences between changes in a particular variable in UKCIP02 and those (at a particular probability level) in UKCP09 will generally have a number of contributory reasons; identifying these would be a major undertaking. UKCIP02 projections should not be seen as some benchmark against which all successive projections must be compared and differences explained. The advent of new methodologies (allowing us to quantify uncertainty) and the inclusion of more recent knowledge (for example, carbon cycle feedbacks) give the UKCP09 projections many advantages over those in UKCIP02, and it is strongly recommended that users no longer employ UKCIP02 in isolation.

4.4 What effect do user choices have on the probabilistic projections?

In this section we show some probabilistic projections, generally in the form of PDFs of changes in climate. In the User Interface, the user can make choices using the following selection criteria:

- emissions scenario (Low, Medium and High);
- future time period (7 overlapping 30-yr periods from 2010–2039 to 2070–2099);
- spatial averaging (25 km grid square, administrative region, river basin or marine region);
- temporal averaging (generally month, season, annual);
- geographical location;
- variable; and
- change in climate, or future climate.

We compare below the PDFs which result from a number of these choices; Table 4.7 lists these and the figures that illustrate them. In general, the comparisons hold other choices fixed at a setting which maximises the differences between the choices being compared, in most cases this is for the 2080s under the High emissions scenario. We illustrate these comparisons using temperature and precipitation quantities.

Note that, with the exception of those for the three different emission scenarios (as shown in Figures 4.18 and 4.19), the User Interface cannot combine different PDFs on the same plot. We have combined them in this section to highlight differences.

Figure	Sensitivity explored	Variable used as example	Emission Scenario	Time periods	Spatial average	Temporal average	Location
4.18 4.19	Emissions scenario	Maximum temperature	L, M, H	2020s 2080s	Administrative region	Summer	SE England
4.20	Time period	Minimum temperature	H	2020s 2050s 2080s	Administrative region	Winter	W Scotland
4.21	Spatial average	Wettest day of the season	H	2080s	Administrative region, 25 km	Winter	N Scotland
4.22	Temporal average	Precipitation	H	2080s	Administrative region	January, Winter	NW England
4.23	Location (Administrative region)	Mean temperature	H	2080s	Administrative region	Summer	SW England Wales N Scotland N Ireland
4.24	Location (25 km)	Mean temperature	H	2080s	25 km	Summer	In Dorset Gwynedd Shetland Co Antrim
4.25	Variable	Mean temperature, Maximum temperature, Warmest day of the season	H	2080s	Administrative region	Summer	SW England
4.26	Climate change or future climate	Maximum temperature	H	2080s	25 km	Summer	In East Anglia

Table 4.7: Comparisons shown in this chapter which explore the sensitivity of PDFs to various user choices of emissions scenario, future time period, spatial average, temporal average and location. Locations have been chosen to give a wide geographical spread, but are not aimed to be comprehensive or representative.

4.4.1 How are PDFs affected by choice of emissions scenario?

Figure 4.18 shows that, for the first future time period (2020s), the PDFs are very similar for each of the three emissions scenarios. In part this is due to the long effective lifetime of CO₂ and the inertia of the climate system and in part due to the offsetting effects of increases in greenhouse gases and in sulphur dioxide emissions (which produce sulphate aerosols that cool climate) in the three emissions scenarios.

Unlike Figure 4.18, Figure 4.19 shows that, by the time period of the 2080s, the differences in the PDFs of summer mean daily maximum temperature between the three emissions scenarios are well marked. They still overlap substantially, showing that uncertainties associated with emissions, whilst important, do not dominate those associated with projecting climate response. Differences may be more or less pronounced in other variables.

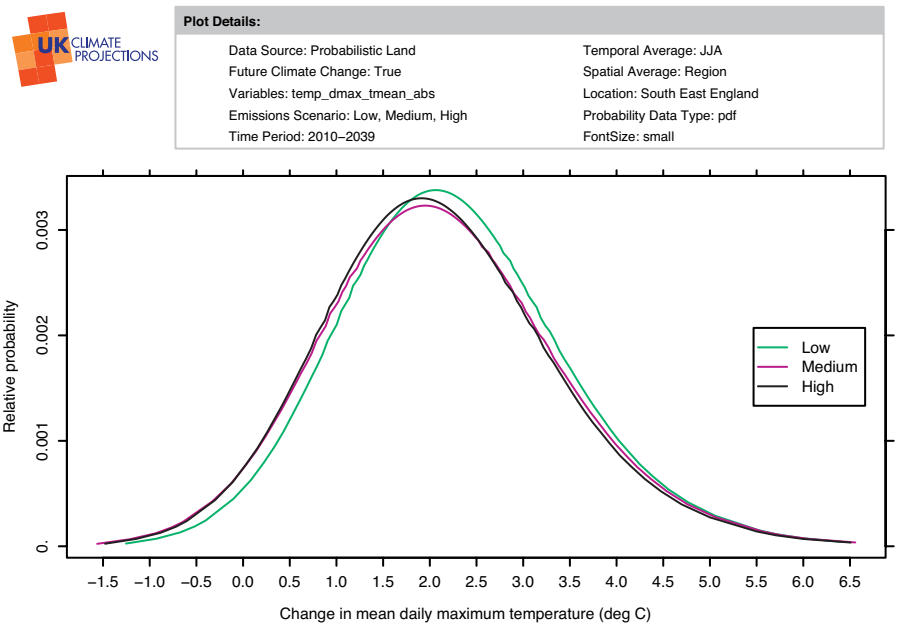


Figure 4.18 : PDFs of change in summer-mean daily maximum temperature in SE England for the Low (green), Medium (purple) and High (black) emissions scenarios, for the 2020s. (Note that this is an example graphic taken directly from the User Interface, showing the plot details in a box above the plot.)

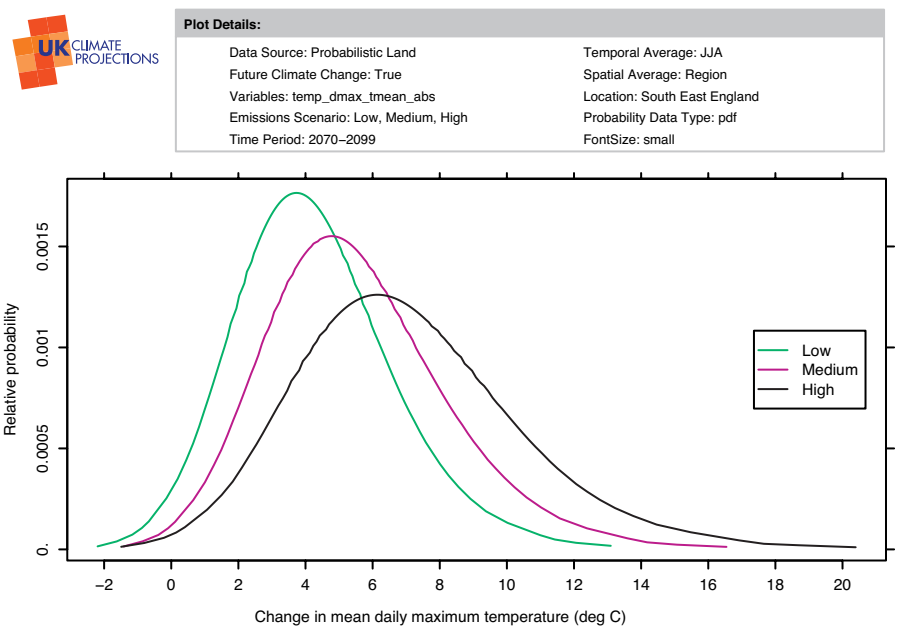


Figure 4.19: As Figure 4.16a but for the period of the 2080s.

4.4.2 How are PDFs affected by choice of future time period?

As might be expected, Figure 4.20 shows that the distribution moves to higher temperature changes with time, and becomes wider, reflecting the growth in uncertainty.

4.4.3 How are PDFs affected by choice of spatial averaging?

PDFs are available for each individual 25 km square, and also for two types of aggregated land areas: administrative regions and river basins. The change over an administrative region (for example, N Scotland) will, by definition, smooth out the variation from square to square seen in the 25 km resolution map. The PDFs for administrative regions are provided because it is not possible for users to create these for themselves by simply averaging the PDFs of changes for constituent 25km squares.

Figure 4.21 shows the PDF for the administrative regional average and, in contrast, the PDFs for two grid squares within in having particularly high and low changes compared to the mean. The variability from square to square will be mainly due to factors such as mountain and coastal effects but also, as explained earlier, reflect the varying relative influences of different causes of uncertainty at different locations.

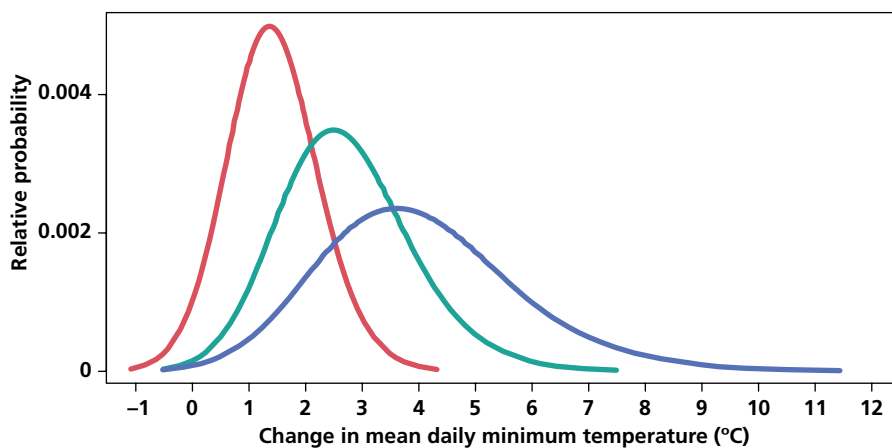


Figure 4.20: PDFs of change in winter mean daily minimum temperature averaged over W Scotland for the High emissions scenario, by the 2020s (red), 2050s (green) and 2080s (blue).

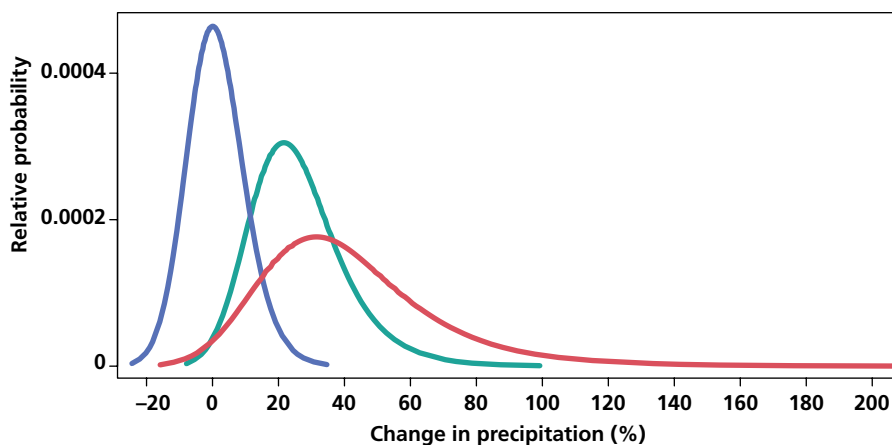


Figure 4.21: Change in winter-mean precipitation (%) by the 2080s under the High emissions scenario. PDF for the North Scotland administrative region (green) compared with PDFs for the 25 km squares in the region projected to experience a relatively high (red) and low (blue) change at 90% probability.

4.4.4 How are PDFs affected by choice of temporal averaging?

Figure 4.22 shows, as expected, that the uncertainty of a monthly average change is greater than that of the seasonal average change, largely due to the natural variability being greater at the shorter temporal scale. It also shows that changes in the central estimate for a particular month can be quite different from that in the corresponding seasonal mean.

4.4.5 How are PDFs affected by choice of geographic location?

Here we show some examples of PDFs of change in mean summer temperature for four administrative regions (Figure 4.23), together with single 25 km squares within these regions (Figure 4.24).

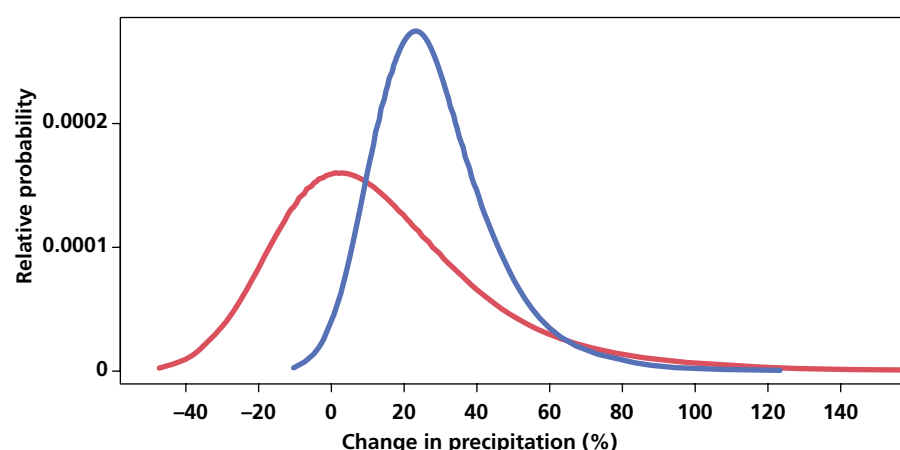


Figure 4.22: PDFs of change in precipitation for NW England by the 2080s under the High emissions scenario, showing means for winter (blue) and for the month of January (red).

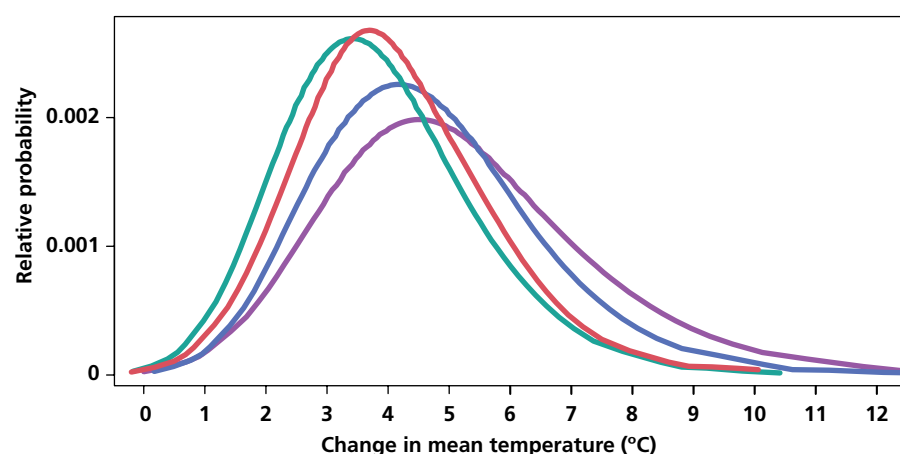


Figure 4.23: The projected change in mean summer temperature by the 2080s under the High emissions scenario for the four administrative regions of N Scotland (green), Northern Ireland (red), Wales (blue) and SW England (purple).

Figure 4.23 shows that the distribution of summer mean temperature moves to larger changes, and with correspondingly greater uncertainty, as the location of interest moves from N Scotland to Northern Ireland to Wales and finally to SE England; consistent with the geographical pattern of changes shown by the maps earlier in this chapter. The changes in the 25 km squares within the regions (Figure 4.24) show a similar progression as the regions themselves but some details are different.

4.4.6 How are PDFs affected by choice of mean or extreme variables?

Figure 4.25 shows that the most likely change in the summer-mean daily maximum temperature is greater than that in the summer mean temperature. The uncertainty in the warmest day of the summer is much greater than that in the summer-mean daily maximum temperature, which in turn is greater than that in the summer-mean temperature.

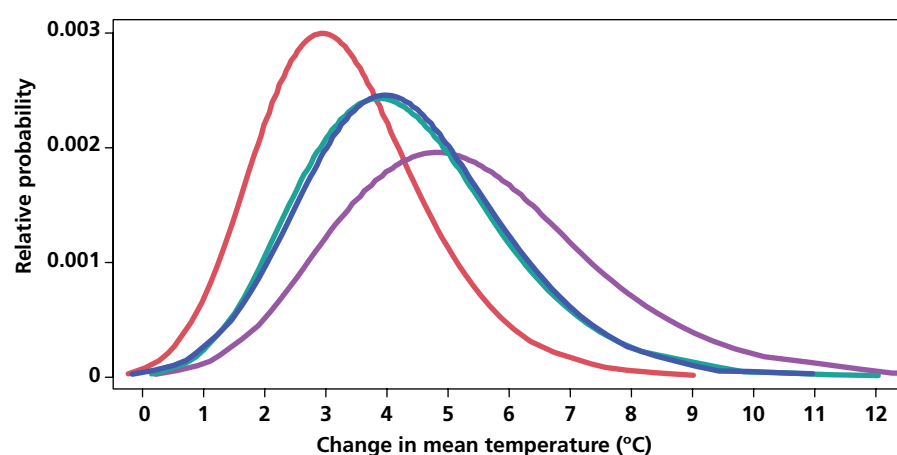


Figure 4.24: PDFs of change in the mean summer temperature by the 2080s under the High emissions scenario, for four 25 km grid squares including parts of Dorset (purple), Gwynedd (green), Shetland (red) and Co Antrim (blue).

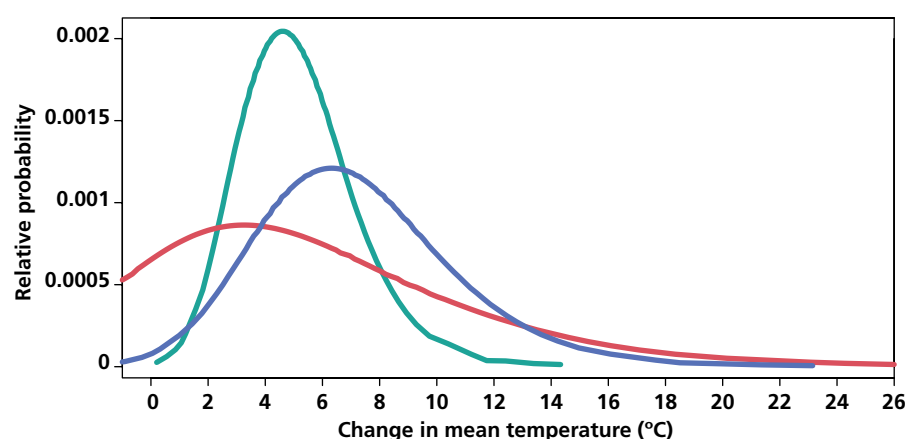


Figure 4.25: Comparison of the PDFs of change in summer mean temperature (green), summer mean daily maximum temperature (blue) and the warmest day of the summer (red) by the 2080s under the High emissions scenario, all for the administrative region of SW England.

4.4.7 How are PDFs affected by choice of climate change or future climate?

Users have the choice of seeing projections of some variables as climate change or as future climate. Climate change is that between the chosen time period and the 1961–1990 baseline 30-yr period. Therefore, we calculate projections of future change from model simulations by subtracting the simulated baseline period from the simulated future values. This reduces the impact of model bias on the projected change, though of course it does not guarantee that the projected change will be correct. Projections of absolute values for future climate variables are then obtained by adding the projected changes onto the observed baseline value.

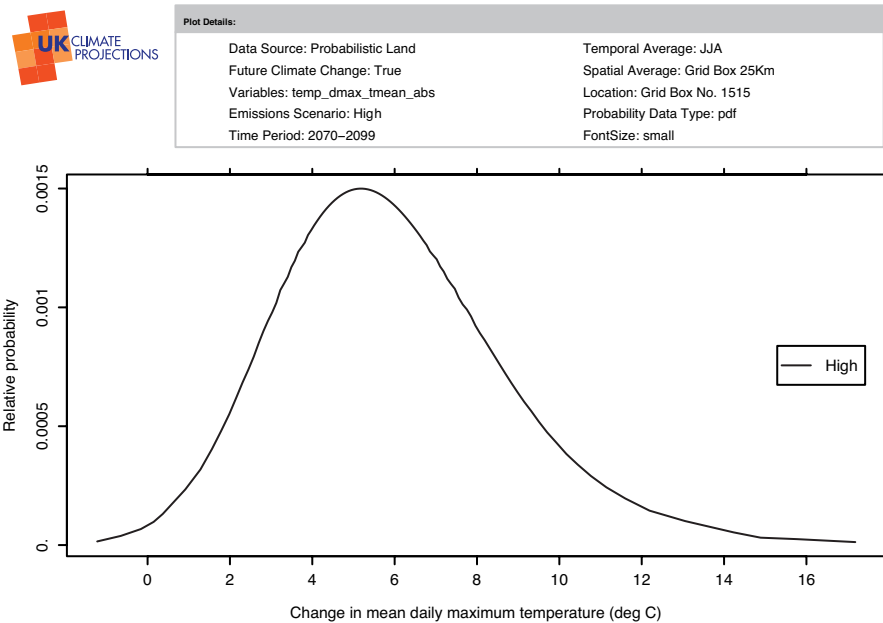


Figure 4.26: A PDF of the change in summer-mean daily maximum temperature, for a 25 km square in the East of England, by the 2080s under the High emissions scenario.

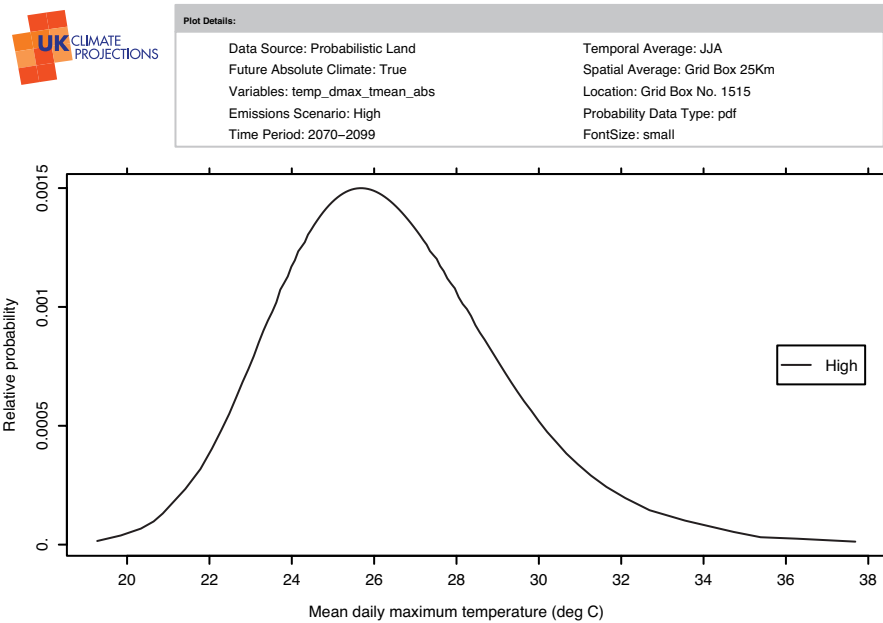


Figure 4.27: A PDF of the projected future summer-mean daily maximum temperature, for a 25 km square in the East of England, by the 2080s under the High emissions scenario.

Figure 4.26 shows a PDF of the change in summer-mean daily maximum temperature, for a 25 km square in the East of England, by the 2080s under the High emissions scenario. In Figure 4.27, this change has been added to the 1961–1990 observed summer-mean daily maximum temperature, to give a projection of the summer-mean daily maximum temperature for the 2080s. Note that the two PDFs have the same shape, but the future climate PDF in Figure 4.27 is shifted by about 20°C relative to the climate change PDF in Figure 4.26 — where 20°C represents the baseline summer-mean daily maximum temperature at that location.

4.5 Probabilistic projections changing with time

In addition to the PDF and CDF curves, the User Interface can be used to explore how projections change with time over the course of the century, using a “plume of probability”. Essentially, this takes the values of change (for a certain quantity, location, emissions scenario, etc.) corresponding to the 10, 33, 50, 67 and 90% probability levels for each of the seven future time periods, and joins them together with straight lines. We show examples below of changes with time

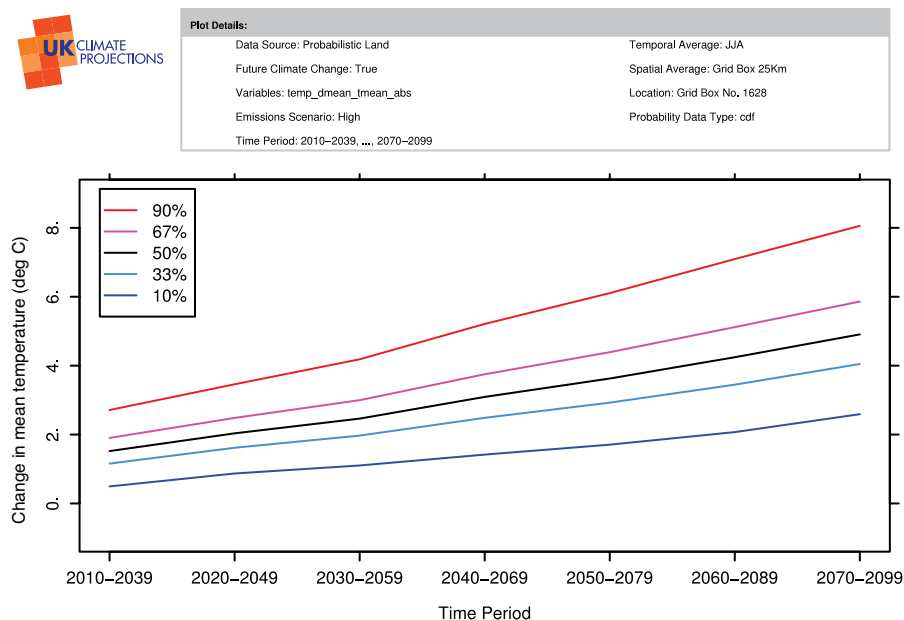


Figure 4.28: The progression from the 2020s to the 2080s of change in summer mean temperature under the High emissions scenario, for a single 25km grid square in Central London. Changes at probability levels of 10, 33, 50, 67 and 90% are indicated by different colours.

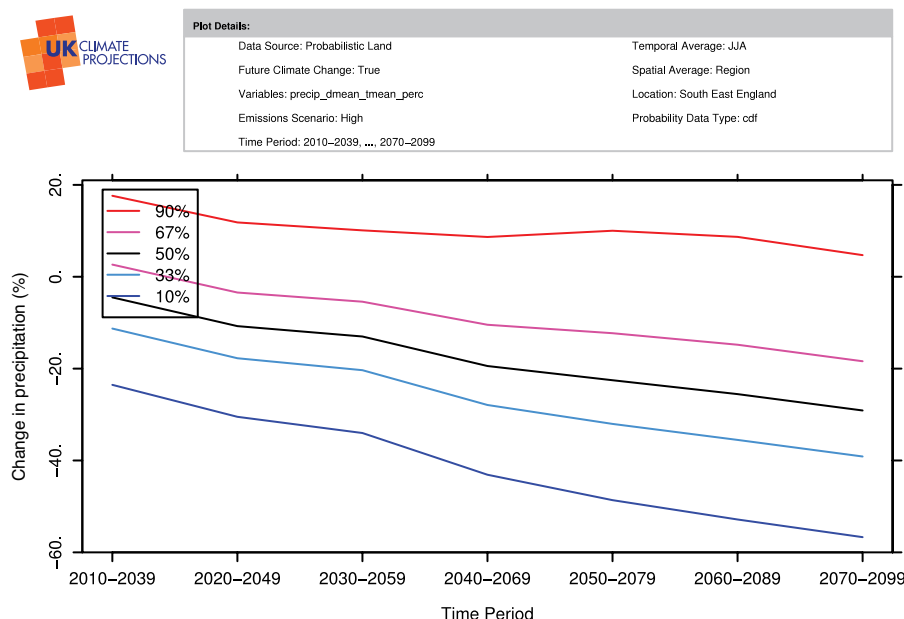


Figure 4.29: As Figure 4.24 but for changes in summer-mean precipitation.

summer mean temperature (Figure 4.28) and summer mean precipitation (Figure 4.29) for a 25 km square in Central London under the High emissions scenario. Thus the top line in Figure 4.28 shows how the temperature change that is very unlikely to be exceeded increases decade by decade through the century; the middle line shows how the central estimate increases with time, etc. This type of output can be provided by the User Interface for any variable, any emissions scenario and any location.

Plumes show that the width between the 10 and 90% probability levels is already substantial by the 2020s. In the case of precipitation (Figure 4.29), in particular, the width of the plume increases only modestly through the century. The main reason for this is that, at the scale of 25 km, natural internal variability is a big component of the overall uncertainty, and this does not increase with time. Plumes for larger areas (for example, administrative regions) will have a smaller component from natural variability, and do show more growth with time. This reflects the relatively larger components from model uncertainty, carbon cycle feedbacks, etc., which do grow with time. For even larger areas, for example Northern Europe, plumes are even more divergent (not shown here), reflecting the relatively even smaller component of overall uncertainty from natural internal variability at this larger spatial scale.

4.6 The joint probability of the change in two variables

The User Interface allows a calculation to be made, not just of the probability of change in a single variable, but of the joint probability of changes in (some, but not all) combinations of two variables. These can be used to explore specific impacts on targets (such as crops) which are vulnerable to changes in both variables. The User Interface can create plots of joint probability of changes in two variables, chosen by the user, such as that shown in Figure 4.30. This shows an example for two variables commonly used in combination, change in precipitation and that in mean temperature, in summer, by the 2080s under the High emissions scenario. Values of joint probability density are shown by the red contour lines, and have been multiplied by 1000 to make them more readable. So, referring to Figure 4.30, for a precipitation change of -50%, a simultaneous temperature change of 5°C is about 9 times more likely than a change of 1°C, as the joint probability densities are 18 and 2 respectively.

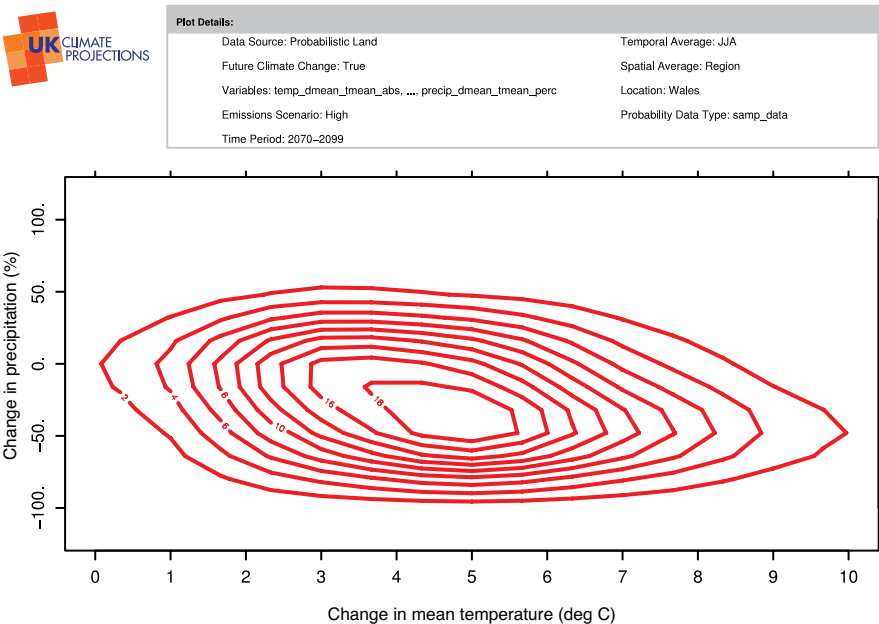


Figure 4.30: The joint probability distribution function of changes in summer-mean temperature and that in precipitation, by the 2080s under the High emissions scenario, for the administrative region of Wales. The red lines are contours of probability, multiplied by 1000, with units of per °C per %. (This plot is direct from the User Interface.)

Annex 4 describes the way in which data on the variables is held in batches in the User Interface. Users can explore joint probabilities among those variables in the same batch, but not between variables in different batches. Based on preferences expressed by users, efforts have been made to include within the same batch those variables for which joint probabilities are of particular interest.

4.7 Corresponding changes in global-mean temperature

We have included annual-mean, global-mean temperature as one of the variables for which we make probabilistic projections in UKCP09, although this data is not available from the User Interface. Changes to global mean temperature, for the three emissions scenarios and three future time periods, is shown in Table 4.8.

Table 4.8: The 10, 50 and 90% probability levels of changes to the global mean temperature (°C), for all three emissions scenarios and three future time periods, as calculated by the UKCP09 methodology.

	2020s			2050s			2080s		
Emissions	10%	50%	90%	10%	50%	90%	10%	50%	90%
High	1.0	1.3	1.6	2.1	2.7	3.3	3.4	4.3	5.3
Medium	1.0	1.3	1.6	1.9	2.4	3.0	2.6	3.4	4.2
Low	0.9	1.2	1.6	1.6	2.1	2.6	2.0	2.6	3.4

4.8 Variables for which probabilistic projections cannot be provided

For certain variables (soil moisture, latent heat flux, snowfall rate and wind speed) it was not possible to provide probabilistic projections of future changes in UKCP09.

In the case of **soil moisture**, different definitions of this variable are used by different modelling groups, making it impossible to construct PDFs combining results from variants of Met Office models with those from other climate models. Without this key aspect of our methodology, it was not possible to provide probabilistic projections.

In the case of **latent heat flux** we found that projected changes from two of the alternative climate models were often well outside the range of the Met Office model variants (see Chapter 3, Section 3.2.10). In this situation, our method of combining results from the Met Office model variants and the alternative models could not be guaranteed to provide a robust indication of the probabilities of different outcomes, and hence PDFs were not provided.

In the case of **snowfall rate**, the models sometimes project small but non-zero values in the future, implying changes relative to the baseline climate that are close to the absolute lower bound of –100%. Under these conditions, statistical contributions to the uncertainties captured in the UKCP09 methodology were found to become unrealistically large, and hence probabilistic projections were not provided.

Creating a PDF of **wind speed** was not possible because projections of this variable were not available from the source of other climate model data. However, it is

possible to estimate changes in wind speed using daily average values of the northerly and easterly components of wind, which are available. Figure 4.31 shows two examples, in winter over Scotland and in summer over Northern England, comparing changes from 17 variants of the Met Office global model with those from 15 alternative climate models. There is considerable variation in the changes projected by both ensembles, and little consistent evidence of a systematic change in wind speed. The agreement between the two ensembles varies with season and location (even within the UK).

In the absence of a UKCP09 probabilistic projection for these four variables, there are three possible alternative sources of projections of transient changes during the 21st century:

- the 17-member ensemble of variants of the Met Office GCM,
- the 11-member ensemble of variants of the Met Office RCM,
- the ensemble of other global climate models, available from the PCMDI website.

Data from the first two (Met Office GCM and RCM variants) is available from the Climate Impacts LINK project, operated by BADC; see <http://badc.nerc.ac.uk/data/link>. Data from alternative global climate models can be accessed from the Program for Climate Model Diagnosis and Intercomparison (PCMDI), based in California, which has collected model output from simulations contributed by modelling centres around the world, as part of the Coupled Model Intercomparison Project (CMIP3) of the World Climate Research Programme. The CMIP3 multi-model dataset can be freely accessed for non-commercial purposes via http://www-pcmdi.llnl.gov/ipcc/about_ipcc.php.

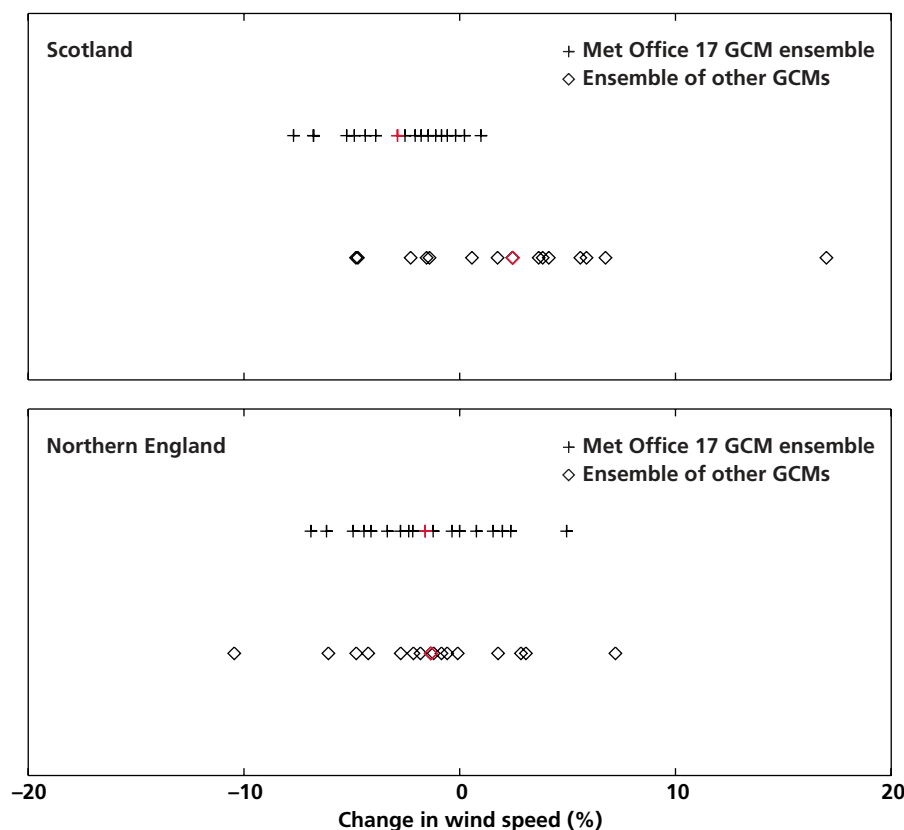


Figure 4.31: Projected percentage changes in wind speed (estimated from daily northerly and easterly components) by the 2080s under Medium emissions. Top panel: for a grid box over Scotland, winter average. Bottom panel: for a grid box over northern England, summer average. The values shown in top row in each panel come from the Met Office global model ensemble, and those in the bottom row from an ensemble of other global climate models. The red symbol in each case shows the average of all members of that ensemble.

Each type of data has advantages and disadvantages. The data from other global climate models, and that from the 17-member Met Office GCM ensemble, is at a relatively coarse resolution. The Met Office RCM has a finer resolution (25 km) and hence provides more information on possible regional variations across the UK. The range of modelling uncertainties explored in the 17-member Met Office GCM ensemble, and the 11-member Met Office RCM ensemble, is not as wide as that explored in the variables for which probabilistic projections are provided in UKCP09. The RCM data is only available for the Medium emissions scenario.

In the case of snow and wind speed, we recommend the use of changes from the 11-member Met Office RCM ensemble in the first instance. Although RCM wind speeds do not validate particularly well against current climate, the percentage changes in wind speed can be expected to be reasonably robust. Changes by the 2080s in winter-mean wind speed averaged over the 11 members of the RCM ensemble is shown in Figure 4.32; these are small, consistent with the evidence from global model projections shown in Figure 4.31.

Changes by the 2080s in the winter mean snowfall rate, averaged over the 11-RCM ensemble are shown in Figure 4.33; typically there are reductions of 65–80% over mountain areas and 80–95% elsewhere. Chapter 5 gives details of the data available from the RCM ensemble, its advantages and limitations. Of course, users may wish to extend their analysis, and investigate the robustness of any adaptation decisions, using data from other global climate models (although note that, in the case of wind, the PCMDI data only gives changes in northerly and easterly wind components, as mentioned above). We have not looked at possible alternative projections of soil moisture and latent heat flux, although both are available from the 11-member Met Office RCM ensemble via LINK. It is recommended that users do not revert to UKCIP02 scenarios in isolation, for any of the variables that are not available in UKCP09.

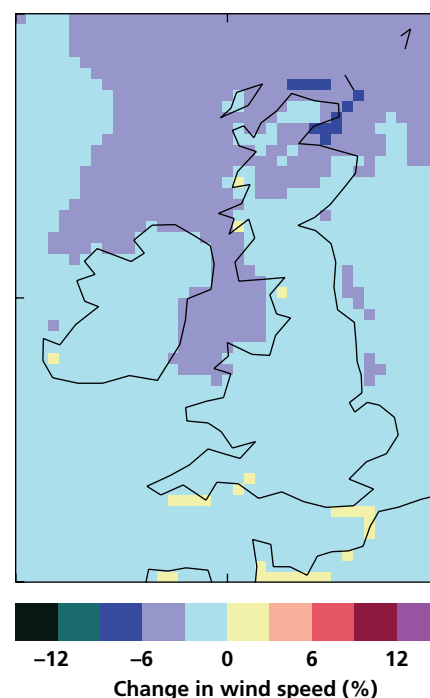


Figure 4.32: Percentage changes in mean wind speed in winter, by the 2080s (relative to 1961–1990) under the Medium emissions scenario, averaged over the 11 members of the Met Office RCM ensemble.

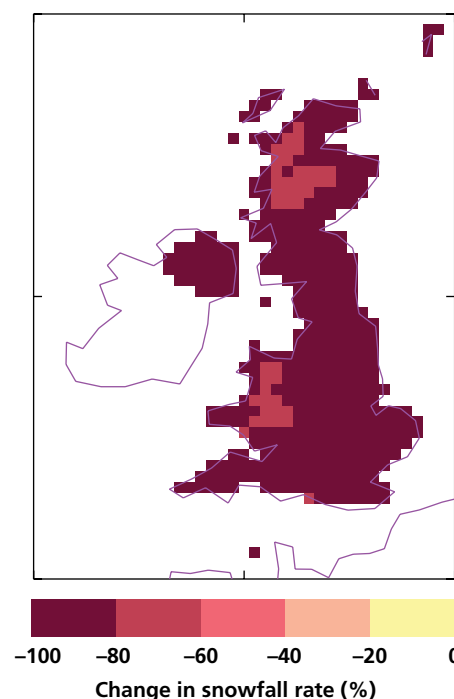


Figure 4.33: Percentage average changes in mean snowfall rate in winter, by the 2080s (relative to 1961–1990) under the Medium emissions scenario, averaged over the 11 members of the Met Office RCM ensemble.

5 Projections from the ensemble of regional climate models

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

5.1 Regional climate models

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

- RCMs simulate spatial contrasts in time-averaged climate at a scale much smaller than that of the driving GCM, in particular where there are significant regional influences arising from surface features such as mountains and coastlines (see Figure 5.1).
- The higher resolution of RCMs also allows improved representation of climate variability, particularly aspects associated with small scale meteorological processes. As a result, they can provide skilful (though not perfect) projections of regional climate extremes, such as localised intense precipitation events, which cannot be captured in GCMs.
- The higher resolution of RCMs allows small islands to be explicitly represented in the model.
- While RCM projections are designed to be consistent with their driving GCM projections at large scales, some types of climate impact, such as changes in river flow, are likely to be so strongly dependent on the fine scale detail that the use of downscaling, either based on RCM data or a statistical method, is essential for the generation of a credible assessment of future changes.

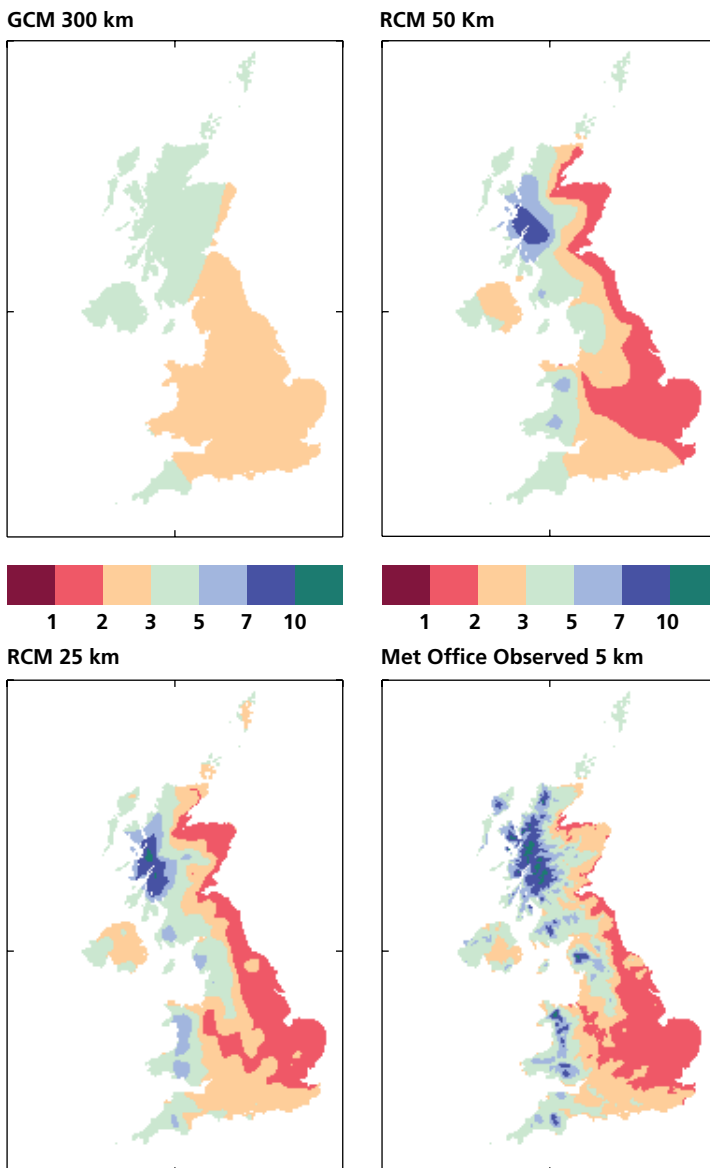


Figure 5.1: The distribution of winter precipitation over Britain (bottom right map) for 1961–2000, compared to simulations for the same period from a GCM (top left), and from two versions of the corresponding RCM at 50 and 25 km resolution, both driven with boundary conditions derived from analyses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

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

5.2 RCM experiments

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

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

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

5.3 Advantages and disadvantages of data from the RCM ensemble

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

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

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

2. It follows from point (1) that temporal sequences of, for example, daily temperature and precipitation over any set of 25 km squares can be used to study the impacts of the evolution of these variables when spatial consistency is required, for example when modelling flow in large river catchments.
3. Changes in long term averages of key variables are fed into the Weather Generator, which then generates characteristics of daily sequences, using a set of statistical relationships derived from present day observations and assumed not to change in the future. The influence of climate change feedback processes (see Chapter 2, Box 2.1) on characteristics of daily time series (for example runs of consecutive hot or dry days) therefore enters only through their effects on the input long term averages. Each of the RCM projections also accounts for effects of feedbacks on aspects of daily variability *not* explained directly by changes in the long-term average, subject of course to the uncertainties associated with climate model projections.
4. Each of the RCMs give a continuous time series of day-to-day data from January 1950 to December 2099 (see, for example, Figure 5.3). The UKCP09 probabilistic projections, however, give changes in *long term averages* of climate for particular 30-yr periods. This means that daily time series from the Weather Generator, fed by inputs from the probabilistic projections, will be typical of the average climate throughout the relevant period, but will not show any trend in climate change within that period.
5. There are a large number of variables available from the RCM ensemble, at many model levels over both land and sea (for details see the LINK website); the Weather Generator outputs a more restricted number of variables at the land surface only — although these are the ones most commonly used in impacts research.

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

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

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

2. It follows from (1) above that users of RCM data should check projections of time-averaged climate change for variables of interest, to see where in the UKCP09 probability distributions they lie. An example is shown in Figure 5.2; this is for a specific variable and different variables and time periods will show different distributions of the 11 RCM variants within the probability distributions. Such an exercise can provide an assessment of the relative likelihood of the time-averaged changes in any given RCM projection, just as it can for any set of time-averaged changes selected to drive the Weather Generator. Note, however, that it would be unwise to assume that the corresponding daily time series possess the same relative likelihood. This is because limitations in current climate modelling capability, or in the statistical assumptions used in the Weather Generator, imply that projections of future changes in detailed regional variability cannot be assumed to carry the same level of credibility as corresponding projections averaged over long periods. In the case of the Weather Generator, the statistics of changes in variability (for a given set of time-averaged changes) can be sampled more robustly than in the case of the RCM, by running multiple realisations with different initial conditions. However the results are still conditional on the assumptions indicated above.
3. The RCM data are projections of simulated climate of the future, rather than ready-made projections of climate change. If the latter are required, then the user will need to difference data sets data for the two periods between which the change is required, for example 2060–2099 and 1990–1999. This does give the user the flexibility of using any number of different future time periods, and indeed baseline periods, of any length, rather than the 30-yr time periods and 1961–1990 baseline period used in UKCP09. As with all model data, that from the RCM will contain biases, due to systematic errors of various sorts — note that these biases will also affect projections from the weather generator. Creating projections of climate change by taking RCM differences as described above will remove the effect of historical model biases. This does not, of course, imply that the future values will then be error free, due to the uncertainty in modelling future changes themselves.
4. When using RCM data to drive models of climate impacts, the issue of model bias again needs to be considered. For example, in some cases the impacts model can be driven with daily data for both a future time period and a reference time period. The difference can then be taken as a plausible realisation of the impact of climate change. However, in other cases, the bias in the RCM may produce implausible results for the present climate from the impacts model, in which case a bias adjustment to the impacts by subtracting present from future may be inappropriate.

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

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

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

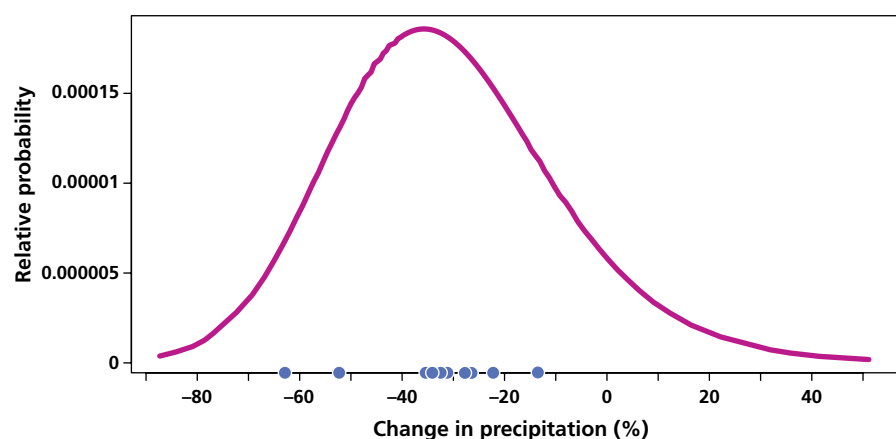


Figure 5.2: A UKCP09 probability distribution function, of change in mean summer precipitation at a 25 km square near Portsmouth, by the 2080s under the Medium emissions scenario. The added blue dots show the same change as projected by each of the 11 members of the RCM ensemble. Of course the PDF may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

5.4 Examples of data from the RCM ensemble

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

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

5.5 Some applications of RCM ensemble data

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

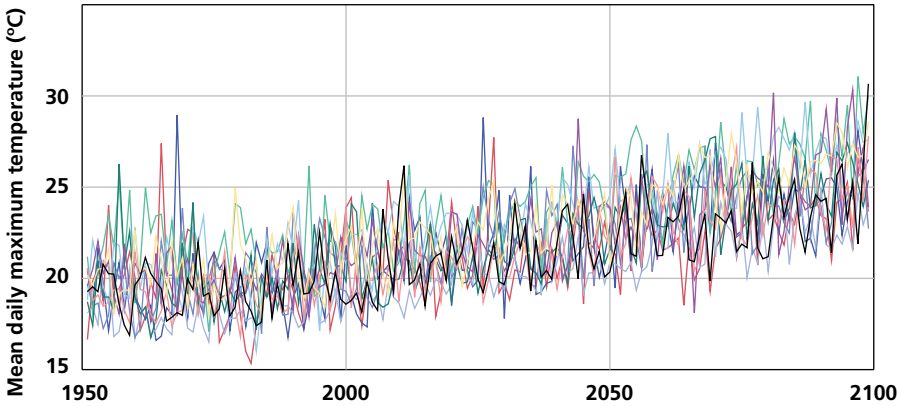


Figure 5.3: Simulated summer (JJA) seasonal-mean daily maximum temperature for a 25 km grid point in Berkshire, 1950–2099, under the Medium emissions scenario, from each of the 11 RCMs.

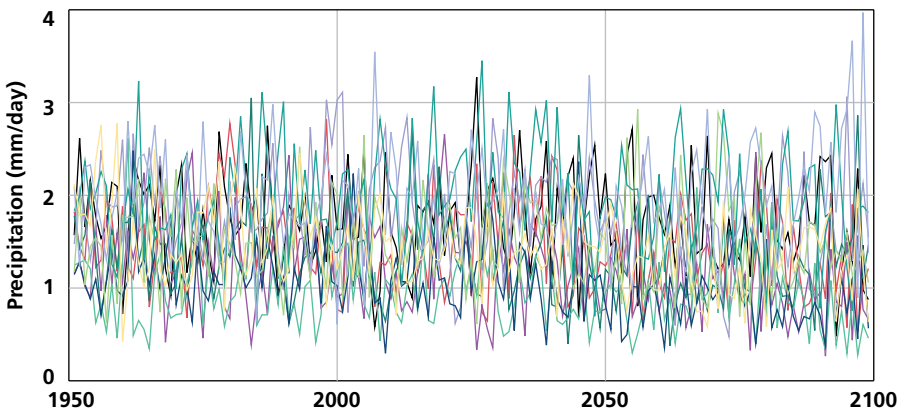


Figure 5.4: Simulated summer (JJA) seasonal-mean daily precipitation for the 25 km grid point near Inverness, 1950–2099, under the Medium emissions scenario, from each of the 11 RCMs.

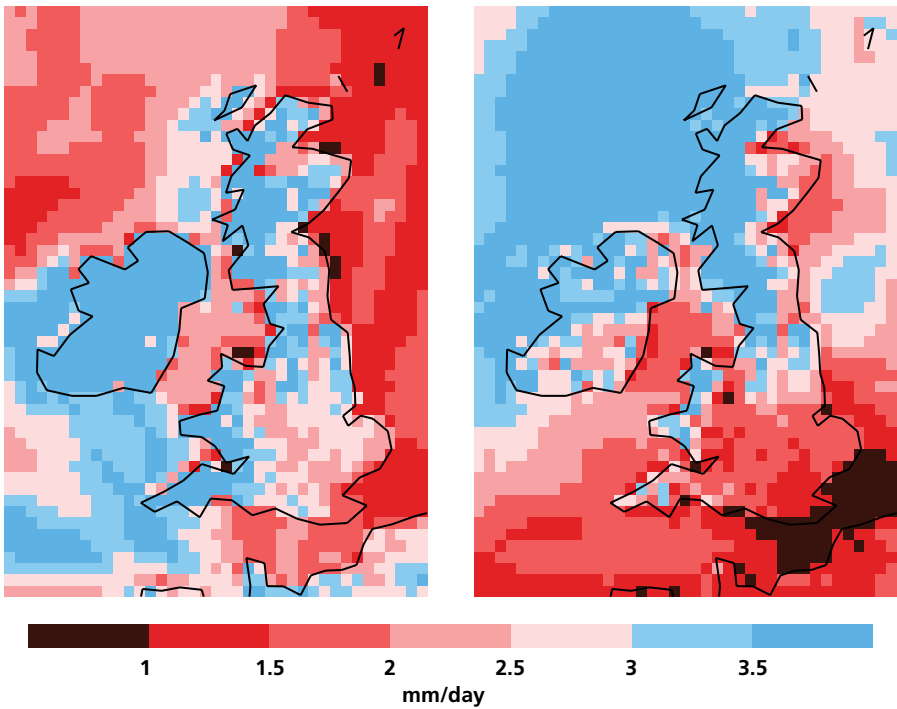


Figure 5.5: A map of summer (JJA) average precipitation (mm/day) from one member of the 11-member RCM ensemble, averaged over the period 1961–1990 (left) and over the period 2070–2099 under the Medium emissions scenario (right).

5.6 Reference

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

Annex 1: Emissions scenarios used in UKCP09

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

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A1.1 Background

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

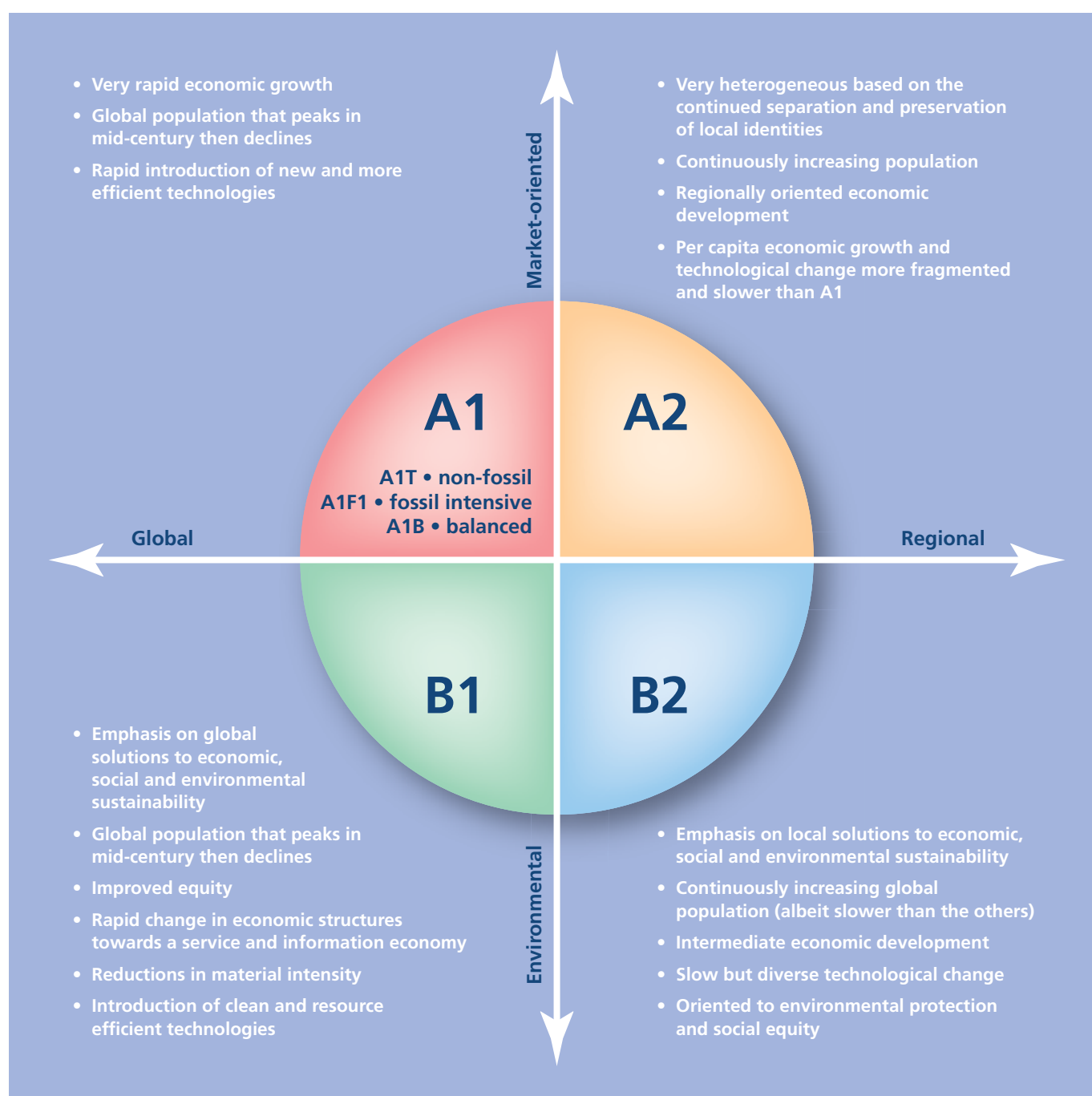
SRES emissions scenarios are structured in four major *families* labelled A1, A2, B1 and B2, each of which represents a different storyline. They are commonly shown as in Figure A1.1, in which the vertical axis represents the degree to which society is economically or environmentally oriented in the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

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

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

The *High*, *Medium*, and *Low* emission scenarios in the UKCP09 report correspond to the A1F1, A1B and B1 SRES scenarios. The High and Low emission scenarios are the same as those of the same name used in UKCIP02. They span almost the full range of SRES scenarios, with cumulative (2000–2100) CO₂ emissions of 2189 GtC and 983 GtC respectively. SRES A2 and B2 storylines, with higher, continuously increasing population scenarios (to 15.1 and 10.4 billion in 2100 respectively), are

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



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

Extreme high or low emissions scenarios, for example very high rates of fossil fuel combustion or strong mitigation in response to concerns over climate change, are also not considered in the projections available from UKCP09. The UKCP09 Low emissions scenario (SRES B1) does, according to some models, result in approximate stabilisation of CO₂ concentrations between about 500 and 600 ppm. However, when the full (ocean and land) climate–carbon cycle feedback is included, as is done in UKCP09, then the CO₂ concentrations will vary over a wide range.

A1.2 Relevant work since the publication of SRES

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

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

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

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

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

Raupach *et al.* (2007) have compared recent global carbon dioxide emissions, estimated by two US government groups, EIA (Energy Information Administration) and CDIAC (Carbon Dioxide Information Analysis Center), with those assumed in the SRES scenarios. They find that CO₂ emissions increased by more than 3%/yr between 2000 and 2004, compared to 1.1%/yr for 1990–1999. This rate of 3%/yr is faster than that in any of the SRES scenarios, and it might be inferred from this that the latter underestimate future emissions, and this would mean that the UKCP09 projections are also an underestimate. However, there are obvious dangers in using comparisons over such a short period to draw conclusions about emissions over the next decades and century.

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

A1.3 References

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Annex 2: Sensitivity of UKCP09 projections to key assumptions

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

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A2.1 Introduction

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

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

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

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

A2.2 Sensitivity studies

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

- i. Some assumptions are currently untestable (see discussion in Section 3.3). This is an inevitable consequence of any probabilistic projection method, due to limitations in scientific understanding, modelling capability, or computational resource. For example, we neglect the possibility of non-linear interactions between uncertainties in regional climate feedbacks arising from atmospheric, carbon cycle, sulphur cycle and ocean processes, because it is not yet feasible to run large ensembles of climate model simulations in which all of these processes are simultaneously perturbed.
- ii. Some choices are based on a mixture of scientific reasoning and feasibility. For instance, we aim to use historical observations of a wide range of different climate variables to constrain our projections, because this reduces the risk that a model variant could be given a high weight by achieving a good historical simulation of a limited set of variables through a chance compensation of errors in its detailed representations of physical processes. We achieve this by using many thousands of pieces of observational information (consisting mainly of multiyear averages of global fields of several different variables in different seasons of the year), while noting limitations imposed by compromises in our experimental design, and by lack of availability of data from other climate models. In principle, we could test the impact of withholding some of the observational variables used in our analysis. However each of the observables (Section 3.2.9) was chosen to provide information about a different aspect of historical climate, and as such provides information with a significant degree of independence

from that provided by the other variables. Removing one or more of these would therefore significantly degrade our ability to provide an observational constraint which effectively discriminates between physically plausible and implausible model variants, so the results of such a sensitivity test would be less credible than the UKCP09 results. We therefore do not investigate such a test here.

- iii. Other choices are subjective. These can be divided into three groups, explained in this paragraph, and in (iv) and (v) below. First, there are a number of choices in our procedures which require expert judgement, but can be supported by diagnostic checks. These include, for example, choices between alternative statistical regression models in the emulation, timescaling and downscaling techniques described in Chapter 3. Another example relates to the use of observational data. While we wish to use as many observational variables as possible (as explained above), in practice we have to reduce the information to a limited set of global spatial patterns (multivariate eigenvectors), in order to make our statistical calculations tractable. These eigenvectors explain the main variations in simulated values of the observable variables found in a large ensemble of perturbed climate model variants (see Section 3.2.9). We use six eigenvectors, based on diagnostic tests indicating that this choice strikes a reasonable balance between the need to include enough information to calculate weights which are effective in capturing variations in simulation quality between different model variants, and the risks of trying to include too much information. Use of too many eigenvectors could result in (a) the inclusion of noisy patterns which do not capture physically meaningful variations in behaviour across our ensemble of alternative model variants, and (b) the risk that too few model variants would receive a non-negligible weight, in which case it would not be possible to obtain statistically robust projections when approximating an integration over all possible model variants (i.e. over all points in the model parameter space) using a finite sampling strategy (see Section 3.2.12). However, we test the sensitivity to this choice by recalculating selected results assuming retention of five eigenvectors (see following discussion of Figure A2.1).
- iv. Some choices are subjective in principle, but are also limited by what information is available. An important example is the set of alternative climate model results available for use in our calculation of the effects of structural model errors (*discrepancy*, see Section 3.2.8). We recognise that if a larger sample had been available we might have obtained different results; however, we show below that reducing the set of climate models used has a limited impact on our probabilistic projections for surface temperature and precipitation, compared with the total uncertainty expressed through the spread in the UKCP09 probability distributions.
- v. The third category of subjective choices encompasses those which are based on expert judgement, and are essentially unconstrained by objective checks or practical issues such as availability of resources. In our case, the most obvious example consists of the expert distributions for uncertain climate model parameters controlling surface and atmospheric processes, which form a fundamental prior input to our Bayesian method of climate projection (see Section 3.1). In our integration over model parameter space, we assume that these parameters are equally likely within the middle 75% of the range estimated by experts, and that the probability drops linearly to zero at the minimum and maximum values. However, alternative choices could also be justified, so the sensitivity of the results to these needs to be tested (see

below). This is feasible, because our method includes a statistical emulator of climate model output which can estimate results likely to be obtained for any given combination of parameter settings.

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

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

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

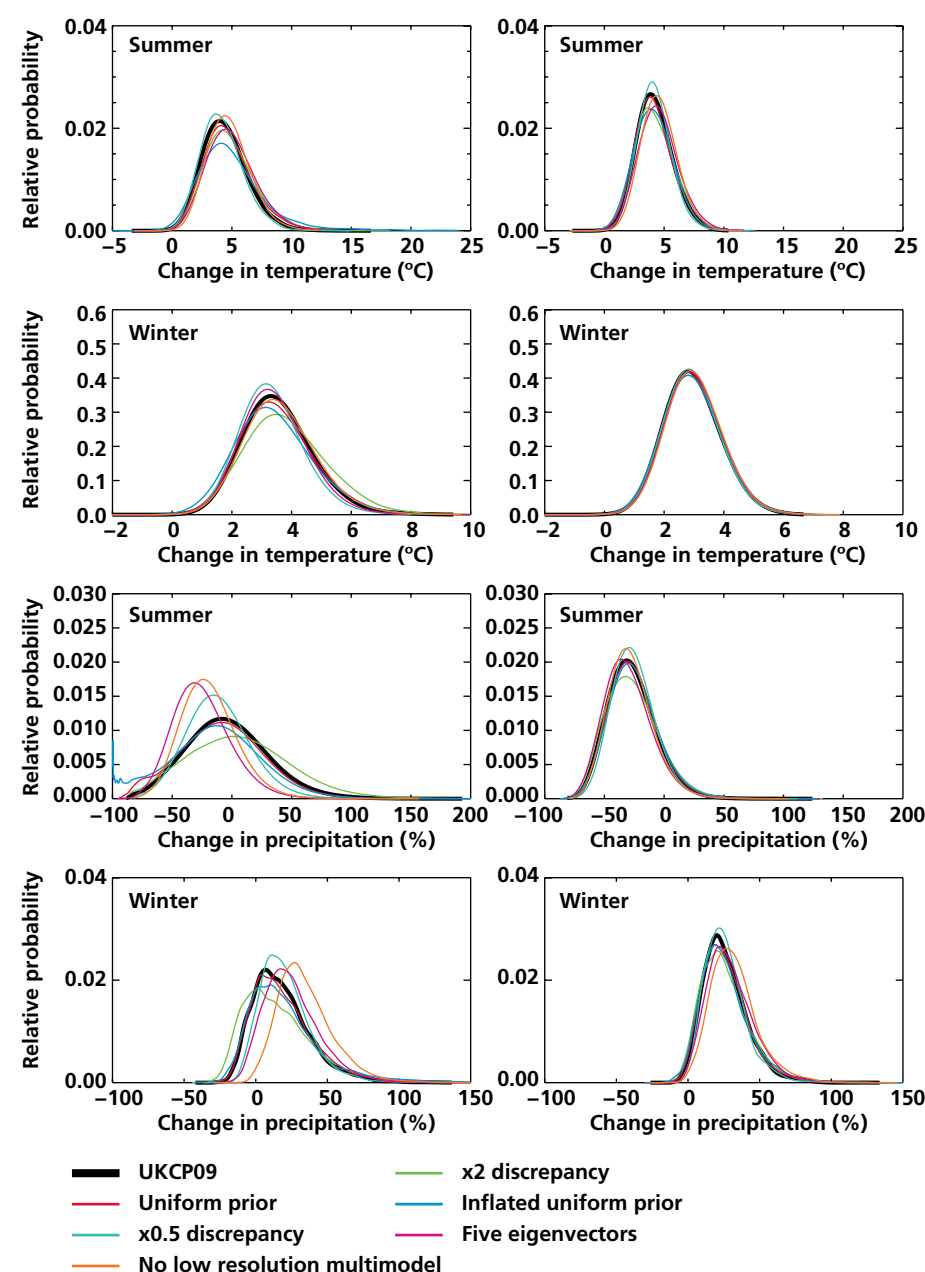


Figure A2.1: Probability distributions from six sensitivity tests (coloured) compared to UKCP09 results (black). The tests were done for summer and winter, for absolute changes in mean temperature (°C), and percentage changes in mean precipitation, for 2070–2099 relative to 1961–1990. Results are presented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

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

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

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

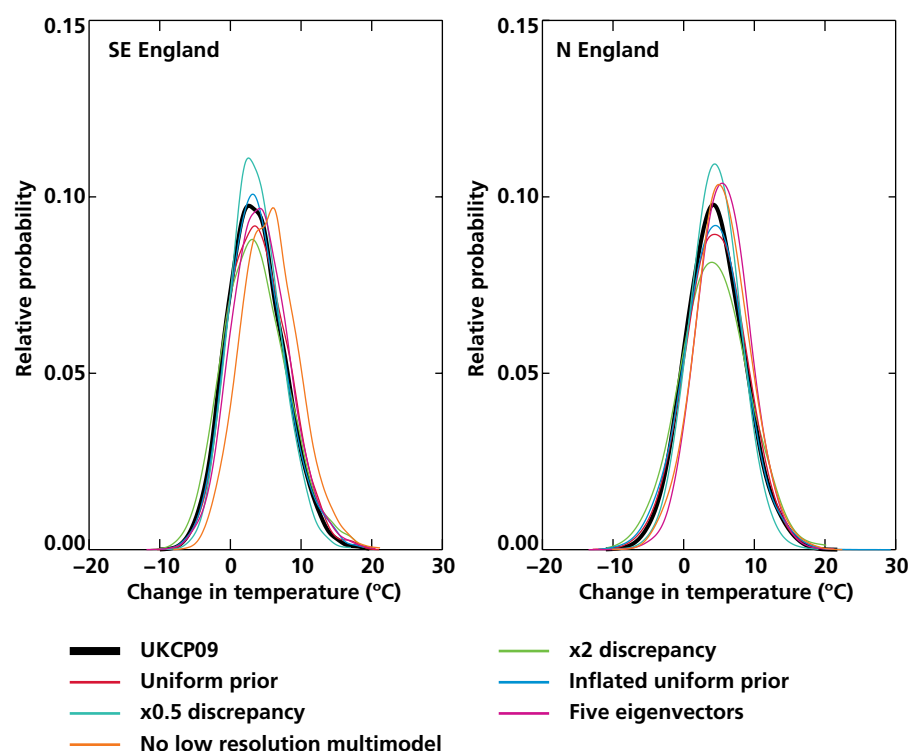


Figure A2.2: Posterior probabilistic projections from six sensitivity tests (coloured) compared to UKCP09 results (black), for summer changes in a typical warmest day of summer (°C), defined as the 99th percentile of daily maximum temperatures during June to August. Changes are shown for the global climate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

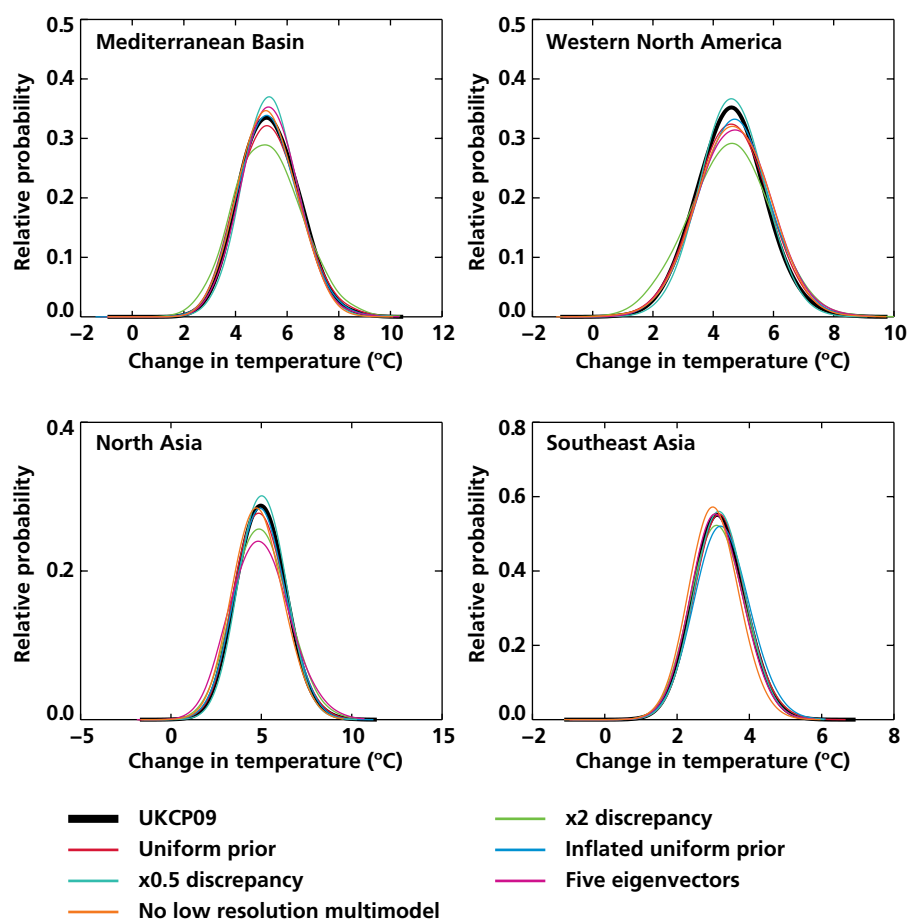


Figure A2.3: Posterior probabilistic projections from six sensitivity tests (coloured) compared to UKCP09 results (black), for summer changes in average temperature (°C) for 2070–2099 relative to 1961–1990, over a number of regions defined by Giorgi and Francisco (2000). Sensitivity tests are as described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

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

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

A2.3 Comparison of UKCP09 methodology against alternative approaches

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

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

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

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

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

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

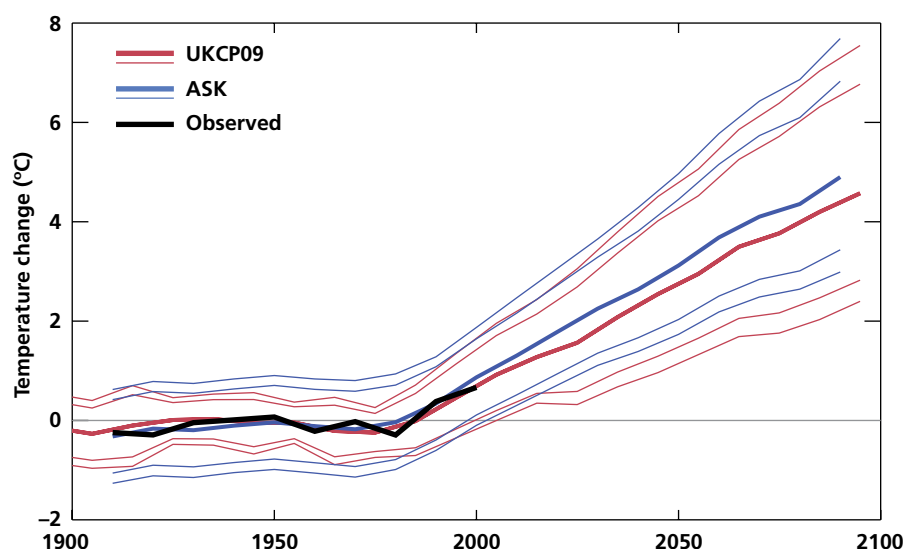


Figure A2.4: Comparison of probabilistic climate projections for changes in 10-yr annual mean 1.5 m temperature (°C) in response to SRES A1B (i.e. UKCP09 medium) emissions. Changes shown are for Northern Europe, relative to 1906–2005, from two methods: UKCP09 (red) and an updated version of Stott *et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

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

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

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

A2.4 Contributions to uncertainty in the UKCP09 projections

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

- **Parameter uncertainty**, arising from uncertainties in the values of climate model input parameters that control key physical processes. UKCP09 is based on a comprehensive strategy for sampling parameter uncertainties in the atmospheric component of the HadCM3 climate model, by combining a large ensemble of model simulations with emulation of the outputs of possible model variants for which we do not possess an actual simulation (Section 3.2.3). In addition, we sample parameter uncertainties in ocean and sulphur cycle processes using a more limited strategy based on 17 member ensembles of alternative model variants. We define parameter uncertainty to include all of these sources of uncertainty (including uncertainty arising from emulator error in the case of atmospheric parameters), but note that atmospheric parameters provide the dominant contribution. Our method for the quantification of uncertainties in carbon cycle processes, which we consider under a separate heading below), also contains a substantial contribution from parameter uncertainties associated with terrestrial ecosystem processes in HadCM3C (the configuration of HadCM3 including an interactive carbon cycle).
- **Structural uncertainty**, which measures the additional uncertainty due to modelling errors which cannot be resolved by varying uncertain parameters in HadCM3 (Section 3.2.8). As a proxy for this, we use information from alternative contemporary climate models, assuming that errors in our ability to predict their historical and future simulations of climate form reasonable estimates of structural errors in the ability of HadCM3 to simulate the real climate system. Note that our strategy estimates the impacts of structural errors in atmospheric processes, but not in ocean transport or sulphur cycle processes.
- **Timescaling uncertainty** is the uncertainty that arises from the need to predict time-dependent climate responses from the simulations of the equilibrium response to doubled levels of carbon dioxide which form the basis of our strategy for sampling uncertain atmospheric model parameters (see Sections 3.2.4 and 3.2.6). The uncertainties associated with timescaling include the effects of internal variability. We remove these in the analysis below, in order to isolate uncertainties arising from methodological assumptions in our procedure, for example that time-dependent climate changes can be assumed to be linearly related to changes in globally averaged temperature.

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

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

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

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

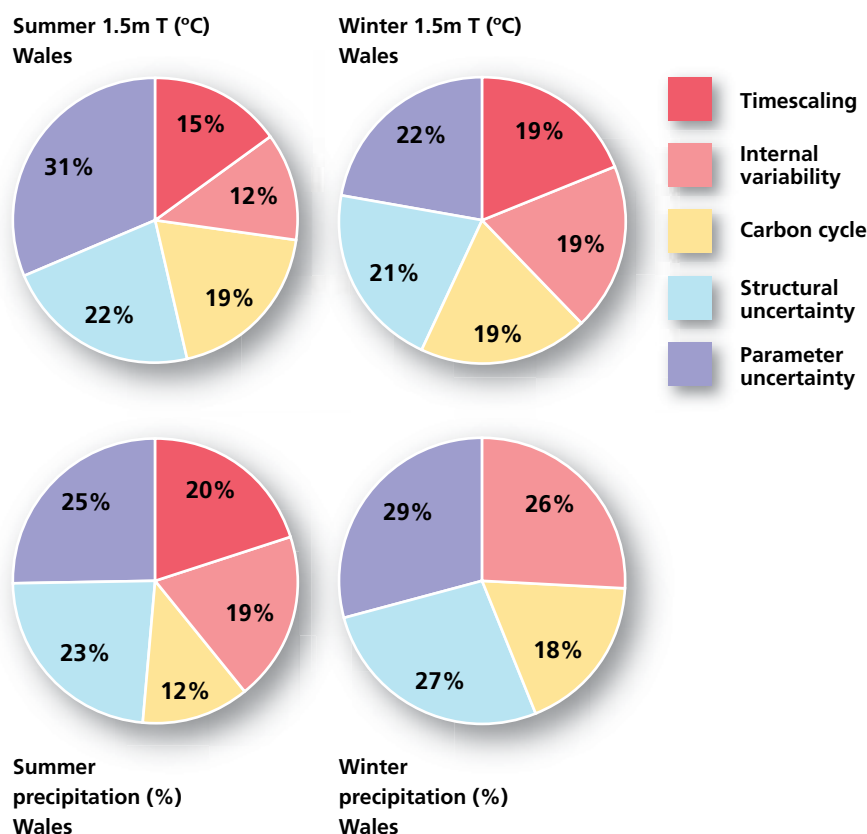


Figure A2.5: The relative contributions of different components of uncertainty to the overall spread in UKCP09 projections. These are calculated for summer and winter and for changes in temperature and percentage changes in precipitation for the Wales global climate model grid box, considering projected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

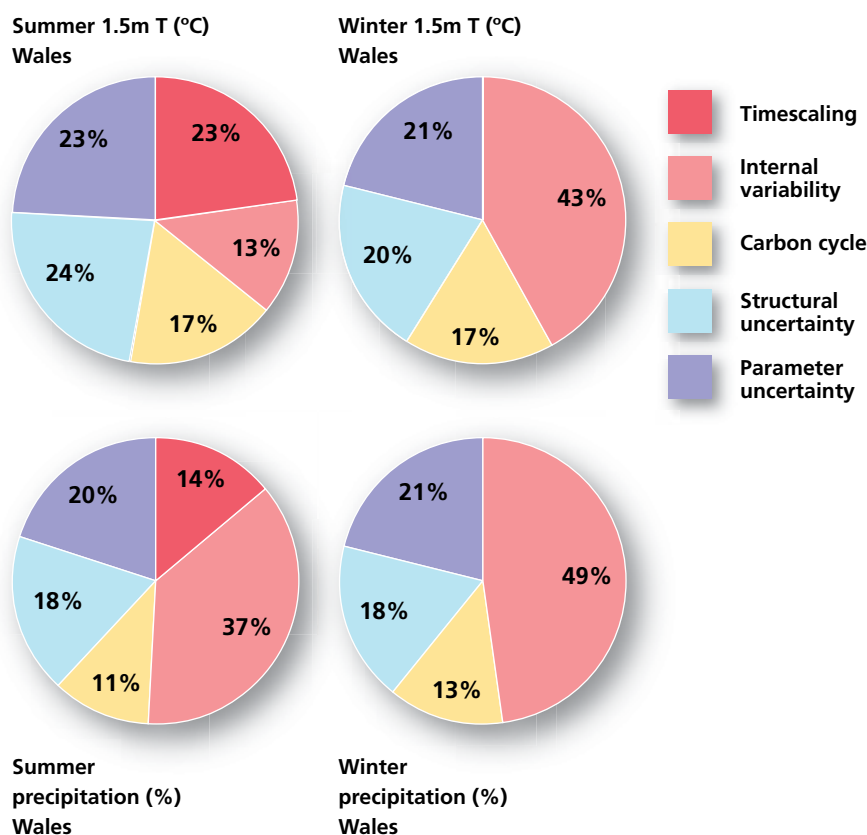


Figure A2.6: As Figure A2.5 but for 2010–2039.

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

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

Downscaling uncertainties

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

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

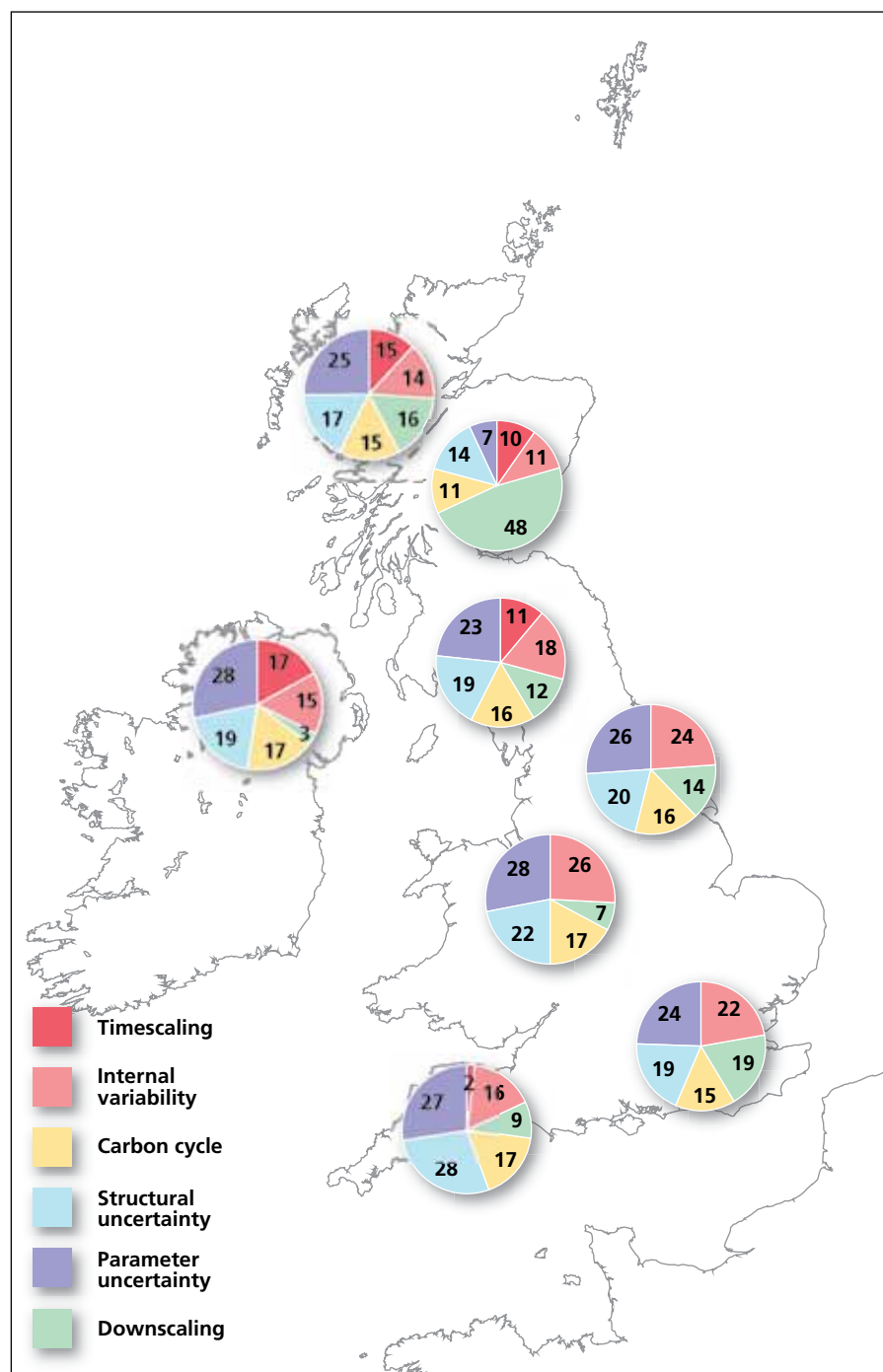


Figure A2.7: Contributions to the uncertainty in winter precipitation changes for 2070–2099 relative to 1961–1990, at selected 25 km grid squares. Contributions are calculated as in Figures A2.5 and A2.6, and also include that due to downscaling from global climate model grid squares to regional climate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

is left to future work; however, a good example would be local enhancements or reductions in precipitation caused by the effects of mountains or coastlines. These local modifications vary substantially between the different members of our regional model ensemble in some regions, due partly to differences in the projected changes in the regional atmospheric circulation. The results of Figure A2.7 demonstrate that the contribution of downscaling uncertainty can vary significantly from region to region. The contribution also varies with future period, tending to be larger for relatively near-term projections (e.g. for 2010–2039) compared with projections for the end of the coming century (not shown). This is because our metric of downscaling uncertainty does not (typically) increase proportionately as the forced response increases in the global model

(see Figures 3.9 and 3.10, noting the scatter of the changes about the regression lines), suggesting that much of it may arise from locally generated internal variability. Further examples will be given on the UKCP09 website (see <http://ukclimateprojections.defra.gov.uk>). Finally, we note that our analysis relates specifically to uncertainties quantified by the downscaling strategy chosen for UKCP09, and does not consider potential additional uncertainties associated with the structural assumptions made in the approach (see Section 3.2.11).

A2.5 Summary

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

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

- Internal variability in climate projections is inevitable, and to some extent represents an irreducible component of uncertainty. However, recent results suggest there is potential to predict some aspects of internal variability out to a decade or more ahead, by initialising climate model projections using estimates of current observed climate anomalies in the ocean (Smith *et al.* 2007; Keenlyside *et al.* 2008), rather than the current practice of using random initial states typical of pre-industrial conditions.
- Timescaling uncertainty could in principle be removed. This would require future versions of our methodology to be based upon very large ensembles of projections of time-varying climate change carried out using the model configuration in which the atmosphere is coupled to a dynamical three-

dimensional ocean module. This would remove the necessity to estimate the results of such an ensemble from simulations of the equilibrium response to doubled carbon dioxide carried out using a simple mixed layer representation of the ocean. In practice, prospects for achieving this will depend on the level of available computing resources relative to the cost of running future climate models.

- Parameter uncertainty can be reduced by developing better climate models. This is a long term, ongoing task, to which significant resources are being devoted in the Met Office Hadley Centre. An additional route is through the development of improved observational constraints. This could be achieved by developing metrics which test the ability of climate models to simulate relevant physical processes in a more detailed manner (e.g. Williams *et al.* 2005). More effective ensemble designs could also help, by reducing errors associated with emulation of climate model results for parameter combinations at which we lack a climate model simulation.
- Structural uncertainty could be reduced by a worldwide improvement in the quality of climate models, assuming that such developments lead to a narrowing of the spread of systematic biases found in different models. It is also possible, however, that improvements in models could lead to a broadening of structural uncertainty. This could happen, for example, if developments in spatial resolution or in the parameterisation of physical processes were to lead to the discovery that climate change feedbacks are more uncertain than currently thought, because current models underestimate the potential role of certain processes (see Annex 3).
- Carbon cycle uncertainty is a major source of uncertainty in projections of globally averaged temperature, and hence on the UKCP09 projections, through their links with global temperature. Improved understanding and modelling of terrestrial and oceanic ecosystem processes would help to reduce this component of uncertainty. In UKCP09 there is no formal or comprehensive use of observations to constrain carbon cycle feedbacks (though a simple metric based on historical global carbon cycle budgets is used to rule out a small subset of the available model projections). Development of a more sophisticated and comprehensive approach (such as the approach taken in UKCP09 to constrain projections according to their representations of physical climate system processes) could therefore also help to reduce uncertainties associated with carbon cycle processes.
- Downscaling uncertainty consists of: (i) a combination of internal variability generated at fine scales in regional climate model simulations (independent of the larger scale information supplied by the driving global model simulations); plus (ii) uncertainty in the component of the fine scale response controlled by the global model inputs. In principle the need for a specific downscaling strategy could be removed, by basing future projections entirely on global climate model simulations run at the spatial resolution for which users require projections. This would remove the component of uncertainty arising from type (ii), and would subsume type (i) into the global model simulations. In practice, however, this will not be feasible for the foreseeable future, so we anticipate a continuing need for downscaling methods. Downscaling uncertainties of type (ii) could potentially be reduced by investigating more sophisticated regression techniques which allow the regional model changes to be inferred more accurately from global model variables. Note also that the UKCP09 method does not support the use of observations of fine-scale

aspects of climate to constrain the detail added to the projections through downscaling (which could reduce the uncertainty if included), and also omits any consideration of structural errors associated with downscaling (which could increase the uncertainty). Addressing these limitations would require larger ensembles of regional climate model simulations, including some made using regional models from other modelling centres (e.g. Christensen *et al.* 2007), and hence containing different structural assumptions from those employed in the perturbed physics ensemble of Met Office model variants.

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

A2.5 References

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Annex 3: Strengths and weaknesses of climate models

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

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Tim Hinton, and Tom Howard,
Met Office Hadley Centre*

A3.1 What are climate models?

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

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

The size of the grid boxes is limited by the amount of computer power available. Halving the size of the grid boxes in the horizontal and vertical direction makes the model more than 10 times slower to run. A balance must be achieved between resolution and run-time to ensure that enough model experiments can be performed to cover a range of future possibilities. The resulting grid boxes in a global climate model are a few hundreds of kilometres wide in the horizontal. Even in the regional version of the climate model (RCM) they are 25 km, so they cannot resolve all the atmospheric motions and interactions in a single cloud which evolve on much smaller scales. For this reason, small-scale processes must be parameterised, i.e. the effect of the small-scale processes on the grid-box scale variables must be simplified in some way.

The critical aspect for climate prediction is that many of the physical processes that are parameterised in climate models are also involved in the physical feedbacks which determine the effect of increasing greenhouse gases on climate, and set some of the regional aspects of climate change. Also important are interactions between the parameterised processes and the coarsely resolved dynamical motions. Parameterisations are necessarily simplified estimates of how the real-world works; hence there is inherent uncertainty in the modelling approach. In UKCP09 we systematically explore these uncertainties by varying parameters in the Met Office Hadley Centre climate model and include information from other climate models in order to quantify the uncertainty in climate predictions arising from parameterised processes.

A3.2 Some basic assumptions and common misconceptions in climate modelling

Critical examination of the performance of climate models, leading to revision and improvement of the models, is a necessary and ongoing activity within climate modelling (see below). Nevertheless, it is worth stating some the inherent features of all models.

1. Climate models are based on fundamental physical laws (at the very basic level, for example, Newton's third law of motion) expressed in terms of mathematical equations. They are not, as in some prediction endeavours, statistical fits to past observations.
2. Each component of a model is thoroughly tested; often using data from field experiments or dedicated process models representing, for example, the detailed structure of a cloud. Models and their components are subject to scientific peer review.
3. In short-term prediction areas (weather forecasting, for example) model predictions can be validated or verified against a large sample of past cases. In long-term climate prediction (for example, 50 yr into the future), direct verification of this type is impossible. However the suitability of models as tools for long-term prediction can be established, to some degree, by assessing their ability to pass a range of tests of their physical credibility, including replication of recent climate statistics, historical changes in climate (see Figure A3.1, opposite), or performance in shorter-term predictions of weather for days and weeks into the future and in making predictions of climate on monthly and seasonal time scales.
4. Models cannot be adjusted to give any answer a climate modeller might wish to get about climate change. The complexity of the system precludes

this. Many features of the past and future climate produced by models, for example, the climate sensitivity — the global mean temperature change for a doubling of CO₂ — could not have been predicted or somehow set when the model was put together. During model development it is the case that optimisation occurs to make the model's fields best fit observations of present-day climate. However, this is often somewhat *ad hoc*, and only in the case of some reduced complexity models has it been attempted systematically.

In the UKCP09 methodology, ensembles of simulations of variants of the Met Office model, have been used to quantify physical relationships between aspects of historical model performance and simulated future changes. That is, to identify the observational tests, in terms of different mean-climate variables and trends, which are most strongly related to the projection of future climate change. These relationships are then be used to determine weights which calibrate the relative contribution of different ensemble members when quantifying uncertainties in predicted future changes. The weights are set according to the strengths of correlations between the simulated values of observable historical variables, and non-observable future variables. The use of the perturbed physics approach allows, in some sense, the *de-tuning* of the model in order that the fit with observations, which may have been used during the model development phase, may then be used in the weighting scheme (describe in more detail in Chapter 3 and Annex 2). This ameliorates the impact of *double counting* the observations, i.e. using the observations to first tune the model and then using them again in the weighting scheme, which may over-constrain the predictions.

Models will never be able to exactly reproduce the real climate system; nevertheless there is enough similarity between the climate model and the real world to give us confidence that they capture (albeit with uncertainty) key processes known to be important in determining the sign and magnitude of predicted future changes. We can be confident that the models can provide some inference about the real world, as is done in, for example, successive IPCC reports. Nevertheless, we do recognise that there are uncertainties and that there are deficiencies common to all models, including the Met Office model. The whole point of the UKCP09 probabilistic projections is to express the credibility of the model projections in terms of the probability of different outcomes. The model deficiencies are taken account of in the probability or credibility limits of the probabilistic projections.

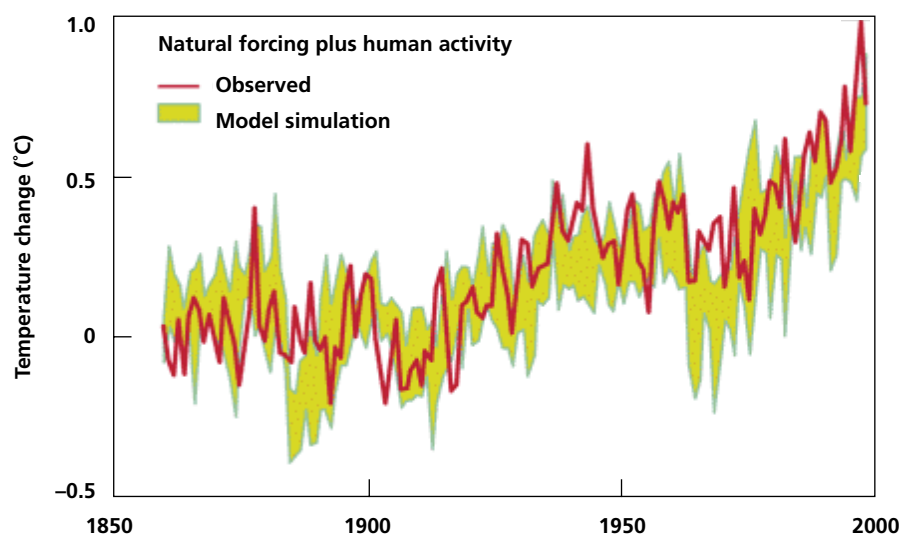


Figure A3.1: Observations of changes in global mean temperature, 1860–2000 (red) compared to the simulation using the HadCM3 climate model driven by observed changes in man-made forcing (greenhouse gas and sulphate aerosol concentrations), natural forcing (solar radiation and volcanic aerosol) and including natural variability (green band). Decadal-scale variability and trends are reasonably well simulated by the model Stott *et al.* (2000).

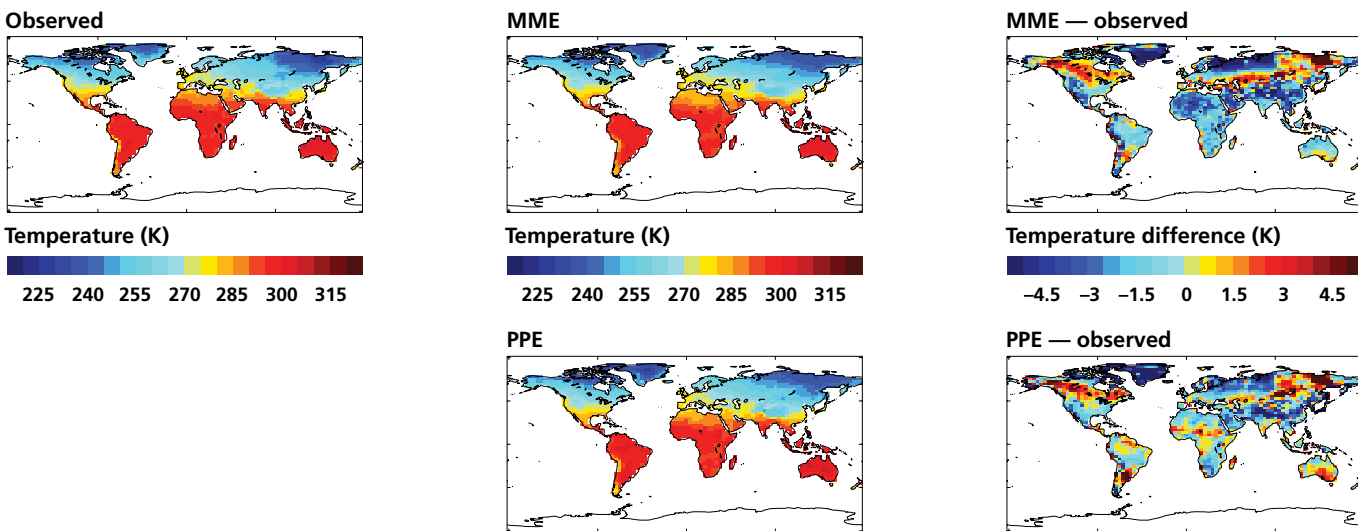
A3.3 Large-scale and small-scale processes and climate change

The current generation of climate models can capture the broad-scale features of present day climate (Figures A3.2 and A3.3) and historical climate change (Figure A3.1). This is particularly true for surface variables such as temperature and mean sea-level pressure and for those three-dimensional fields which capture the large-scale structure of winds and temperatures throughout the atmosphere. Even for fields such as mean precipitation, the models are able to reproduce many of the large-scales features with some fidelity. These features are generated by the dynamical and physical processes in the model and are not prescribed.

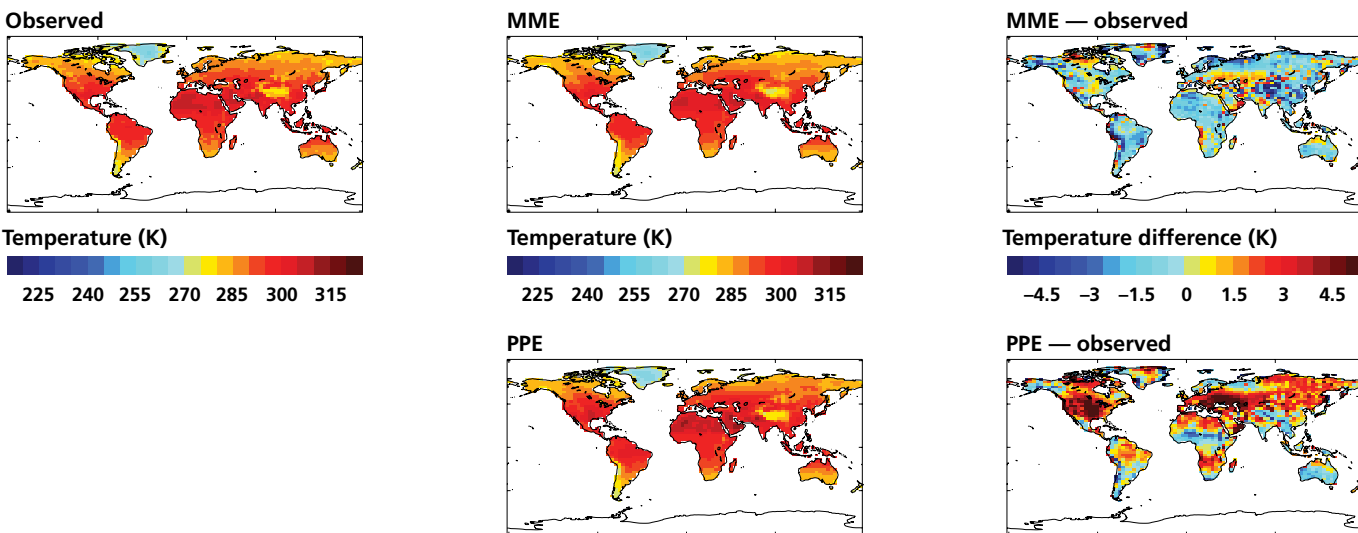
Nevertheless, models are certainly not perfect even on large-scales, as evident in Figures A3.2 and A3.3 which show differences between the model ensemble mean fields and the observations. For example, the ensemble mean of the HadCM3 ensemble with perturbations to atmosphere-component parameters (PPE_A1B — see Chapter 3) shows a clear warm bias in summer Northern Hemisphere continental regions (which we discuss later). In addition, there are biases which are common to both the perturbed physics and multi-model ensembles. Models tend

Figure A3.2: Winter (top two rows) and summer averaged surface air temperature 1961–1990 in K from observations (left column), absolute values from the multi-model ensemble (MME) mean of all the CMIP3 climate models and from the mean of the versions of HadCM3 with perturbations made to atmospheric parameters (PPE_A1B middle column) and model ensemble mean minus observed mean (right column). The model fields are plotted only where the observational data exists. The multi-model ensemble is those models from the Third Climate Model Intercomparison Project (CMIP3). The members are not the same subset of models as the multi-model ensemble used to generate the UKCP09 PDFs, referred to in Chapters 1–3, which employ data from models coupled to simple mixed layer oceans.

Winter mean temperature



Summer mean temperature

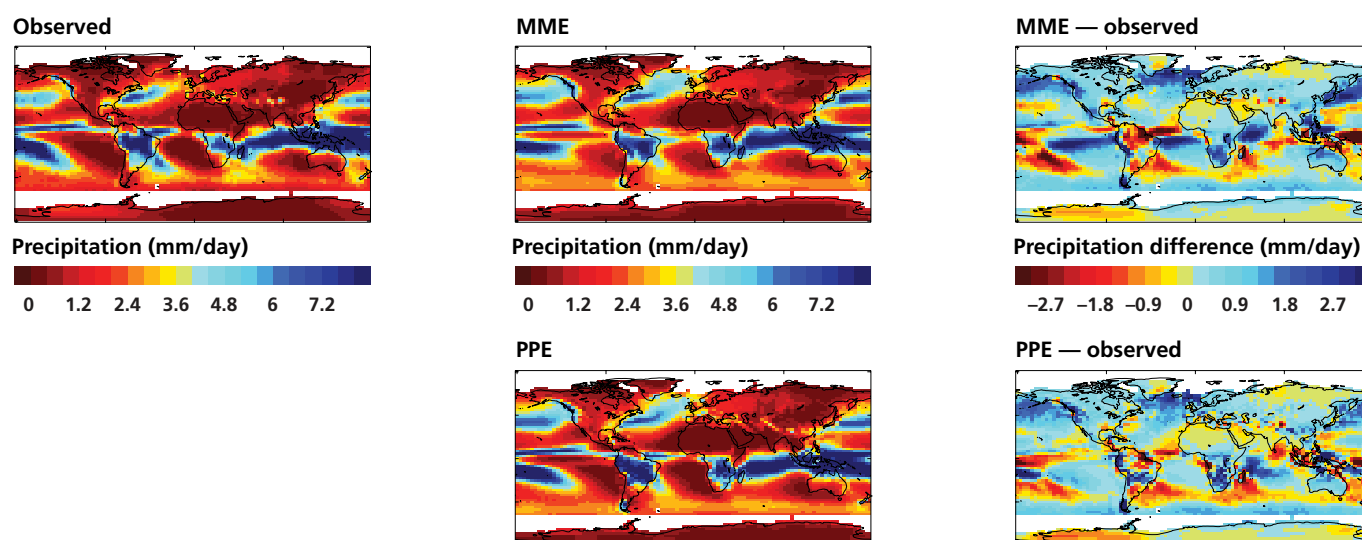


to produce a *double ITCZ* (Intertropical Convergence Zone) in the Pacific whereby zonally-oriented large-scale rain bands appear in both hemispheres, where in reality, the southern hemisphere rain band is oriented NW–SE. In addition, variables such as convective (shower) precipitation can be highly localised so are harder to model, as are fields such as surface winds. When regional factors are important — for example in highly mountainous regions — global models may find it hard to capture the small-scale details of the present day climate. Hence there is plenty of room for improvement in climate models and this is an extensive field of research, both within the Met Office Hadley Centre and internationally. (Further discussion of model evaluation is presented below and can also be found in, for example, Chapter 8 of IPCC AR4. Discussion of the mean climates of the regional model versions can be found in Chapter 5 of this report.)

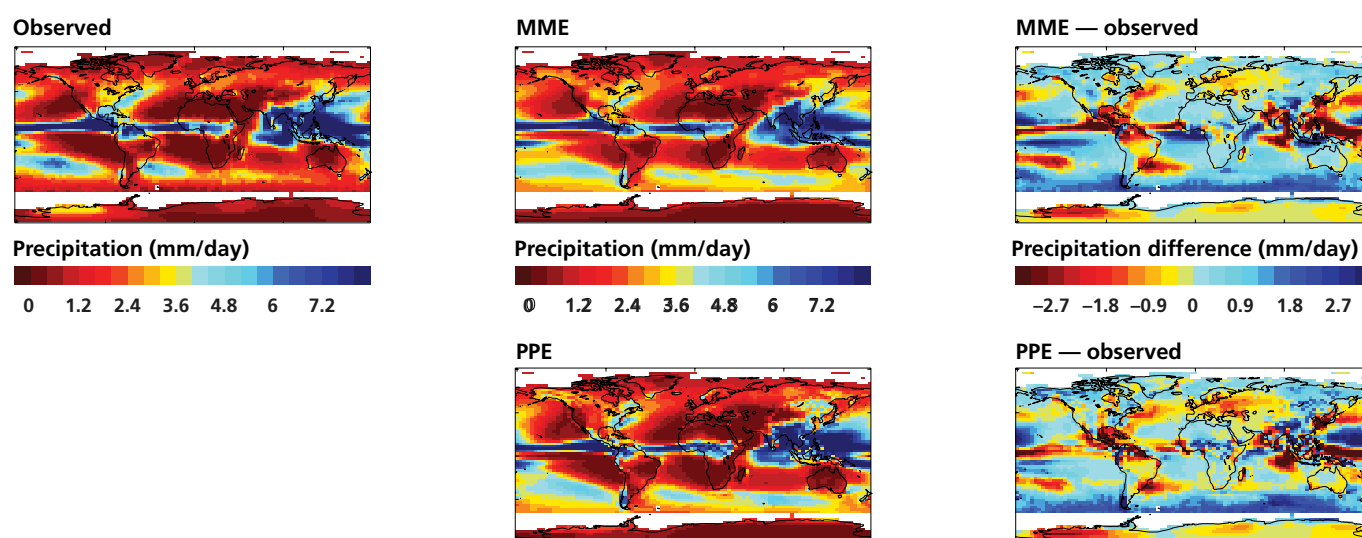
A critical issue for prediction is how these model errors and biases affect the pattern and magnitude of climate change. The main drivers of climate change are global in nature in terms of their radiative forcing and there is a significant degree of commonality between models in terms of their large-scale projections of mean future change (Figure A3.4). The commonality is stronger in the case

Figure A3.3: Winter (top two rows) and summer averaged precipitation 1961–1990 in mm/day from observations (left column), from the multi-model mean of all the CMIP3 climate models and from the mean of the versions of HadCM3 with perturbations made to atmospheric parameters (PPE_A1B middle column) and model ensemble mean minus observations (right column). The model fields are plotted only where the observational data exists.

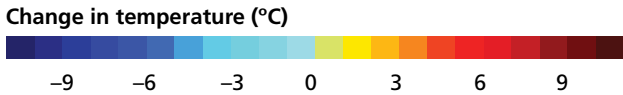
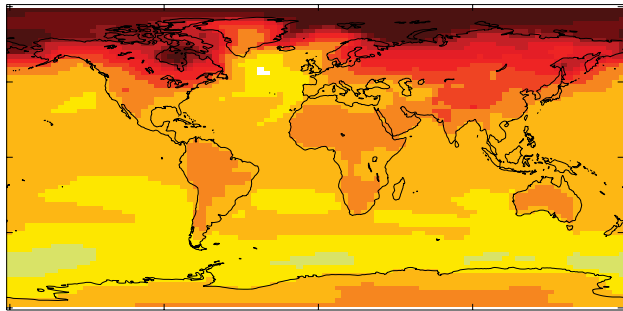
Winter mean precipitation



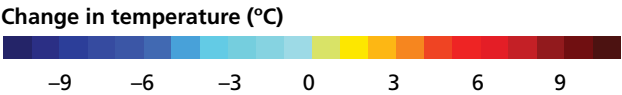
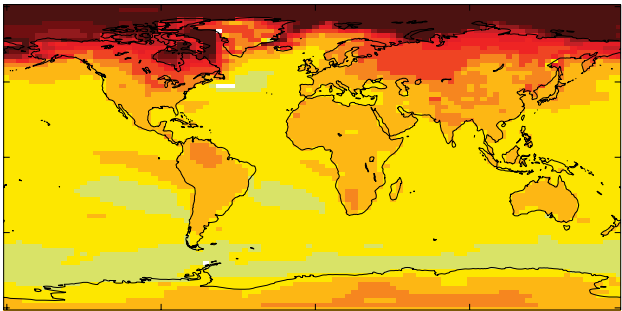
Summer mean precipitation



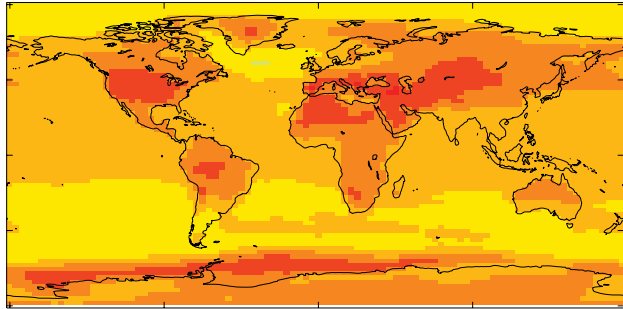
Winter MME



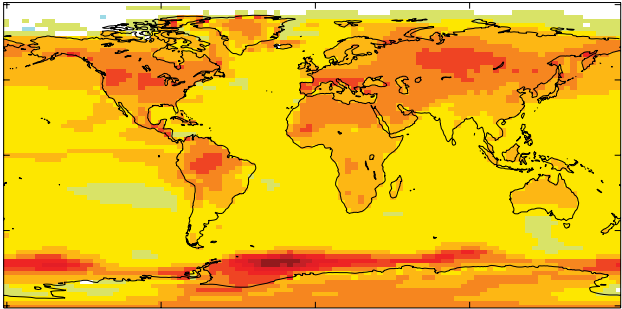
Winter PPE



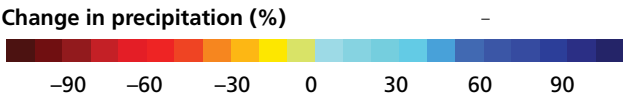
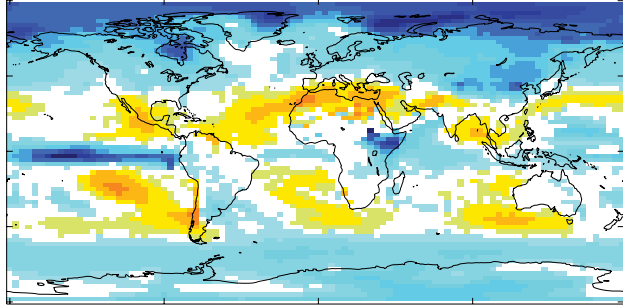
Summer MME



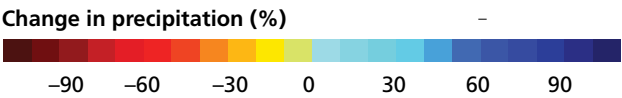
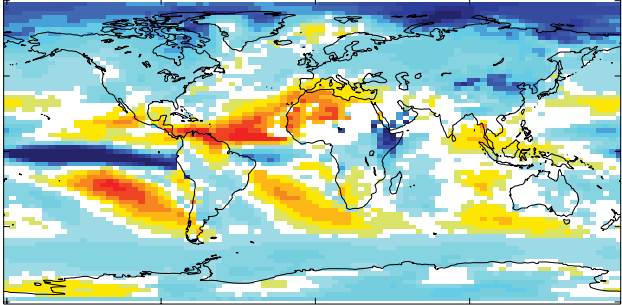
Summer PPE



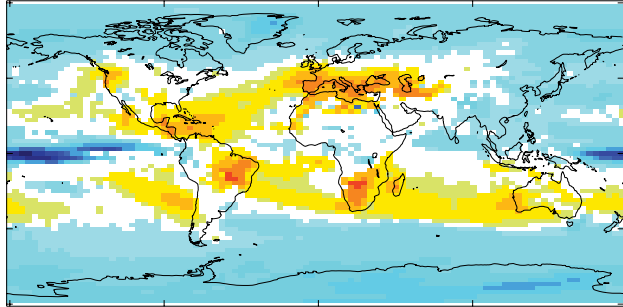
Winter MME



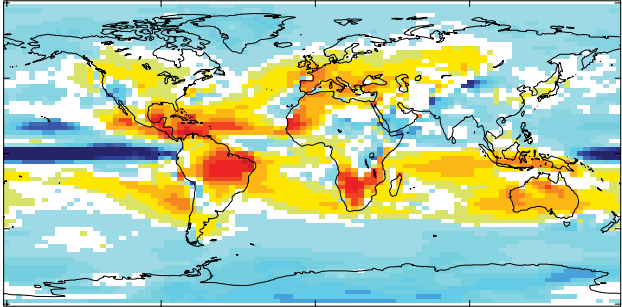
Winter PPE



Summer MME



Summer PPE



of temperature, but there are also similar patterns of response in terms of the mean precipitation in models. Different models all show greater warming over land compared to over the ocean and greater warming at high-latitudes in comparison with the tropics in the winter hemisphere. The latter may be understood in terms of simple physical reasoning: in this case, albedo feedbacks whereby snow or ice covered regions become exposed as the planet warms and, as a result, more sunlight is absorbed by the underlying surface. Other important feedbacks include the positive water-vapour feedback; water vapour (a potent natural greenhouse gas) will increase as air temperature increases. The directions of such feedbacks are relatively well understood but their absolute magnitude is still under investigation. Feedbacks from clouds represent a significant source of uncertainty in total global feedbacks and these may also drive variations in local climate changes (clouds remain one of the most-complex and most-studied of feedbacks under climate change). Because of these global-scale uncertainties, the PDFs presented in this report are (a) constructed from a relatively large number of ensemble members which explore uncertainties in large-scale feedbacks and (b) constrained by a number of observed large-scale fields; the relative likelihood of each model version in its ability to simulate the large-scale nature of climate and historical climate change is taken into account (see Chapter 3).

Looking more locally, we see similar patterns of warming in both summer and winter in region of the UK and NW Europe, with the multi-model ensemble mean showing a slightly greater ensemble mean warming than in the case of the perturbed physics ensemble mean. Perhaps more surprising is the similarity of the patterns of precipitation change in the two different ensembles, with increased precipitation during the winter over much of NW Europe and a drying in the Mediterranean region in summer. This indicates common physical mechanisms for the change between different models. Nevertheless, those physical mechanisms may act in subtly different geographical areas and with different strengths in different models. In the summer case, the perturbed physics ensemble drying extends more into the north and over the UK, whereas in the multi-model ensemble the line of zero mean change cuts the UK. This is why it is so important to include information from other climate models in UKCP09.

For some variables the response to climate change may be quite different in different perturbed physics or multi-model members and the resulting PDFs of change quite wide. We should not necessarily assume that the use of the multi-model ensemble in generating the PDFs provides some kind of upper-bound uncertainty in the predictions. The existence of common errors in multi-model and perturbed physics ensembles may, for example, impact the pattern or magnitude of the climate change response seen in all ensembles. There may be other possible formulations of models which could give rather different responses that could affect the level of uncertainty in the PDFs. Nevertheless, without any evidence of the possibility of very different climate change, the most defensible approach is to look to the multi-model ensembles to provide evidence for a *discrepancy* in PDFs generated from the perturbed physics ensembles (see Chapter 3 and Annex 2 for more details). The impact of model formulation (e.g. horizontal and vertical resolution) on the magnitudes and patterns of climate change is a very active area of research.

In general, regional aspects of climate change may be influenced by local regional processes such as the enhancement of rainfall on the windward-side of mountainous regions. Hence the use of the ensemble of regional-model simulations and statistical downscaling techniques in generating the PDFs presented here. Importantly, the regional models are driven by output from the

Figure A3.4 (opposite): Ensemble mean response in the years 2071–2100 minus the mean climate averaged 1961–1990 under SRES scenario A1B from two different types of global climate model ensembles. Left panels from the CMIP3 multi-model ensemble, right panels from the 17-member HadCM3 ensemble (PPE_A1B in Chapter 3) with perturbed atmospheric parameters. The fields are only shaded when greater than 66% of the ensemble members agree on the sign of the projected change. Top row, winter (DJF), surface air temperature. Second row, summer (JJA) surface air temperature. Third row, DJF precipitation. Fourth row, JJA precipitation. A similar figure appears as Figure TS.30 in the IPCC AR4 Technical Summary.

global models that represent the large-scale pattern of climate change. Hence there is an internal consistency in the information which is derived completely from model output.

A3.4 The ability of models to represent modes of variability

A3.4.1 The North Atlantic Oscillation

Modes of variability like the NAO do occur spontaneously in climate models. Causes of long-term variations in the NAO are still under investigation.

The North Atlantic Oscillation (NAO) is one of the dominant modes of variability of Atlantic-European winter climate. It can be broadly described as a see-saw of atmospheric pressure between the Azores and Iceland and is sometimes discussed in relation to a hemispheric mode of variability, the Northern Annular Mode (NAM), with the see-saw between polar and mid-latitude bands of air. When the NAO is positive, winters in the UK tend to be milder and wetter. When it is negative, winters tend to be colder and drier. HadCM3 does simulate the broad spatial and temporal characteristics of NAO variability reasonably well and is certainly competitive when compared to other climate models (e.g. Stephenson *et al.* 2006).

Of particular research interest has been the long term trends in the NAO observed in recent times (see Figure A3.5) that cannot be easily explained in terms of long-term natural internal variability in climate models (e.g. Gillett, 2005). There are conflicting theories about the causes of these trends in the climate literature. They may be related to variations in sea-surface temperatures in the N. Atlantic or remote ocean basins (Rodwell *et al.* 1999; Hoerling *et al.* 2001; Sutton and Hodson 2007), or be related to trends and variability in stratospheric winds (Scaife *et al.* 2005) or both. They might even be explained in terms of chance year-to-year fluctuations which are in no way predictable. None of the models in the 17-member ensemble of HadCM3 with perturbed atmosphere parameters (PPE_A1B) capture the exact observed low-frequency temporal behaviour of the NAO — no free-running climate model does. Yet the general level of variability in each of the members is similar to that seen in the observations and one member (highlighted in red in Figure A3.5) does capture some low-frequency trends in the period around 1950–2000 which are reminiscent of those seen in the real world (quite by chance of course).

None of the perturbed physics ensemble members show significant NAO trends into the future. Some sub-sets of the multi-model archive have been shown to produce positive NAO trends (e.g. Osborn *et al.* 2004) and the recent IPCC

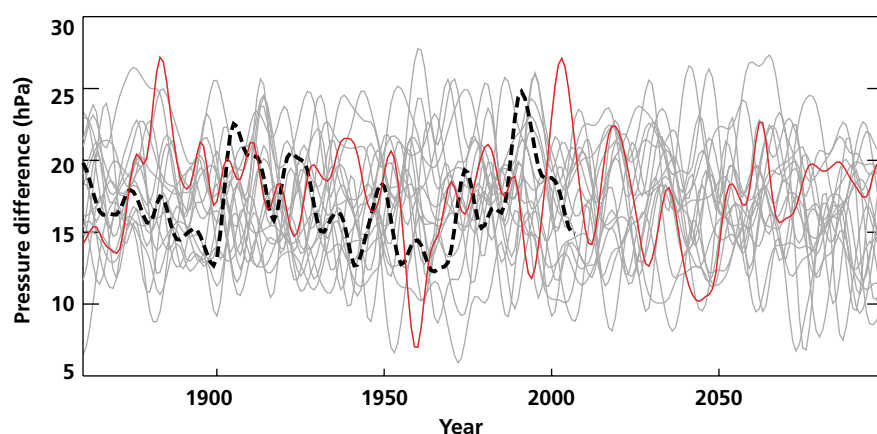


Figure A3.5: Gibraltar minus Iceland mean sea level pressure difference averaged in the winter seasons from observed (thick dotted line) and from the 17 member ensemble of HadCM3 with perturbations to parameters in the atmospheric (PPE_A1B in Chapter 3) component of the model (grey lines). A low-pass filter has been applied to remove year-to-year variability and highlight low-frequency NAO behaviour. An ensemble member with similar magnitude variability to that observed (occurring by chance) is highlighted in red.

assessment concluded that the most recent models showed a trend towards positive NAM and NAO, but with considerable spread among models in the latter. Clearly there is some uncertainty and possible dependence on what index is used to define the NAO/NAM and which models are examined. A corollary of this is that the coherent aspects of future climate changes in winter in the N. Atlantic sector (e.g. Figure A3.4) thus appear to be largely driven in the models by the direct response to the radiative forcing from greenhouse gas increases, rather than any response involving coherent changes in the NAO. This radiative response is the dominant response and no models show changes in dynamical modes of variability such as the NAO which might oppose or severely alter this response.

A3.4.2 Storm tracks and blocking

HadCM3 does simulate the main hemispheric pattern of storm tracks and some aspects of Atlantic-European blocking.

(a) Storm tracks

Greeves *et al.* (2007) show that HadCM3 does capture the main large-scale features of the northern hemisphere circulation, with storm activity concentrated in regions of the Pacific, Atlantic and Mediterranean. These storm tracks are not prescribed in the model but rather evolve as a consequence of the location of mountainous regions, the land–sea contrast and because of preferred regions for development of weather systems. The simulation of storm tracks shows only a modest improvement when model resolution is doubled for example, so the need to quantify uncertainties, achieved in UKCP09 through the use of ensemble simulations of HadCM3 and other contemporary climate models, is unlikely to be removed in the foreseeable future; the computing cost of a high resolution model would have prohibited the use of large ensemble simulations for UKCP09. However, some benefits of higher resolution are achieved in the regional-model downscaling step. A notable generic feature of regional models is their ability to generate many more weather features such as troughs and frontal waves.

It is possible to investigate the behaviour of storms and storm-tracks in climate models using a variety of model outputs. Sophisticated tracking techniques which identify individual cyclones and anticyclones and produce summary statistics of their behaviour may be contrasted with more simple approaches which use time-filtered daily mean-sea-level-pressure fields. Care should be taken in the interpretation as different analysis techniques can sometimes produce subtly different results.

Here we use a simple analysis of mean-sea-level-pressure anomalies, time filtered to retain 2–6 day variability, from the 17-member HadCM3 ensemble with Medium emissions and with perturbations to atmospheric parameters, which are used to drive the regional model simulations. For UK winter, the ensemble mean track of cyclone activity in the models (blue squares in Figure A3.6) is somewhat to the south of its observed position (as given in the ECMWF ERA40 re-analysis of observations). Nevertheless, the track position is closer to that observed than many of the equivalent simulations performed with the CMIP3 models red squares. In addition, the Met Office perturbed physics ensemble has a tighter cluster of storm track strength which, for each member, is only slightly weaker (~10%) than observed. The same southerly track extent is true of the position in other seasons in the ensemble mean, but in those cases the cyclone count is down by around 5–20% (figure not shown). The perturbations to HadCM3 do result in some spread in the position and intensity of the cyclone track between model versions, with ensemble members between 0 and 6 degrees too far south and

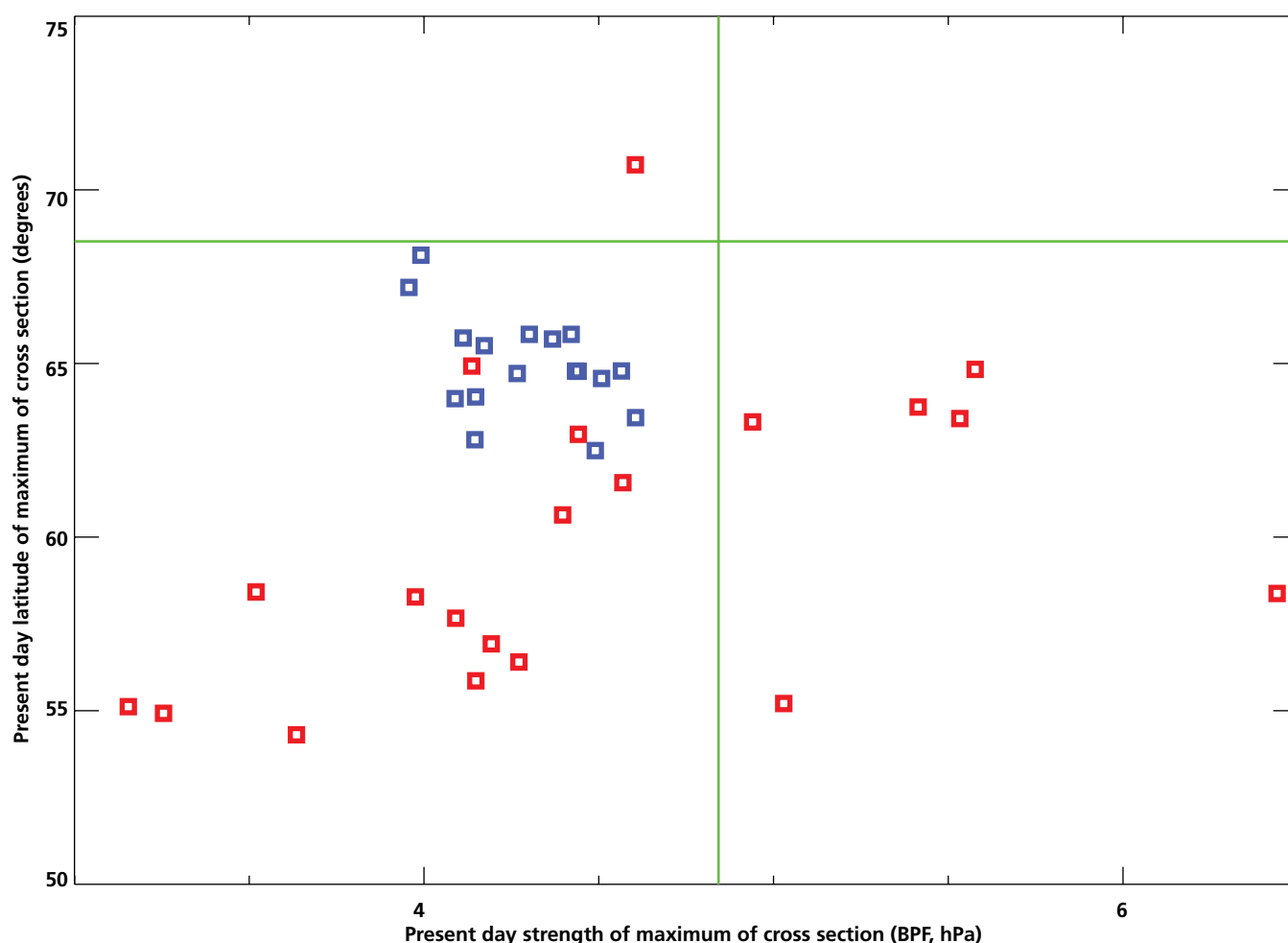
some having strengths as much as 20% too low. However, this spread is smaller than that seen in the CMIP3 multi-model ensemble, where the equivalent range is from 2 degrees too far north to 14 degrees too far south, and range in intensity from 35% too low to 33% too high (Figure A3.6).

Feature-tracking software has also been used to investigation of storms and storm-tracks in these rather coarse-resolution climate models (see Annex 6). Experience tells us, however, that much higher resolution numerical models, such as those used for weather prediction with grid-lengths of the order of 10s of kilometres rather than 100s of kilometres, show much greater fidelity in their ability to simulate the details of individual storms, fronts, etc. that are familiar from looking at daily weather maps. Tropical cyclones which may re-curve into mid-latitudes and become intense storms cannot, for example, be simulated by the current generation of climate models. That is not to say however that such storms are likely to form a major component of the climate change signal. At present, such storms are relatively rare (although may have large consequences) and there is no robust evidence that their frequency will change in the future. Nevertheless, without a number of relatively high-resolution climate model simulations, which will take many years if not decades to realise, it is almost impossible to make any reliable assessments of such phenomena.

(b) Anticyclones and blocking

NW Europe, and in particular the UK, are preferred regions of the globe for anticyclonic events by virtue of being at the end of the Atlantic storm track. The examination of anticyclones turns out to be more complex than the case of

Figure A3.6: Present-day location and intensity of the North Atlantic storm track at the longitude of the UK. The blue squares are from the 17-member HadCM3 perturbed physics ensemble (PPE_A1B in Chapter 3) and the red squares are from the CMIP3 multi-model ensemble. The green lines are from ERA40, and can be thought of as the observed position and strength.



cyclone activity and three different measures have been used to evaluate the ensemble. The inconsistency of the three diagnostics makes it difficult to make a clear statement about the ability of the perturbed physics ensemble to simulate anticyclones, but in general the HadCM3 ensemble is competitive with other climate models.

Further information may be gleaned from the analysis of a particular anticyclonic phenomenon, that of atmospheric blocking. Blocking situations, whereby areas of relatively immobile high atmospheric pressure tend to dominate weather patterns for many days, result in relatively cold, still conditions often accompanied by fog in winter. In summer they tend to be accompanied by dry sunny conditions and heatwaves.

The mechanisms for atmospheric blocking are only partially understood, but it is clear that there are complex motions, involving meso-scale atmospheric turbulence, and interactions that climate-resolution models may not be able to

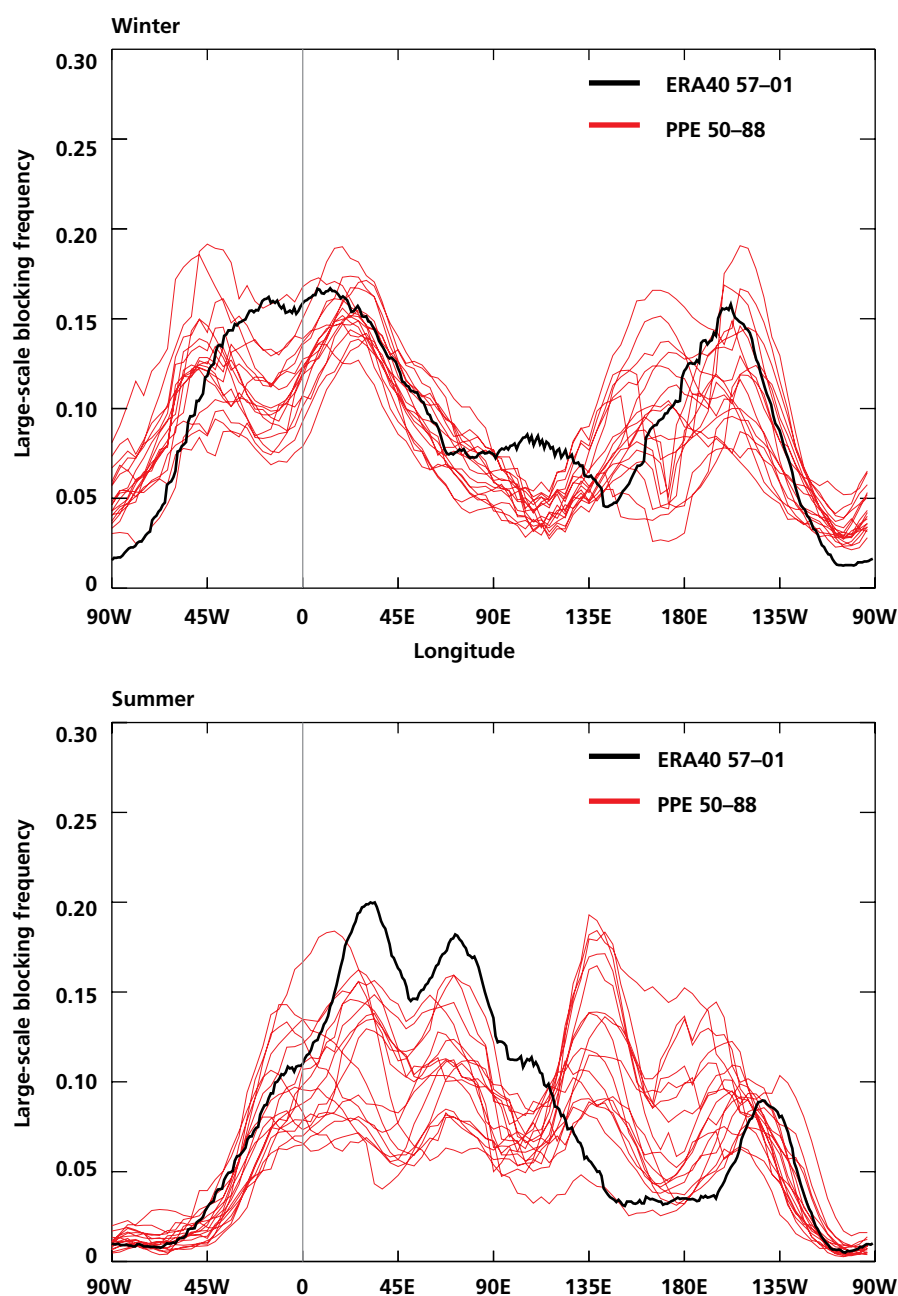
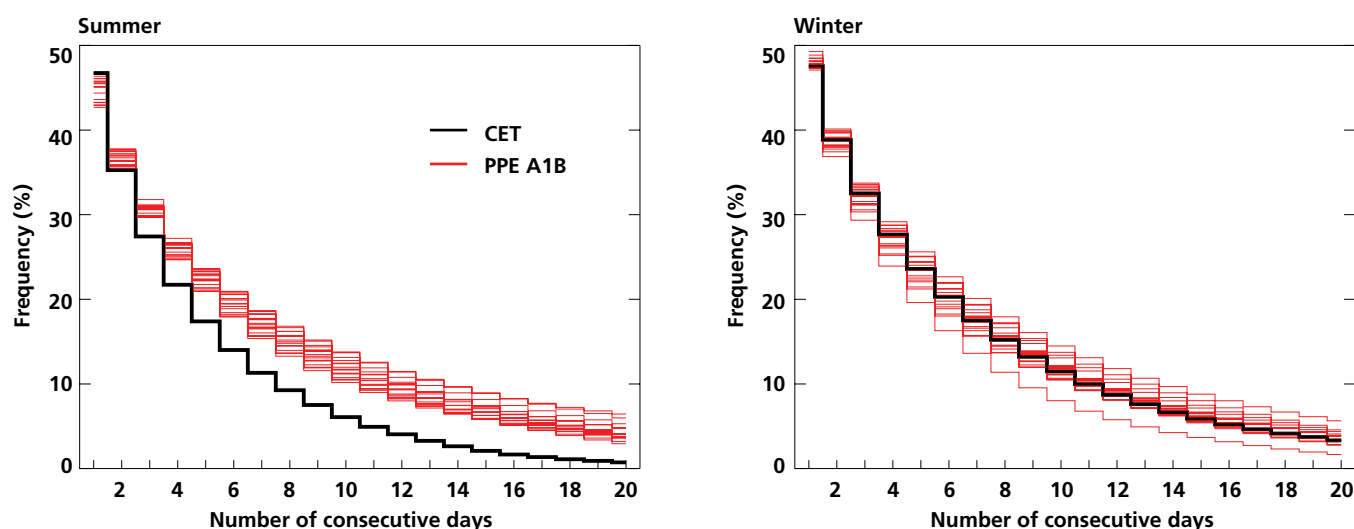


Figure A3.7: The frequency of blocking events in the perturbed physics HadCM3 ensemble (PPE_A1B, red lines) for winter (DJF, top) and summer (JJA, bottom) together with that estimated from ERA40 (thick black lines). The blocking index is calculated following Pelly and Hoskins (2003) and uses a variable latitude to track the location of the model storm track (in contrast to other indices which used a fixed latitude).



represent fully. The prediction of the intensity and duration of blocking events is one of the most difficult weather forecasting situations. The HadCM3 model does represent, with reasonable fidelity, some aspects of present-day atmospheric blocking in the North Atlantic region (see Figure A3.7) with the performance in summer better than that in winter. At other longitudes the model shows less fidelity, in particular in the Pacific sector. (An additional complication is that it is not clear that simply doubling the resolution of a climate model automatically produces a better simulation of blocking — in the case of one Met Office Hadley Centre model, this results in a degradation).

The role of atmospheric blocking under climate change is currently a major topic of research. Might current model errors severely limit the reliability of climate change projections (e.g. Palmer *et al.* 2008; Scaife *et al.* 2008)? Might large changes in blocking, that current models cannot simulate, cause large changes in the frequency of occurrence of summer heat waves for example? Of more practical interest than the diagnosis of blocking frequency is perhaps is the frequency of occurrence of blocking-like weather in the models used in UKCP09. Figure A3.8 shows a diagnostic of occurrences of periods of cold winter and warm summer days in the UK in the PPE_A1B ensemble. For the winter case, each model in the ensemble does a reasonable job of simulating the relative frequency of occurrence of cold spells. In the summer, the model versions overestimate the frequency of occurrence of warm spells (despite the blocking frequency diagnostic being close to that observed around the Greenwich Meridian in Figure A3.7 — other processes are important). Careful evaluation of such diagnostics from the RCM simulations and the weather generators is recommended in cases where such variability is important to the individual user. It should be noted that the UKCP09 PDFs of mean changes and extremes include, by definition, the effects of blocking and changes in blocking from both perturbed physics and multi-model ensembles. Changes in the storm-tracks and blocking are presented in Annex 6.

Figure A3.8: The frequency of occurrence of consecutive days of same-sign temperature anomalies from the Central England Temperature (CET) record (black line) and from an equivalent diagnostic from the 17-member ensemble of perturbed physics HadCM3 (PPE_A1B – red lines). On the left panel there is, by definition, a near 50% chance of a day being warmer than average, a 35% of getting two consecutive warm days, etc. On the right panel, the chance of getting consecutive cold days in winter is plotted.

A3.5 The effect of mean biases in models

The probabilistic approach quantifies uncertainties in the processes and feedbacks associated with summer drying and related impacts.

As highlighted above, biases in present-day summer climates in models are an issue and may effect the response of the model under climate change. Rowell and Jones (2006) examined the different mechanisms for future summer drying

and Jones (2006) examined the different mechanisms for future summer drying under climate change using a matrix of global and regional model experiments. They found that the primary drivers for summer drying in continental Europe are the direct warming coming from enhanced greenhouse gases, coupled with a tendency for a more rapid decline in spring soil moisture which pre-conditions the soil to be dryer prior to the onset of summer. If the soil is moist, then some of the solar heating will be channelled into evaporating this moisture. If the soil is drier, then more of the solar heating will be available to increase temperatures. They also found that the summer soil moisture feedback, whereby reduced soil moisture leads to an increase in surface sensible heating which further reduces soil moisture, was important. Hence future changes in regional climate are driven by a complex array of processes, dependent on both local and remote factors which are included in climate models. Systematic local and remote errors might impact the response derived only from HadCM3 ensembles, but by including results from other models through the discrepancy terms ameliorates this possibility.

In the model experiments used to produce the PDFs presented in this report, a number of processes which control these various feedbacks are perturbed (for example, the number of soil levels accessed for evapotranspiration). Thus we have attempted to explore the uncertainties in the mechanisms for summer drying by using model output from perturbed physics and from multi-model ensembles.

A3.6 Discussion

This annex gives a flavour of some of the issues in climate modelling, with some focus on physical processes that have been major topics of discussion in recent times. A key point is that the UKCP09 PDFs are designed to sample much of the uncertainty introduced by deficiencies in climate models by the use of perturbed physics and multi-model ensembles which in the case of PPEs are weighted by their ability to simulate historical mean climate and climate change. The PDFs represent a measure of the credibility of our current ability to predict climate change.

Much work in climate change research is directed towards both improving climate models and understanding how model deficiencies might impact the magnitude and spatio-temporal pattern of climate change. This research will eventually feed-through to more credible predictions, i.e. PDFs with less uncertainty. Nevertheless, there is a possibility that changes and improvements to models might reveal extreme or very different patterns of climate change outside the range of the UKCP09 PDFs. While we have endeavoured to capture the major feedbacks and their uncertainties and to account for the major deficiencies in models, only future research will be able to tell us if this is the case.

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Annex 4: Probabilistic projection data

The maps and graphs shown in this report, and others available from the UKCP09 website, are generated from a large dataset of probabilistic projections. Chapter 3 describes the methodology developed to produce the projections, and in particular Section 3.2.11 describes the various stages of the procedure. Out of this emerge two products which are described in this annex.

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A4.1 Cumulative distribution functions

The first product from the User Interface is a series of cumulative distribution functions (CDFs). Each of these consist of a set of 107 values of future climate changes corresponding to a set of 107 pre-defined probability levels. These CDFs are provided for each variable at each location, temporal average, future time period and emissions scenario. This is the data which is used to form the CDF or PDF graphs (and plume plots) available from the User Interface, such as those shown in Chapter 4. The set of CDFs for every 25 km square in the UK is used to form maps at the 10, 50 and 90% probability levels, such as those also shown in Chapter 4.

Different probability levels have different levels of robustness. We believe data for probability levels between 10 and 90% to be robust. Probability levels between 1 and 9% and 91 and 99% are to be used with caution as these are less robust and the level of robustness will vary according to which variable is being used. Probability levels less than 1% and greater than 99% are only included so that users can generate plots of PDFs estimated from this CDF data to a similar standard found in the UKCP09 User Interface.

A4.2 Sampled data

Users require values sampled from CDFs to input into their impacts models. For one variable of interest this could be sampled from the appropriate CDF. But most impact models will require more than one variable and it is important to capture in the sampling procedure how these variables depend on each other. The second product described in this annex, referred to as *sampled data* satisfies this requirement and can be thought of as a spreadsheet (Table A4.1); there

are actually two* spreadsheets (known as Batch 1 and Batch 2) for each 25 km grid square and aggregated region (per emissions scenario and per future time period). Each spreadsheet has 10,000 samples (rows), which have been sampled according to weight (a relative measure of how well an individual model variant compares to observations) from a much larger number generated by the probabilistic statistical methodology (see Chapter 3, Section 3.2.11). Each row can be thought of as representing projections at a single location from a single model variant; so the sampled data can be used to look at a consistent set of changes in the seasonal cycle of a climate variable but not at a consistent set of changes at different locations. As the sampling was done by weight, each row can be considered as equi-probable; sampling allows the better model variants to be selected several times within the sampled data set, and rows from the same model variant have the same mean climate change but differ in how the noise was sampled. The columns of each spreadsheet consist of a number of variables for each temporal averaging period. Figure A4.1 shows schematically the variables, emissions scenarios, locations, time periods and temporal averages.

Smaller numbers of rows can be sub-sampled randomly, but the smaller the sub-sample, the greater the chance of the distribution diverging from that of the full sampled population of 10,000. Also, rows can be specified by sample i.d. but this approach requires careful consideration and justification and could lead to a biased decision if used incorrectly. Similar spreadsheets are available for some variables as future climate, rather than climate change, in which the changes have been combined with an observed 1961–1990 climatology. Data sampled from this spreadsheet (for example, changes in precipitation and temperature for a particular 25 km square) can be used as input to an impacts model.

Note that the sampled data has been clipped using the 1 and 99% probability levels from the CDF data for all available variables. That is, for a given combination of variable, location, time period, averaging 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.

The User Interface will allow downloading the sampled data directly; as this is about 0.5 Tbytes in all, users are guided towards defining a suitable subset for their needs. The user could download the data from this request as a csv or CF-netCDF file; the csv option would allow the data to be imported into, and manipulated using, a standard desktop spreadsheet package.

A typical request might be:

- **Variables?** *Mean temperature, mean precipitation*
- **Climate change or future climate?** *Climate change*
- **Emissions scenario?** *High*
- **Location?** *25 km grid box 1628 (London)*
- **Time period?** *2070–2099*
- **Temporal average?** *Winter and Summer*
- **Number of subsamples?** *Random selection of 1000 (of the 10,000 possible samples)*

* Due to limitations in processing, all the variables cannot be included in a single spreadsheet and each location is processed separately.

Low emissions, Grid box 1234, Batch 1					
2020s					
January					Feb...Dec
Sample i.d.	Tmean	Tmax	Tmax99%	Tmin...	Tmean, Tmax...
0	3.3	4.4	5.5		
1	3.8	4.8	5.8		
...					
9999	2.9	4.1	5.1		

Low emissions, Grid box 1234, Batch 2			
2020s			
January			Feb...Dec
Sample i.d.	MSLP	RH...	MSLP, RH...
0			
1			
...			
9999			

Table A4.1: Diagrammatic representation of a segment of the two batches of data for one 25 km grid square under one emissions scenario and for one future time period.

VARIABLE (17)	EMISSIONS SCENARIO (3)	SPATIAL AVERAGE:	TIME PERIOD (7)	TEMPORAL AVERAGE (17)	SAMPLE NUMBER (10,000)
Mean daily temperature Mean daily maximum temperature Mean daily minimum temperature 99th percentile of daily maximum temperature 1st percentile of daily maximum temperature 99th percentile of daily minimum temperature 1st percentile of daily minimum temperature Precipitation rate 99th percentile of daily precipitation rate Specific humidity Relative humidity Total cloud Net surface long wave flux Net surface short wave flux Total downward shortwave flux Mean sea level pressure (some variables can be provided as both climate change and future climate)	Low (B1) Medium (A1B) High (A1FI)	25 km Grid box (440 land cells) <i>or</i> Administrative region (16) <i>or</i> River basin (23) <i>or</i> Marine region (9)	2010-2039 (2020s) 2020-2049 (2030s) 2030-2059 (2040s) 2040-2069 (2050s) 2050-2079 (2060s) 2060-2089 (2070s) 2070-2099 (2080s)	Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec Winter (DJF) Spring (MAM) Summer (JJA) Autumn (SON) Annual (Not all variables are available at monthly resolution)	0 1 2 9,998 9,999

Figure A4.1. Structure of the UKCIP09 Probabilistic Sampled Data for one batch. Some variables can be provided as both climate change and future climate. Not all variables are available at monthly resolution.

Table A4.2: Allocation of variables between the two batches; joint probabilities can be calculated between variables in the same batch only.
 * These variables are required to condition the Weather Generator (UK Climate Projections Science report: Projections of future daily climate for the UK from the Weather Generator). # These variables are not available from the User Interface.

Batch 1	Batch 2
Mean temperature*	Specific humidity
Mean daily maximum temperature	Net surface long wave flux
Mean daily minimum temperature	Net surface short wave flux
99th percentile of daily maximum temperature	Total downward shortwave flux
1st percentile of daily maximum temperature	Mean sea-level pressure
99th percentile of daily minimum temperature	Lag-1 correlation of daily precipitation* #
1st percentile of daily minimum temperature	
Precipitation rate (percentage change)*	
99th percentile of daily precipitation	
Relative humidity*	
Total cloud	
Variance of daily precipitation* #	
Skewness of daily precipitation* #	
Probability of a dry day* #	
Variance of daily mean temperature* #	

Changes (a) with different emissions scenarios, (b) at different locations and (c) in different batches, are not coherent and therefore cannot be combined. If users require a joint probability of changes in two variables, then plots can be provided directly by the User Interface (see Chapter 4, Section 4.6). If users require the joint probability of changes in more than two variables, they can download the variables and perform the necessary calculations offline using their own statistical packages. Joint probabilities (see example in Chapter 4, Section 4.6) can only be created for groups of variables in the same batch; the variables in each batch have been selected to cater for the combinations of variables needed to run the Weather Generator; see Table A4.2 (overleaf). Examining joint probabilities between variables in different batches is inadvisable, and hence the User Interface will not enable this.

Annex 5: Changes to the Atlantic Ocean circulation (Gulf Stream)

A5.1 How does the Atlantic Ocean circulation influence UK climate?

The climate of the UK is influenced by its proximity to the North Atlantic Ocean. The ocean acts as a buffer, absorbing heat in the summer and releasing it in the winter, and so moderating the seasonal cycle of temperature. The ocean also supplies moisture to the atmosphere, some of which falls as precipitation over the UK. These climatic influences are expected to continue under plausible scenarios of climate change.

A further influence of the ocean, which is susceptible to change in future, comes from the *Meridional Overturning Circulation* in the North Atlantic (MOC, sometimes less precisely referred to as *thermohaline circulation*, *conveyor belt circulation* or *Gulf Stream circulation*). Surface circulation in the North Atlantic brings warm and relatively salty water northwards from the subtropics. During transit northward, some of the heat is lost to the atmosphere, particularly in the Northwest Atlantic and Nordic Seas. The resulting cold, salty (and hence dense) water sinks and returns southwards several kilometres below the surface. The MOC thus supplies heat to the atmosphere at higher latitudes.

Richard Wood, Met Office Hadley Centre, and Craig Wallace, National Oceanography Centre

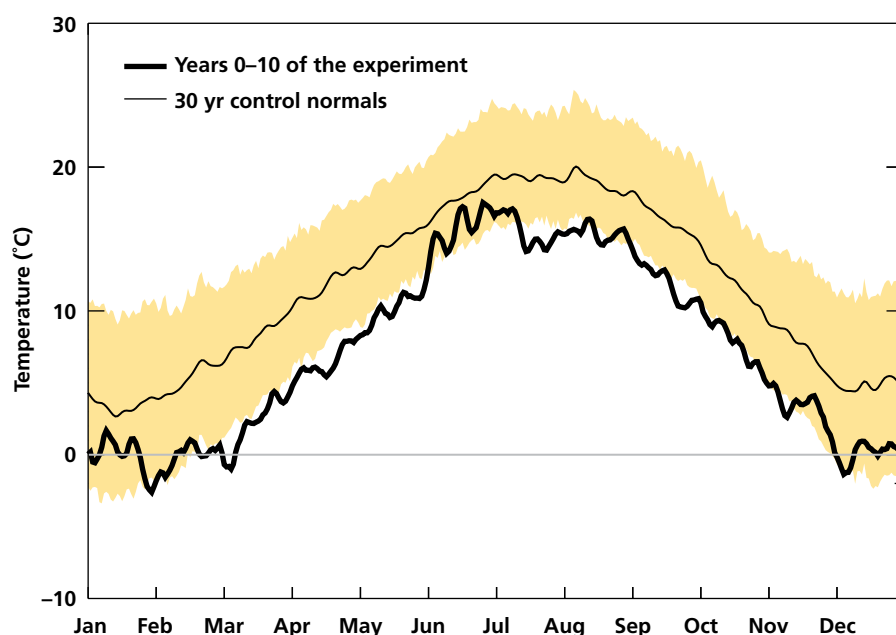


Figure A5.1: Daily maximum Central England Temperature from an experiment using the HadCM3 model in which the MOC is artificially switched off (thick curve). Average values over the 10 yr immediately following the switchoff are shown. This is compared with the same quantity in a control run (thin line), with the 5th and 95th percentiles shown by shading. Greenhouse gases are fixed at pre-industrial values in both model runs. Note that the temperatures are derived directly from the global model without downscaling. From Vellinga and Wood (2002).

The effects of the MOC on climate can be estimated using model simulations in which the MOC is artificially switched off by adding fresh water to the North Atlantic. Figure A5.1 shows the modelled impact of a THC shutdown on daily maximum Central England Temperature, relative to the preindustrial climate. A cooling of around 4°C is seen on average, somewhat more in winter than in summer. In spring and autumn this means that the average daily maximum is less than the coldest 5% of days in the pre-industrial climate.

The model also suggests that without the MOC precipitation would be reduced (by around 20% in both summer and winter, averaged over Western Europe as a whole), but that in winter over high ground more precipitation could fall as snow. The MOC also affects regional sea level by redistributing water within the global ocean (without any change in the global average sea level); without the MOC sea level could be around 25 cm higher over some parts of the UK coastline.

Climate models suggest that the MOC will weaken gradually in response to increasing greenhouse gases (see section below). The effects of such a weakening are included in the UKCP09 projections. However concerns have been raised that the MOC might undergo a more rapid decline, or pass a threshold beyond which it will eventually shut down effectively irreversibly. These concerns are based on a range of modelling and theoretical results and on palaeoclimatic evidence. A number of climate models have an MOC that can exist in both a strong, positive state (as today), and in a weak or reversed state. In many of these, if large scale patterns of precipitation and evaporation strengthen beyond a certain threshold, only the weak/reversed state can exist. A number of abrupt changes to the climate of the North Atlantic and adjacent regions in the past have been linked to fluctuations in the strength of the MOC, believed to have been driven by changes in regional fresh water input. Two marked episodes of rapid change, the 8.2 kyr Event and the Younger-Dryas Event, occurring approximately 8200 and 13,000 yr ago respectively, are particularly apparent in recovered ice and sediment core records (e.g. Taylor *et al.* 1997; Thomas *et al.* 2007). Regional temperatures over Greenland are known to have fallen, by ~6°C during the 8.2 kyr Event and by as much as ~15°C during the Younger Dryas Event. Recent work (e.g. Ellison *et al.* 2006) continues to support the hypothesis that the 8.2 kyr Event was driven by the abrupt discharge of fresh glacial melt water from two dammed lakes over continental North America, Agassiz and Ojibwa. In both these past cases, there was more fresh water locked up in land ice than at present, so these periods may not be exact analogues of the present day, but the palaeoclimatic evidence does point to the sensitivity of the MOC to fresh water input.

Since UKCIP02, progress has been made in both observations and modelling of MOC changes.

A5.2 Is the Atlantic Meridional Overturning Circulation changing?

A number of recent observational studies have attempted to detect signs of recent changes in the MOC. One assessment (Bryden *et al.* 2005) suggests that the overall MOC strength may have decreased by approximately 30% since 1957 (Figure A5.2). However, the sparse nature of the observations used in this study (5 measurements over 5 decades), the possible errors of these observations and the large day-to-day variability of the MOC recently discovered (Cunningham *et al.* 2007; Kanzow *et al.* 2007) highlight the need for additional data to support this conclusion. Furthermore, analyses using Atlantic sea surface temperature patterns as an indirect measurement of MOC strength also conflict with the

conclusion of Bryden *et al.* (2005), citing the recent warming seen in the North Atlantic as indication of a stronger MOC during the 1990s (e.g. Latif *et al.* 2006; Knight *et al.* 2005), although this indirect observational method is based on links identified in climate models rather than directly from observations.

Additional observations farther north also provide evidence for widespread change or variability. For example whilst some studies indicate that, in recent decades, the transport of deep water, forming the return leg of the MOC, through the Faroe Bank Channel (and farther downstream e.g. Bossenkool *et al.* 2007) has decreased by approximately 20% compared to 1950 estimates (Hansen *et al.* 2001), more recent observations (Østerhus *et al.* 2008) call such a trend in to question. Recent large scale freshening of the high latitude North Atlantic, including deep water flowing through the Faroe Bank Channel, has also been the subject of much research (e.g. Dickson *et al.* 2002) but neither the mechanisms of the freshening, nor a clear link with MOC changes, have been established.

In addition to the Faroe Bank Channel, deep returning water also flows through the Denmark Strait, between Greenland and Iceland. Observations within (Macrander *et al.* 2005) and just south (Dickson *et al.* 2008) of the strait do reveal a weakening of the through flow between 1999 and 2003, but this is likely a feature of the natural year-to-year variability, rather than part of any longer-term trend. Deep water from both the Faroe Bank Channel and the Denmark Strait combines south of Greenland to form the Deep Western Boundary Current which is the primary return leg of the MOC south of $\sim 55^\circ\text{N}$. Measurements of this unified current are also sparse, although comparison of what data is presently available (representing 1993–1995 and 1999–2001, respectively) reveals little change in transport (Schott, 2004).

Knowledge of whether or not the strength of the MOC is changing with time has been hampered to date by the lack of continuous, robust measurements. Since the last UKCIP02 report, however, considerable effort has been made to collate

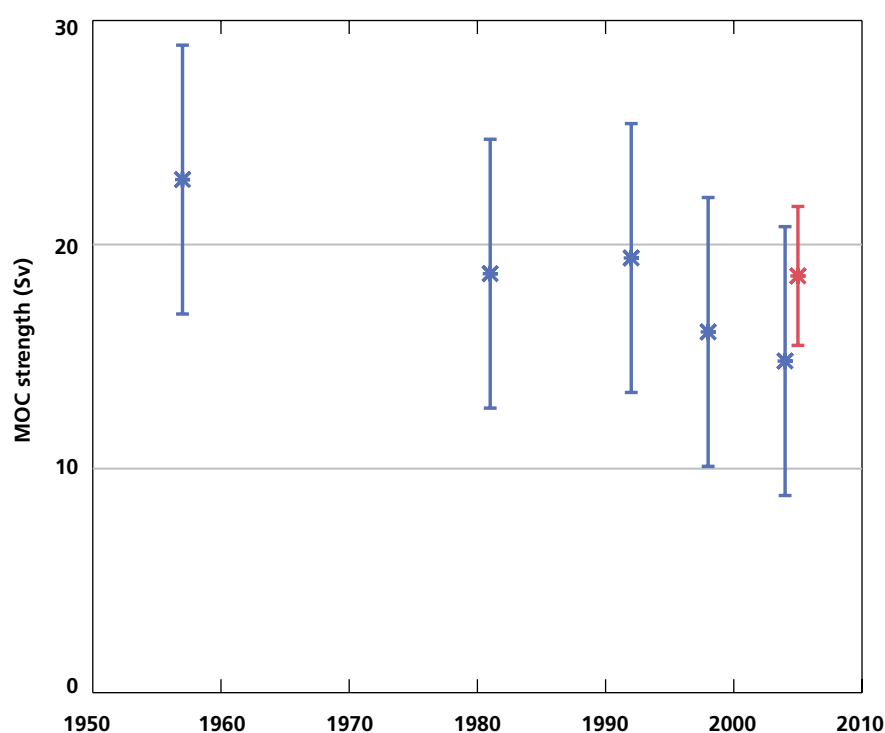


Figure A5.2: Estimates of observed Atlantic MOC strength (asterisks), and associated errors (bars), at $\sim 26^\circ\text{N}$ between 1957 and 2005. Blue denotes calculations incorporating ship-based observations of the free ocean (Bryden *et al.* 2005) whilst the final, red, point incorporates the first year's (April 2004–April 2005) continuous observations from the RAPID mooring array deployed in 2004. The quantity shown is transport in the top 1000 m of the ocean, with positive values indicating northward flow. Units are Sverdrups (1 Sv = 1 million cubic metres of water transported per second).

and analyse existing observations, for example via the ASOF* initiative, and a substantial UK-led monitoring programme, RAPID, has commenced, involving the installation of permanent moorings at a number of locations within the Atlantic Ocean (see <http://www.nerc.ac.uk/research/programmes/rapid/>). Initial results (Cunningham *et al.* 2007; Kanzow *et al.* 2007) have confirmed the ability of this system of moorings to monitor the MOC to a high degree of accuracy. As the time series accrues to a statistically meaningful length scientists will be able to comment with more certainty on whether any long term change is underway.

A5.3 Projections of future changes in the Atlantic circulation

Recent projections, using a new generation of climate models, support the assessment presented in UKCIP02 and suggest that the MOC will weaken gradually in response to increasing greenhouse gases. The models examined in the IPCC AR4, excluding those with a poor simulation of the present day MOC, suggest reductions of between 0 and 50% in the MOC by 2100, under the SRES A1B (UKCP09 Medium) emissions scenario. An ensemble of HadCM3-based coupled models, similar to the one used to generate the UKCP09 probabilistic projections, shows a slightly narrower range of weakening under an idealised scenario of CO₂ increase (Figure A5.3). The effects of the gradually weakening MOC on UK climate are included in the UKCP09 climate projections.

No comprehensive climate model, when forced with one of the SRES emissions scenarios, produces a complete or abrupt MOC shutdown in the 21st century,

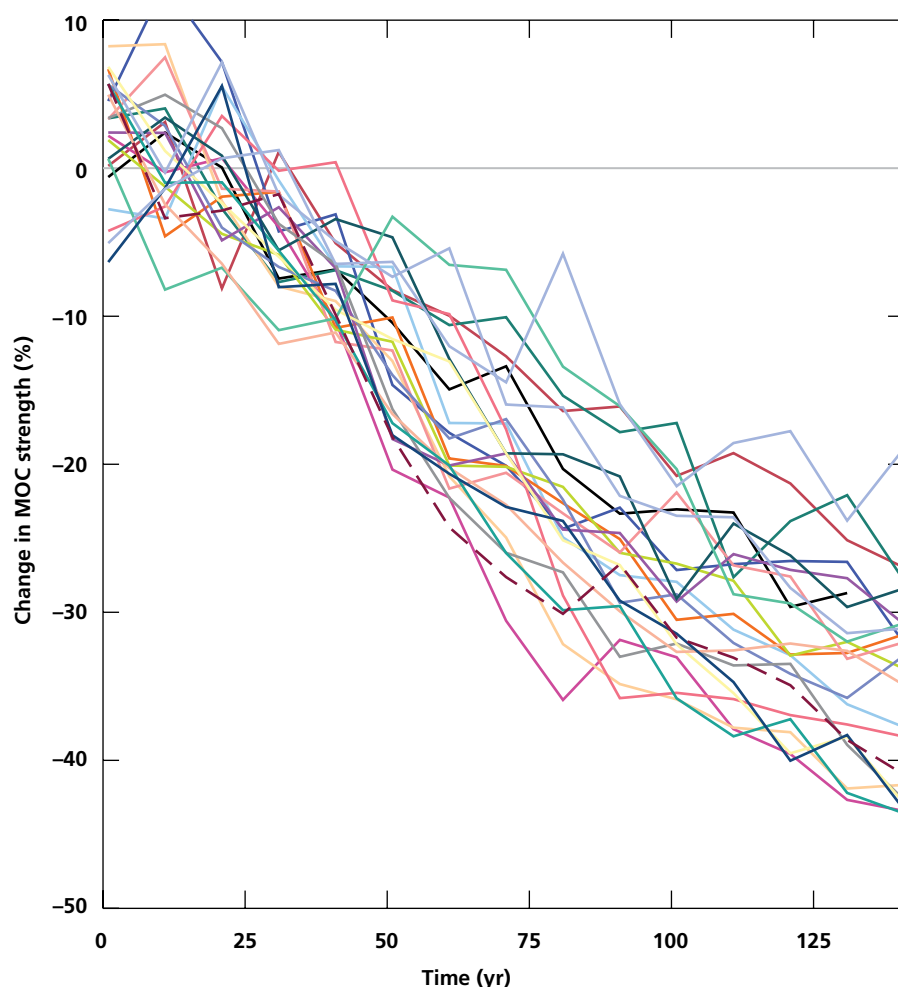


Figure A5.3: Model simulations of the change in MOC strength under an idealised 1%-per-annum increase of CO₂ concentrations. Twenty-two simulations are shown, from a HadCM3-based perturbed physics ensemble similar to the one used to generate the UKCP09 projections. MOC change is expressed as a percentage of its value in the corresponding control run. (Courtesy M. Vellinga.)

* Arctic-Subarctic Ocean Fluxes <http://asof.npolar.no>

consistent with the models shown in Figure A5.3. However models in general do not allow for the possibility of increased fresh water supply due to rapid ice flow from the Greenland ice sheet, which has been observed in recent years; such extra fresh water could result in further MOC weakening. The simulations of rapid MOC changes that have been seen generally come from less complex climate models; such models are computationally cheaper and so the range of possible behaviours can be explored more fully than with the comprehensive climate models used in UKCP09, but, being simpler, the models may omit key processes affecting the stability of the MOC.

Assessing the evidence overall, the IPCC AR4 concludes that it is very likely (>90% chance) that the MOC will weaken gradually over the 21st century in response to increasing greenhouse gases, but very unlikely (<10% chance) that an abrupt MOC change will occur in that time. Longer term changes cannot be assessed with confidence at this stage.

The effects of any rapid MOC changes (beyond the expected gradual weakening seen in most climate model simulations) would be superimposed on any man-made global climate change that had already taken place. Some of the MOC effects, for example any cooling over the UK, would oppose those due to man. Others, however, would reinforce the global man-made signal — for example additional summer drying, and sea level rise reinforcing that due to thermal expansion.

The figures derived from hypothetical MOC shutdown experiments such as those discussed above show that an MOC shutdown, while very unlikely, could produce climatic effects as large as, or larger than, the effects of increasing greenhouse gases. Thus research to improve our understanding of the probability of such events, and to improve the prospects for early warning, continues to be a priority. Recent developments in both models and observations have improved our fundamental understanding of what controls the MOC, and in time this can be expected to narrow the uncertainty over the future of the MOC.

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Annex 6: Future changes in storms and anticyclones affecting the UK

A6.1 Introduction

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It has not been possible to produce probabilistic projections of changes in frequency, strength and location of future storms and anticyclones (often called *blocking* events) — collectively known as synoptic-scale (that is, weather system) variability. This is due to the reasons discussed in Chapter 3, Section 3.3, namely that large differences are found between projections from the Met Office perturbed physics ensemble and those from a multi-model ensemble of alternative climate models (see Figure A6.2). This implies that attempts to construct probabilistic projections would be too dominated by the contribution arising from structural model errors (see Section 3.2.8) to be considered robust. Furthermore, the required storm tracking statistics from other models are not available in any case, thus precluding the use of the UKCP09 methodology (described in Chapter 3) to produce PDFs for this metric. However, storms and blocking events are explicitly modelled in climate models, and the impacts of such synoptic-scale variability and potential changes are considered in the production of PDFs of mean and extreme climate shown elsewhere in this report. Each of the models used in the ensembles which underlie the PDFs, both the perturbed physics and the multi-model, simulate storms and blocking and their integrated impact on those mean and extreme conditions. In addition, the PDFs are constrained by the large-scale observed fields of climate which are partly determined by synoptic-scale variability. In short, the effects of synoptic-scale variability, including potential changes, are taken into account.

Useful information can be gleaned from examination of the present day and future synoptic-scale variability simulated by the Met Office ensemble of 17 HadCM3 experiments (described in Chapter 3, Section 3.2.4) and a multi-model ensemble consisting of 20 alternative coupled models, all using the same SRES A1B (UKCP09 Medium) emissions. Preliminary analysis of these ensembles suggests that the simulated future changes in storms, and their impact on mean climate conditions, are rather modest. Subtle shifts in the position of the North Atlantic storm track are possible, but are inconsistent between different models and different model variants. The frequency and strength of storms remain relatively unchanged in the future simulations, as does the frequency and strength of blocking events. It must be borne in mind, however, that these two ensembles sample a smaller range of uncertainty than do the UKCP09 projections. The IPCC AR4 assessment concluded that the majority of current climate models show a poleward shift of the storm tracks, with some indication of fewer, but deeper, depressions. This can only be concluded when looking at the hemispheric scale;

the UK is very much smaller than this scale and any climate change signal is swamped by natural variability and sampling uncertainty resulting in a lack of any robust signal of changes for the UK.

It is clear from an examination of the model output that, as in the case of previous studies, (e.g. Carnell and Senior, 2002) the main drivers of regional climate change in the UK are thermodynamic in nature, that is, arising directly from the additional man-made greenhouse heating. These processes are sampled by both the HadCM3 perturbed physics ensemble and the multi-model ensemble and constrained by the observational data used in generating the PDFs. Changes in climate that may be attributed to changes in synoptic-scale variability are a relatively small component. That is not to say however that, as models improve in the future that the role of changes in storms and blocking events might become more important. There is a possibility that such non-linear climate change could occur, but based on the current level of understanding and the current ability of climate models, there is no evidence for this.

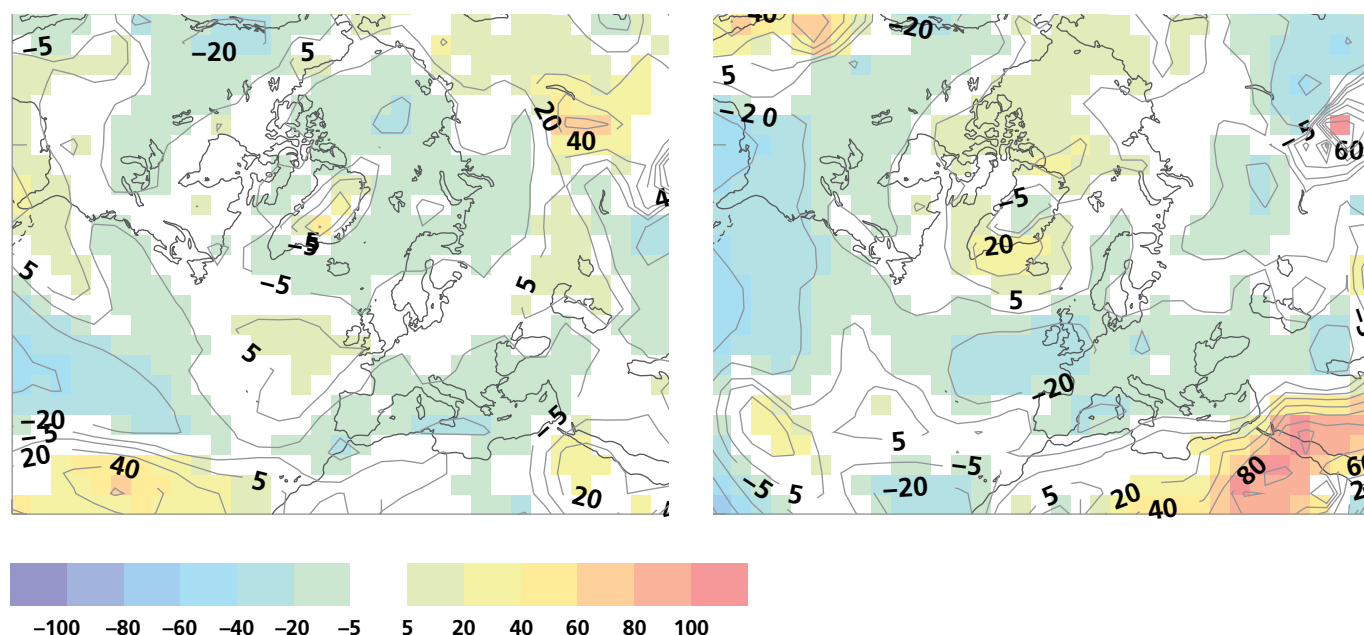
In the sections below we look at changes in storm tracks and blocking from both the 17-member Met Office GCM perturbed physics ensemble and the multi-model ensemble of other climate models.

A6.2 Future changes in mid-latitude depressions

Characteristics of mid-latitude North Atlantic depressions are assessed using two metrics* based on patterns of atmospheric pressure at the surface or at a height of about 2 km (away from the disturbing influence of the ground). As was found from validating the storm climatology of the models (see Annex 3), the different metrics can give a different picture for future changes, although to a lesser degree.

Considering the first metric applied to the 17-member Met Office GCM projections, for most of the UK the storm tracking results suggest little change (<5%) by the 2080s in the number of storms that occur in all seasons except summer where

Figure A6.1: Changes in storm track density (% change) for winter (left) and summer (right) from the HadCM3 ensemble.



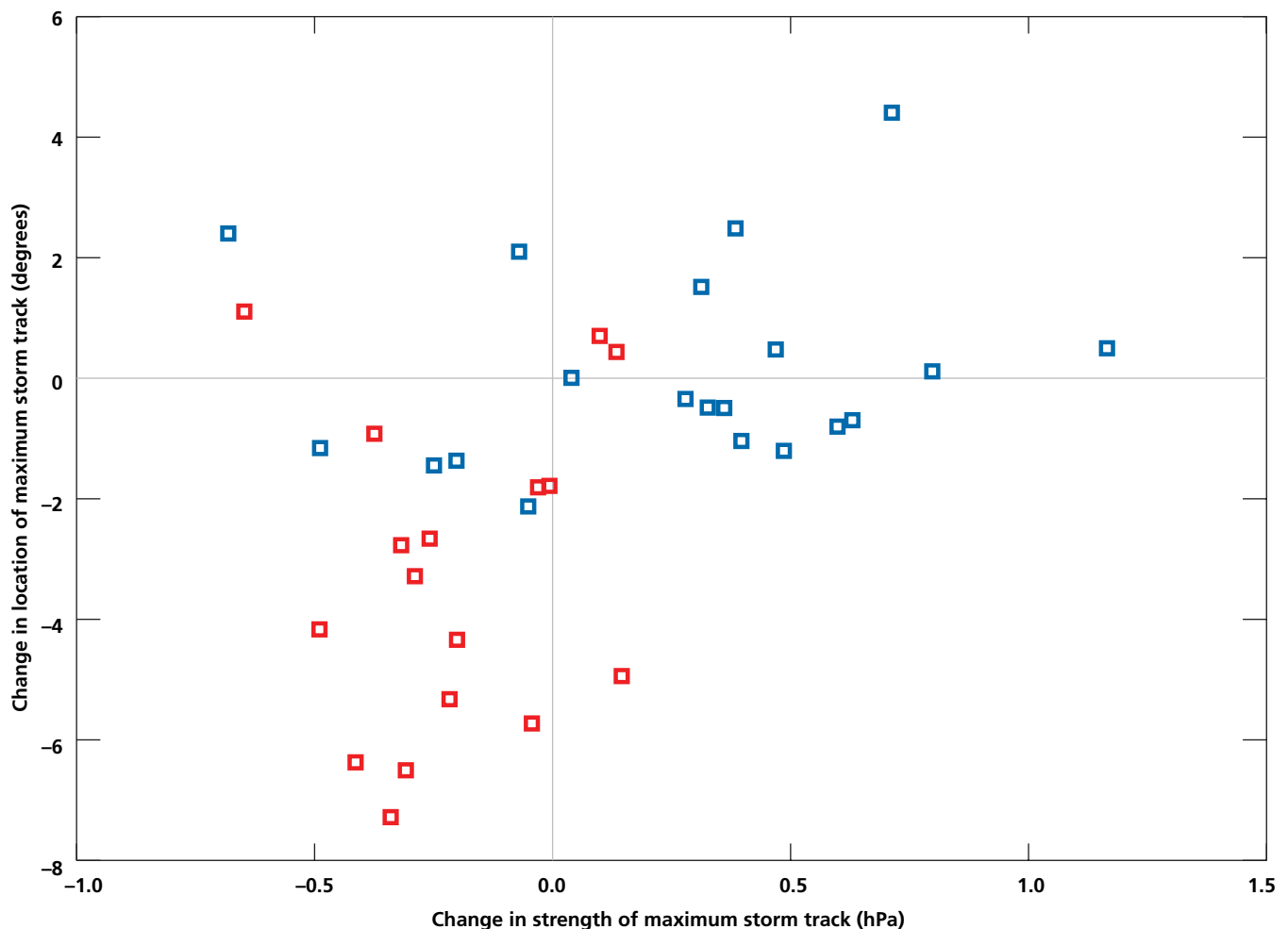
* Specifically (1) the tracking of positive 850 hPa vorticity anomalies and (2) band pass filtered (BPF) daily mean sea level pressure (MSLP).

the ensemble mean shows a reduction of ~20% (Figure A6.1). There is also a suggestion that the south east may see modest reductions in spring and autumn (not shown).

The second metric (not shown here) also suggests little change in winter, spring and autumn, and a reduction in summer. Figure A6.2 shows changes, derived from the second metric, from (1961–1990) to the 2080s under the Medium Emissions scenario, in the location and strength of the storm track over the UK in winter, from both the HadCM3 17-member perturbed physics ensemble and a multi-model ensemble of 20 other climate models. Taking changes between periods removes the climatological biases in the storm track locations from each ensemble member, allowing assessment of the general tendency of the models. The HadCM3 ensemble shows relatively small, and generally negative, changes in the strength of storms, and most of them show a southerly shift in the storm track, up to 7° of latitude. On the other hand, projections from the multi-model ensemble of other climate models for this metric suggests relatively little shift in the storm track but a wider range of, generally positive, changes in strength.

It should be recalled from Annex 3, Figure A3.6, that current positions and strengths of the modelled storm track do not always agree well with observations, and this should be taken into account when assessing the credibility of their future projections. The HadCM3 ensemble shows a better agreement in present day location than most other climate models, and a reasonable agreement in strength.

Figure A6.2: Change in location (degrees latitude) and strength (hPa) of maximum storm track over the UK for winter. The red squares are from the 17-member HadCM3 perturbed physics ensemble; the blue squares are from an ensemble of other international climate models.



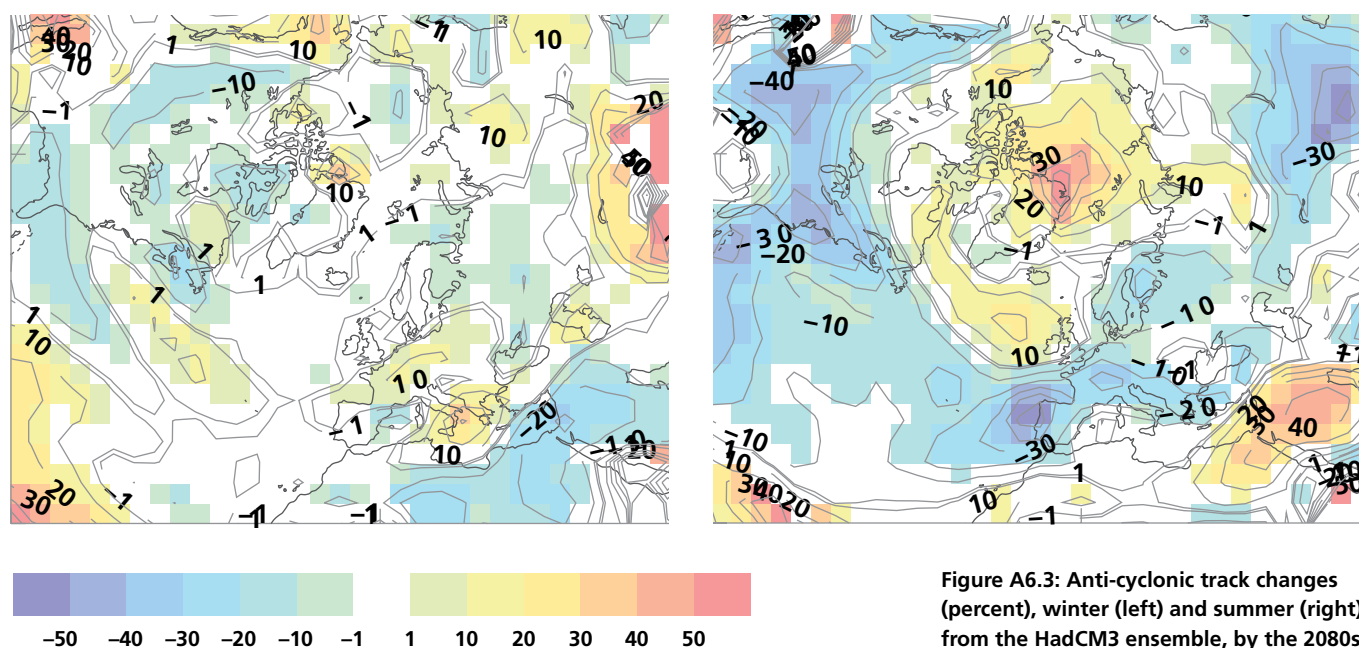


Figure A6.3: Anti-cyclonic track changes (percent), winter (left) and summer (right) from the HadCM3 ensemble, by the 2080s.

A6.3 Future changes in blocking

The strength of anticyclones over the UK, and their duration, are important influences on runs of hot days and high air pollution levels. We diagnose changes in anticyclonic blocking characteristics using three different metrics,* again involving pressure patterns at the surface and higher in the atmosphere. The projected future changes in these three metrics is diverse.

Using the first metric, analysis of the 17-member HadCM3 ensemble suggests there will be 10–20% fewer anti-cyclones over the continent and southern England in summer and similar increases over the northern Atlantic possibly affecting northern UK (Figure A6.3). For winter there is little change.

Using the second metric, an index corresponding to 7-day blocking events in summer, again using the HadCM3 ensemble, shows a centre of decrease west of Ireland affecting the whole of the UK (Figure A6.4).

Changes determined by the third metric, from the filtered analysis of surface pressure, for both the perturbed physics ensemble of HadCM3 and the ensemble of other climate models, are shown in Figure A6.5. For the UK as a whole reductions in anticyclones** in summer (Figure A6.5, bottom) are projected by both ensembles. This is also seen in autumn, with smaller reductions in spring (neither shown). No clear agreement on change in winter is seen, from either the HadCM3 or the alternative model ensembles (Figure A6.5, top).

As these three metrics represent different aspects of the climate system it is perhaps not surprising that the future changes are not that similar, implying that it is difficult to characterise future changes with a single diagnostic but that metrics specific to each impact are required.

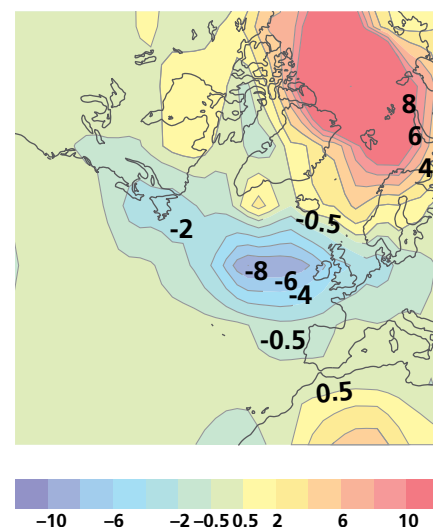


Figure A6.4: Change in number of days with blocking lasting 7 days, summer from the HadCM3 ensemble, by the 2080s.

* These are (1) tracking negative 850 hPa vorticity anomalies, (2) persistent 500 hPa height anomalies (PA) lasting 7 days and (3) low pass filtered (LPF) daily mean MSLP.

** Note that this metric, although dominated by changes in anticyclones, could also be influenced by other slow-moving weather systems.

A6.4 Summary

There is no consistent signal of change in either storms or blocking near the UK in either the ensemble of Met Office models or the ensemble of alternative models. Such changes as are seen are relatively modest, and the potential for substantial changes appears to be small.

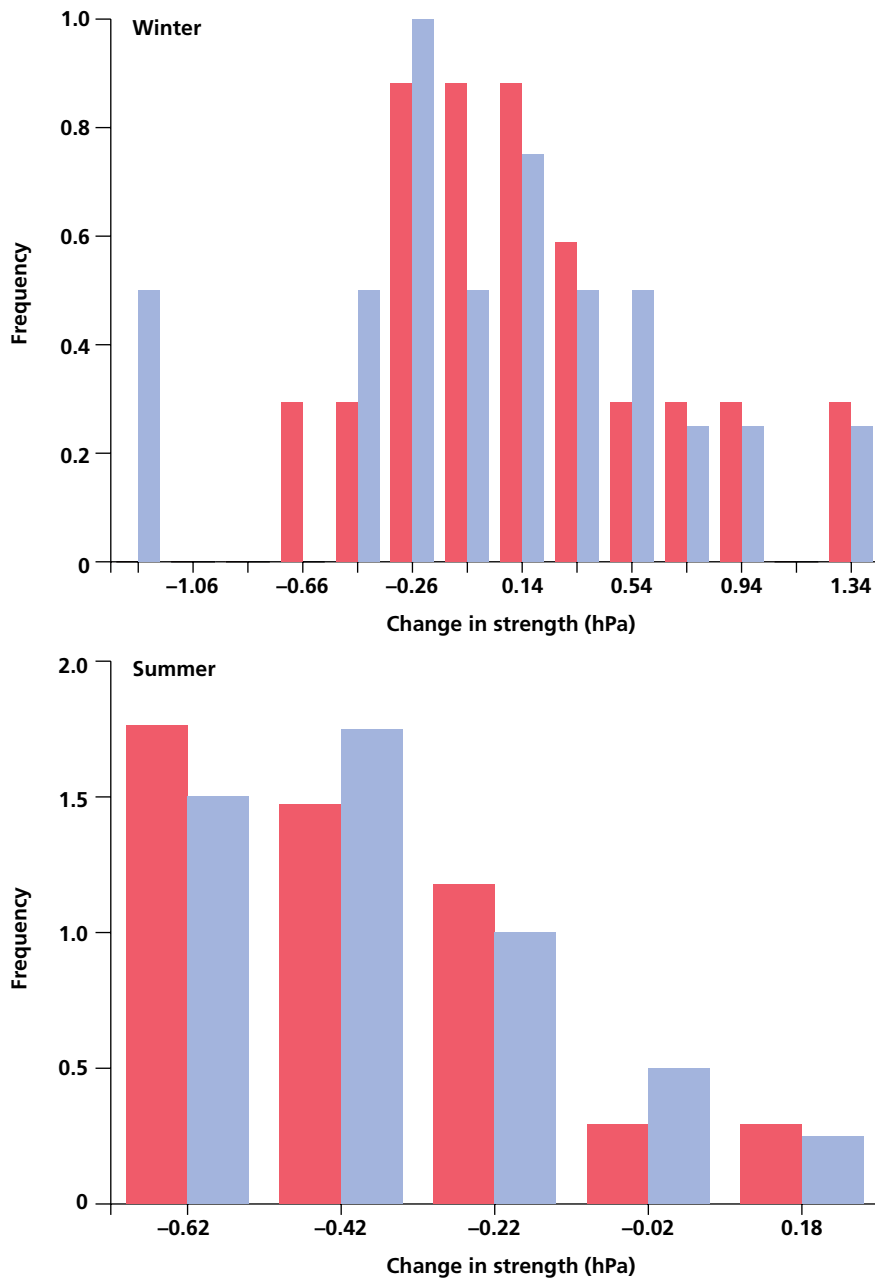


Figure A6.5: Distribution of changes in anticyclone strength for winter (top) and summer (bottom) averaged over the UK. Blue bars are from the multi-model ensemble of other climate models; red bars are from the HadCM3 perturbed physics ensemble.

A6.5 Reference

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Annex 7: Urban heat island effects

A7.1 Causes of the Urban Heat Island and observations

There is growing recognition that the populations, infrastructure, and ecology of built environments are potentially vulnerable to climate change (Wilby, 2007). However, built-up areas also exert significant influences on their local climates, with an *Urban Heat Island* (UHI) being observed in many cities. This is due partly to the influence of the urbanised landscape on the surface energy budget and local meteorology, and partly from sources of heat arising from human activities (*Human Energy Production*, HEP). The nature of the land surface is a key factor influencing the sensitivity of near-surface climates to increasing greenhouse gas concentrations, so the responses of urban climates may be different to those of non-urban climates. Urban areas generally feature a less porous surface than non-urban areas, promoting the removal of precipitation via surface runoff and channelling away through drains, instead of water soaking into the soil. There is also a limitation on evaporation of soil moisture due to built-over surfaces. Both of these limit the evaporation of moisture which is a key factor in the local climate response to warming. Furthermore, the large heat capacity of the built environment causes heat to be stored during the day and released gradually overnight, increasing night-time temperatures in comparison with non-urban area.

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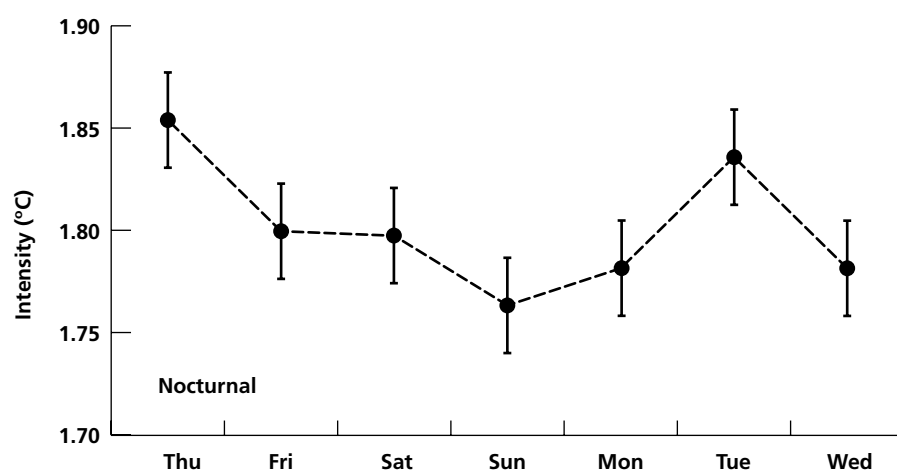


Figure A7.1: Variations in the intensity of London's nocturnal UHI by day of the week reveals a measurable HEP. Sources of artificial heat production (including space heating, air conditioning, transportation, cooking and industrial activity) would be expected to vary on a weekly basis, attaining a minimum at weekends. Assuming that weather patterns are the same regardless of the day of the week, the temperature difference between urban and rural areas should, therefore, be a minimum on Sundays — this is indeed the case. The weekly component amounts to ~0.1°C variation compared with an average nocturnal UHI of 1.8°C throughout the year. Source: Wilby (2003a).

Moreover, increases in anthropogenic heat sources may exert an additional direct forcing of local climates (Figure A7.1). The global total HEP heat flux is estimated as 0.03 Wm^{-2} (Nakićenović *et al.* 1998); although this is a very small influence at the global scale, it may be important for local climate changes in cities (Crutzen, 2004; Forster *et al.* 2007). The annual average HEP over Greater London is estimated from energy use statistics as 11 Wm^{-2} , rising to 57 Wm^{-2} in Westminster, and exceeds 100 Wm^{-2} in some specific areas (Greater London Authority, 2006). (This compares with an annual average net shortwave solar heat flux of $\sim 100 \text{ Wm}^{-2}$ over southern England, although this may be up to $\sim 300 \text{ Wm}^{-2}$ in July.) Temperature measurements taken at an inner city (St. James Park) and suburban site (Wisley in Surrey) suggest that London's nocturnal UHI has intensified by approximately 0.5°C since the 1960s (Wilby, 2003a), partly as a consequence of HEP, increased urbanization, and changing frequency of weather patterns.

A7.2 Future changes in the Urban Heat Island

The regional climate model used in UKCP09 include a scheme which represents the land surface within each 25 km gridbox as a uniform surface, with physical properties determined by parameter values representing the *average* character of the different land surface types within that gridbox (Cox *et al.* 1999). However, the surface types are defined using a land-surface dataset at a $1^\circ \times 1^\circ$ latitude–longitude resolution (Wilson and Henderson-Sellers, 1985). At this resolution there is no contribution from urban surface types, so the Met Office RCM does not include any influence of the urban surface on climate. Furthermore, the RCM does not include heat storage during the day and heat release at night by buildings, or HEP as a term in the surface energy balance. Thus the UKCP09 projections will not take into account changes to any of the factors, outlined in Section A7.1, which could change the intensity of the UHI. If none of these factors were to change, or changes were not significant, then the UHI would not change, and it would be reasonable to add UKCP09 projections of temperature change to an observed baseline urban climate to obtain an urban climate of the future.

In applications of the UKCP09 model output, some account of urban effects could be taken by using statistical downscaling techniques calibrated against data which included urban influences. Previous work has shown that the intensity of the UHI is stronger under the low wind speeds, high sunshine, and low humidity conditions typically associated with stagnant high pressure situations (Wilby, 2003b; McGregor *et al.* 2006). For example, Figure A7.2 shows the strong correlation between the occurrence of anticyclonic weather over Eastern England in summer and the frequency of intense UHI episodes. Assuming

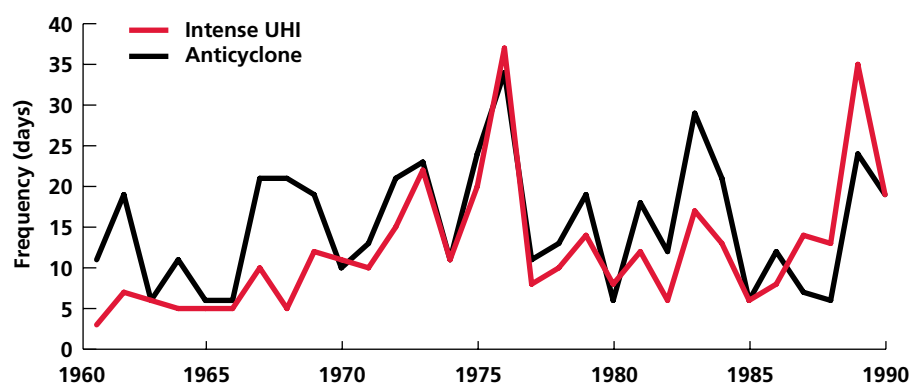


Figure A7.2: The observed frequency of intense nocturnal heat island episodes ($>4^\circ\text{C}$ temperature difference between urban and rural sites) and days with anticyclonic weather over London 1961–1990.

that these downscaling relationships hold under future climate conditions, any changes in circulation during the summer (see Annex 6) would have the potential to intensify UHI by a further 0.5°C by the 2020s (Wilby, 2008). Although there are subtle differences in UHI projections downscaled from different GCMs, all point to continued intensification of London's nocturnal UHI and a greater frequency of intense heat island episodes in summer (see Wilby, 2008). These changes are set against a background of more persistent and intense heatwaves over much of Europe and the USA signalled by other studies (e.g., Meehl and Tebaldi, 2004).

Betts and Best (2004) showed that if the HEP remains unchanged over time, statistical downscaling could be viable. However, if the HEP changes in the future, as is possible under different population and energy consumption patterns, statistical downscaling calibrated against the present-day may no longer be valid. For example, Betts and Best (2004) showed that tripling the HEP from 20 Wm⁻² (similar to that of the inner London boroughs) to 60 Wm⁻² (the Westminster value) significantly altered the average UHI and increased the frequency of extreme UHI events. Even if the HEP is unchanged, statistical downscaling would have to be performed using predictors drawn from the suite of reliable variables in UKCP09 (including air temperatures, precipitation, relative and specific humidity, cloud cover, short-wave radiation and mean sea level pressure). Low confidence in important predictors such as wind speed, and in joint probabilities with other variables, mean that outputs from UKCP09 are unlikely to support conventional statistical downscaling models based on these data. However, probability distributions of changes in predictors such as mean sea level pressure could be used to perturb baseline pressure data and hence estimate sensitivity of simple indices of the UHI (like the frequency of intense heat island episodes shown in Figure A7.2) to changes in atmospheric circulation alone.

Further development of the HadRM3 regional climate model used in UKCP09 is underway to incorporate an updated land surface scheme which simulates separate surface energy balances for the different land surface types, including urban, within a gridbox. This should allow a more realistic representation of the surface temperature and humidity over each land surface type, including a more realistic response to climate warming. A heat capacity term allows for diurnal heat storage and release over the urban land surface, and an additional HEP term allows for the inclusion of this as an input. All these features have been shown to improve the representation of temperature in urban areas in the model, and should facilitate a more realistic representation of the change in urban temperatures over time in response to changes in urban character and extent.

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- Monitor climate variability and change at global and national scales, and use models to attribute recent changes to specific factors such as human activity.
- Quantify and reduce uncertainty in projections of climate change, particularly at a local scale and of extremes, and use this information to inform adaptation strategies.
- Define and assess the risk of dangerous climate change, whether gradual, abrupt or irreversible.
- Assess scientific aspects of options for mitigating climate change and its impacts.
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