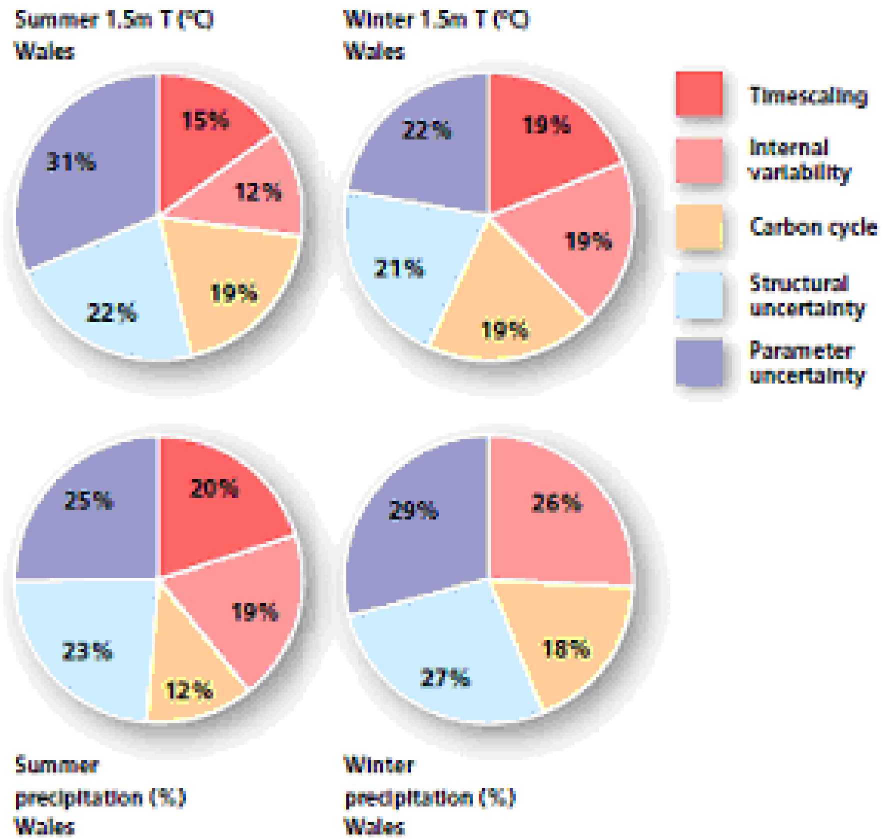

Figure A2.5: The relative contributions of different components of uncertainty to the overall spread in UKCP09 projections. These are calculated for summer and winter and for changes in temperature and percentage changes in precipitation for the Wales global climate model grid box, considering projected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

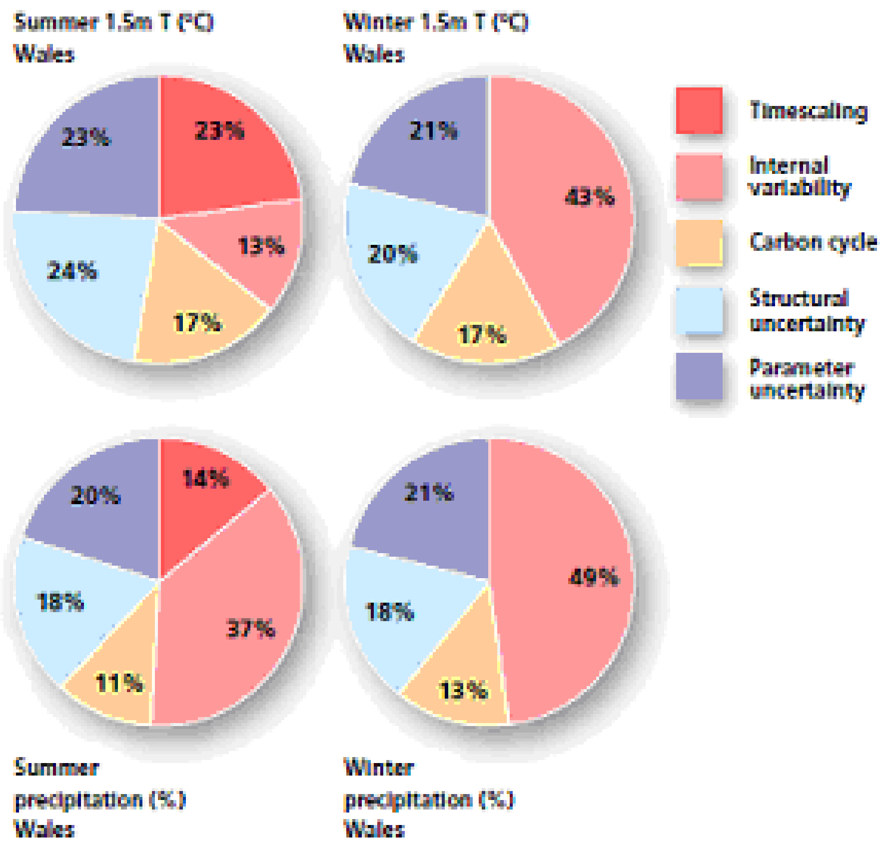

Figure A2.6: As Figure A2.5 but for 2010–2039.

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

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

Downscaling uncertainties

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

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

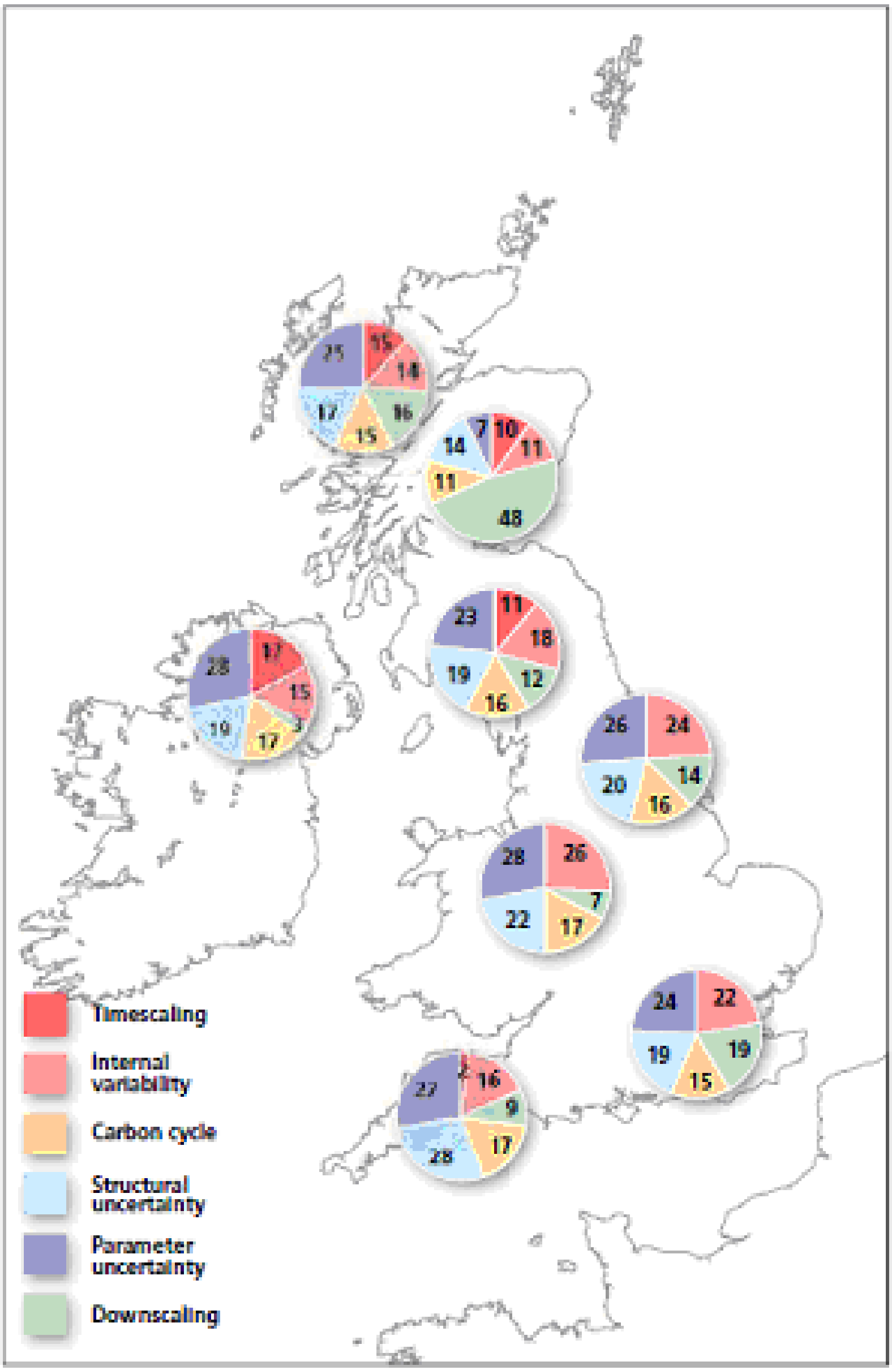

Figure A2.7: Contributions to the uncertainty in winter precipitation changes for 2070–2099 relative to 1961–1990, at selected 25 km grid squares. Contributions are calculated as in Figures A2.5 and A2.6, and also include that due to downscaling from global climate model grid squares to regional climate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

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

A2.5 Summary

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

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

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

- Timescaling uncertainty could in principle be removed. This would require future versions of our methodology to be based upon very large ensembles of projections of time-varying climate change carried out using the model configuration in which the atmosphere is coupled to a dynamical 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.

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Annex 3: Strengths and weaknesses of climate models

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

A3.1 What are climate models?

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

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

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 CO_2 — 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.

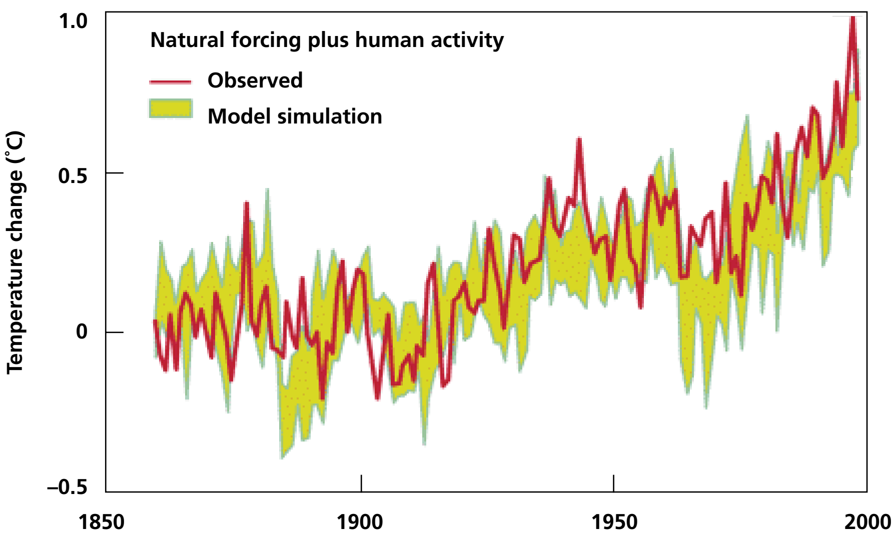


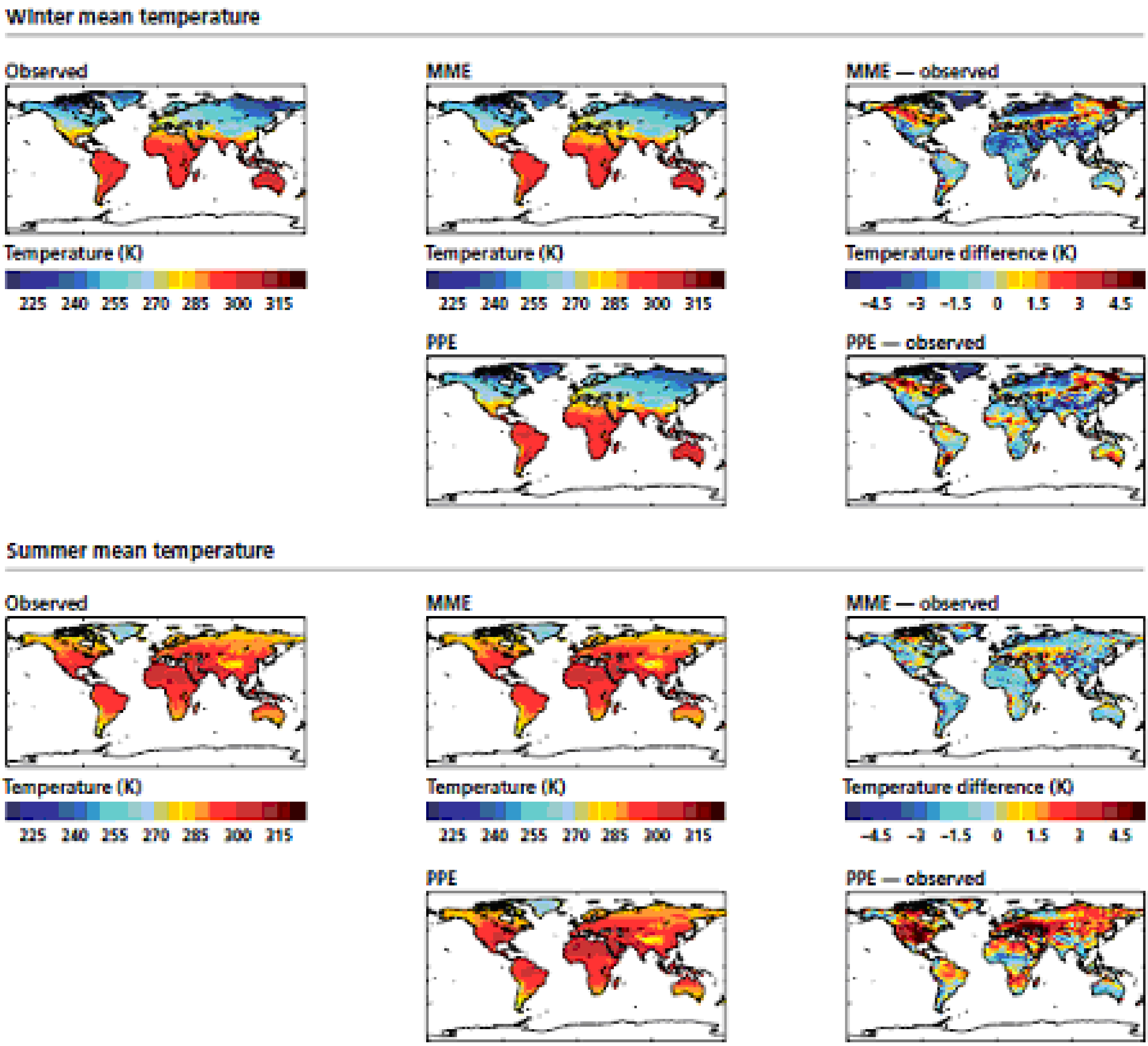
Figure A3.1: Observations of changes in global mean temperature, 1860–2000 (red) compared to the simulation using the HadCM3 climate model driven by observed changes in man-made forcing (greenhouse gas and sulphate aerosol concentrations), natural forcing (solar radiation and volcanic aerosol) and including 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.



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

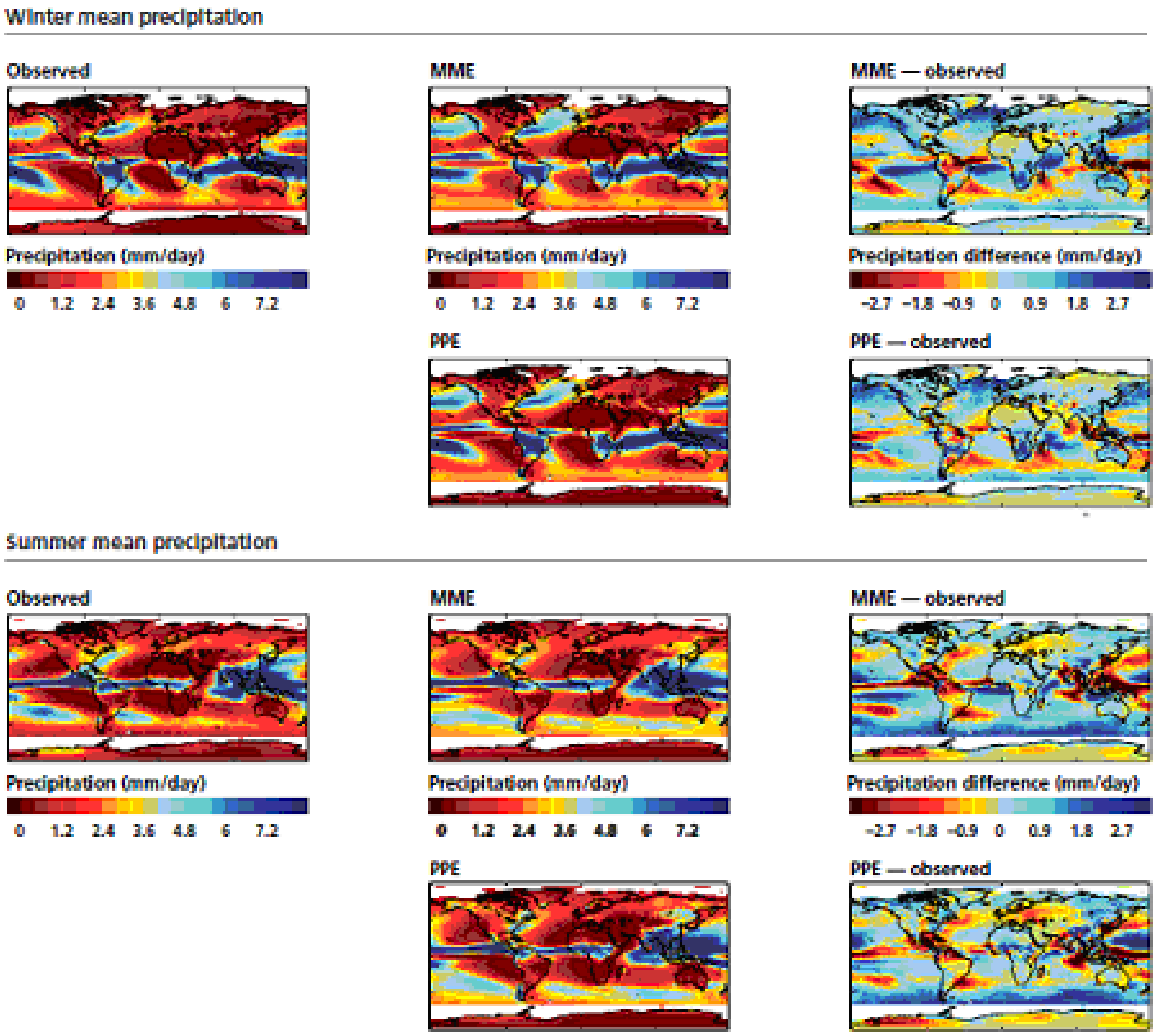
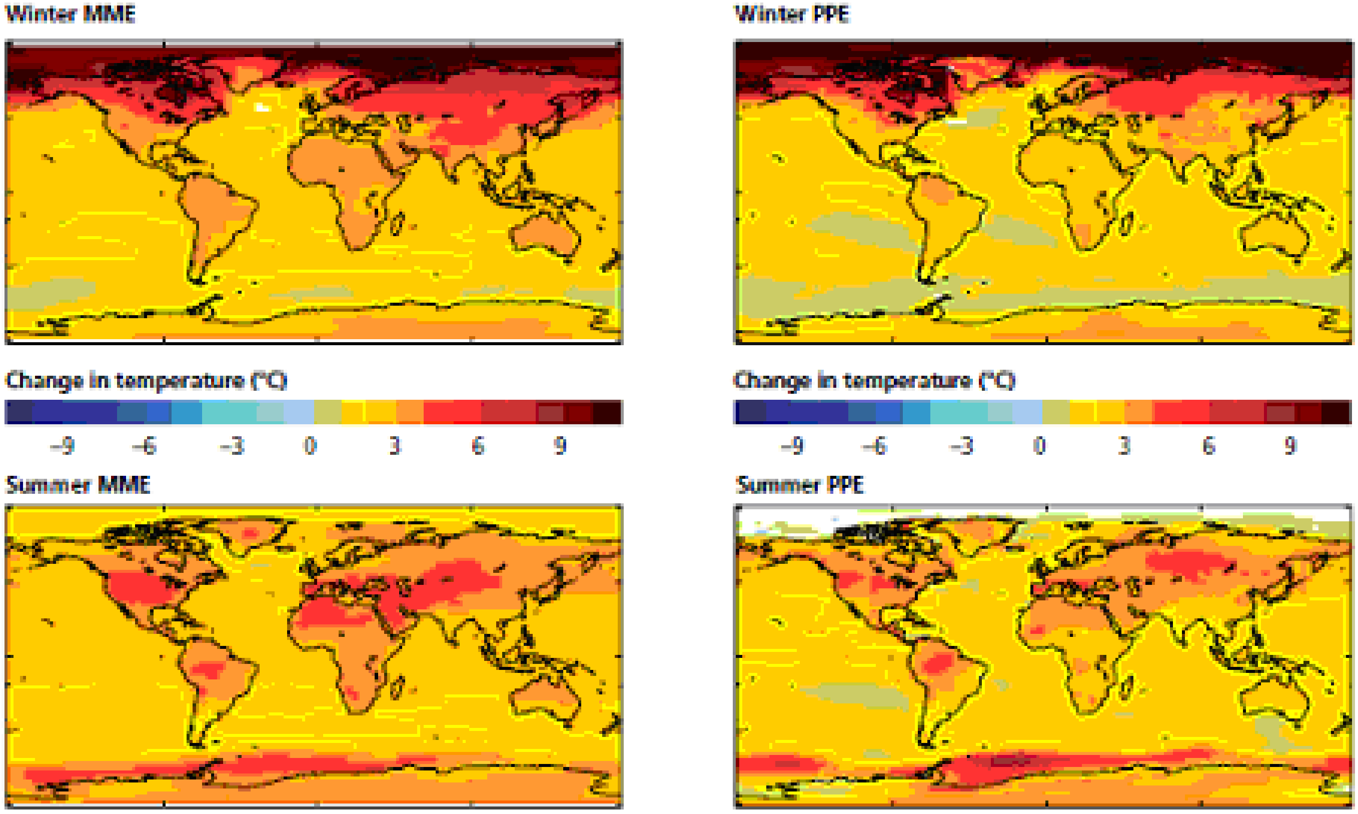
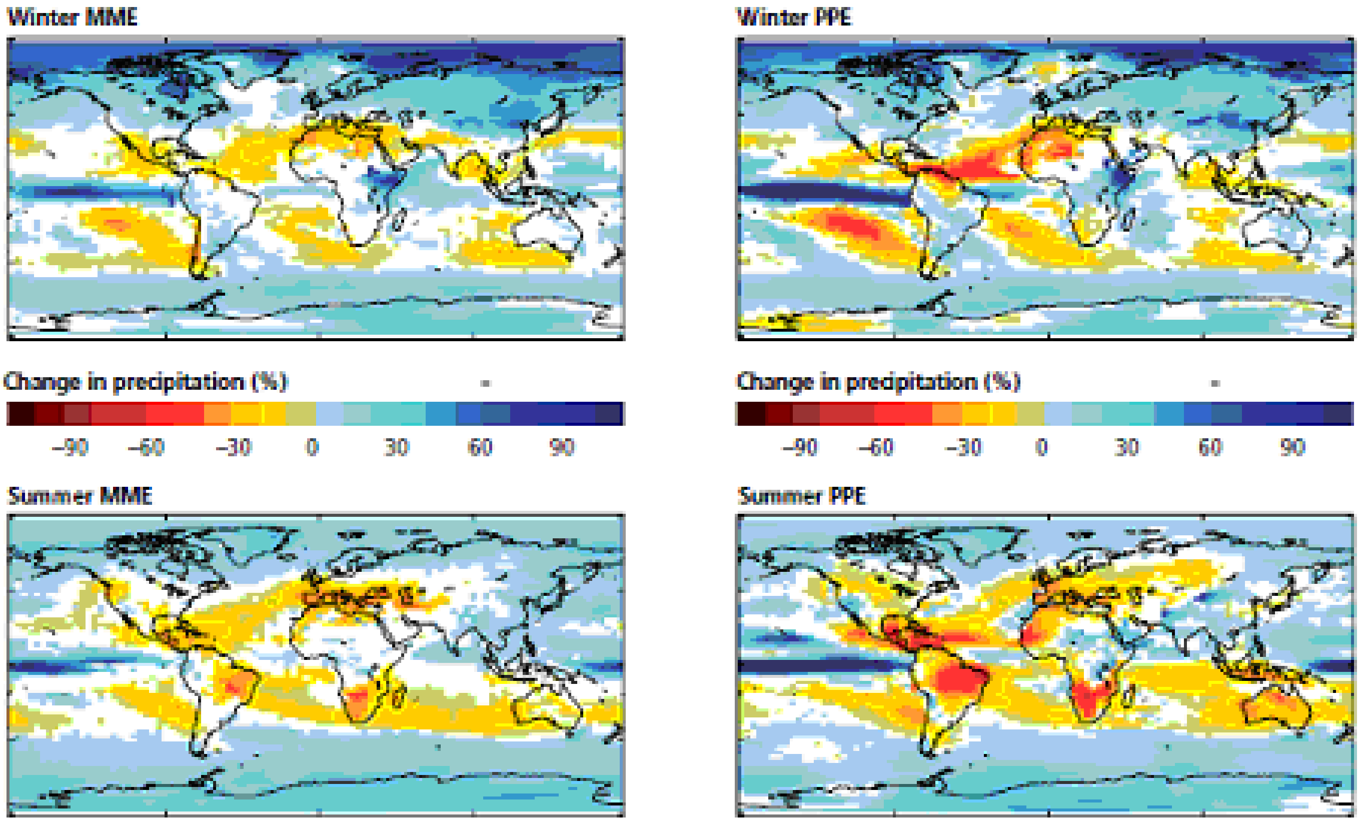


Figure A3.3: Winter (top two rows) and summer averaged precipitation 1961–1990 in mm/day from observations (left column), from the multi-model mean of all the CMIP3 climate models and from the mean of the versions of HadCM3 with perturbations made to atmospheric parameters (PPE_A1B middle column) and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


Winter MME
Winter PPE
Change in temperature (°C)
–9
–6
–3
0
3
6
9
Change in temperature (°C)
–9
–6
–3
0
3
6
9
Summer MME
Summer PPE


Winter MME
Winter PPE
Change in precipitation (%)
–90
–60
–30
0
30
60
90
Change in precipitation (%)
–90
–60
–30
0
30
60
90
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).

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.

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 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

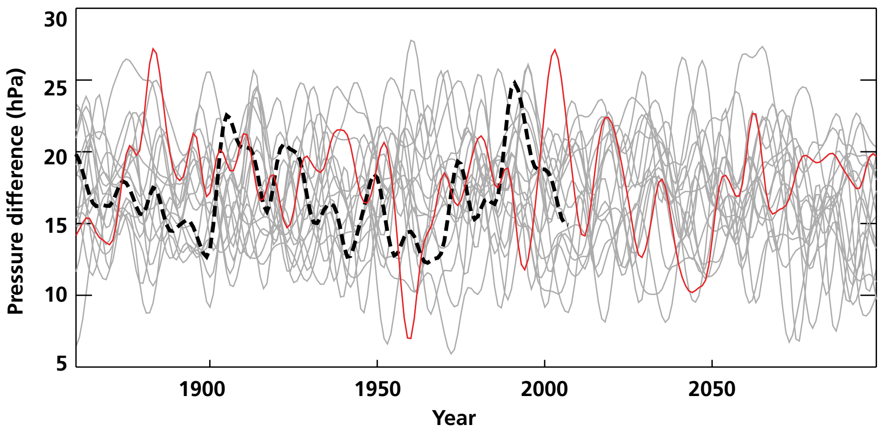


Figure A3.5: Gibraltar minus Iceland mean sea level pressure difference averaged in the winter seasons from observed (thick dotted line) and from the 17 member ensemble of HadCM3 with perturbations to parameters in the atmospheric (PPE_A1B in Chapter 3) component of the model (grey lines). A low-pass 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