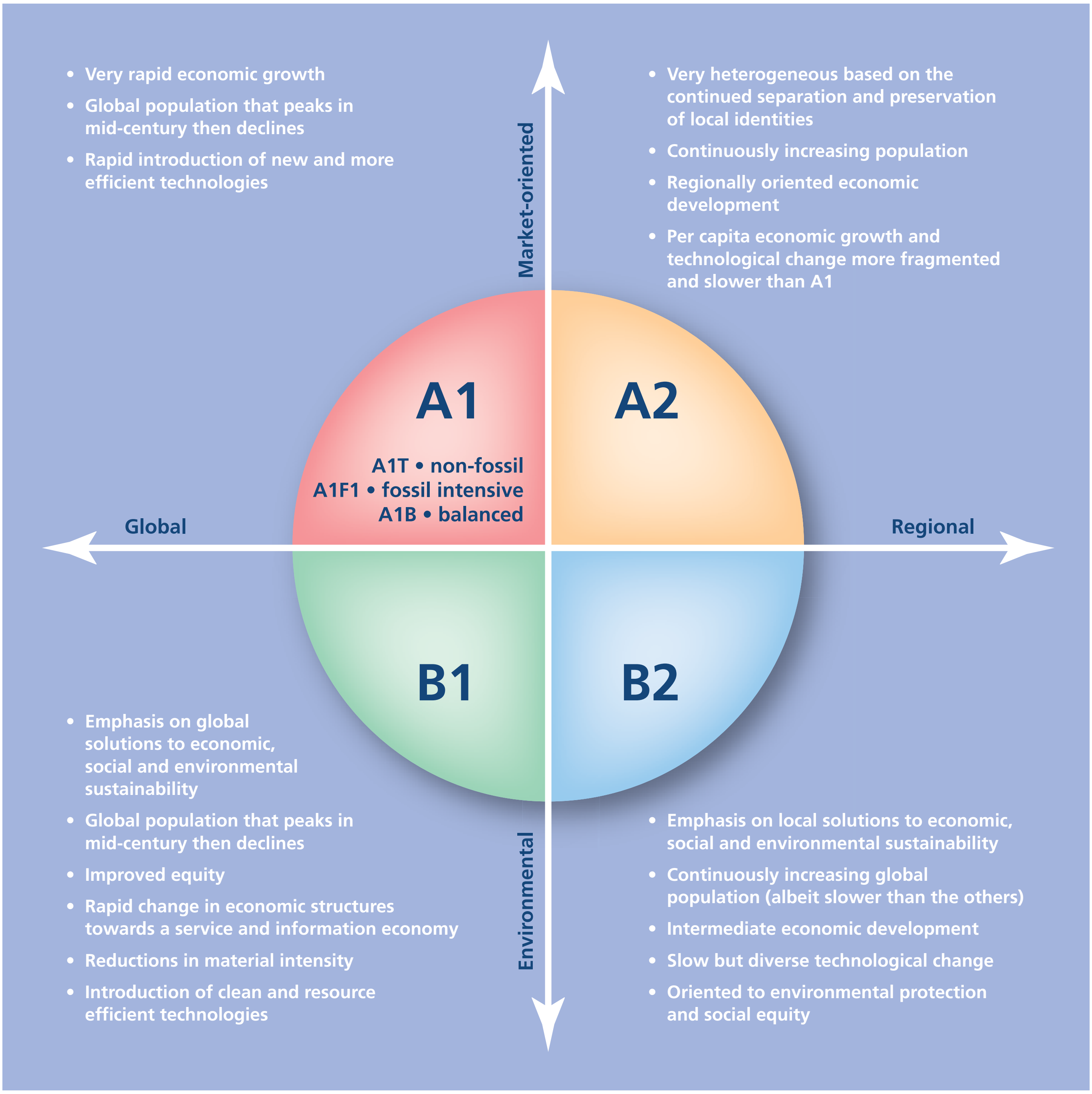
The B1 storyline also describes a convergent, more equitable world, and has the same population scenario as the A1 storyline: however, rapid changes in economic structures towards a service and information economy are assumed, with reductions in material intensity, and the introduction of clean and resource-efficient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

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

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



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

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

A1.2 Relevant work since the publication of SRES

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

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

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

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

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

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

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

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Annex 2: Sensitivity of UKCP09 projections to key assumptions

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

A2.1 Introduction

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

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

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

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

A2.2 Sensitivity studies

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

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

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

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

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

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

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

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

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

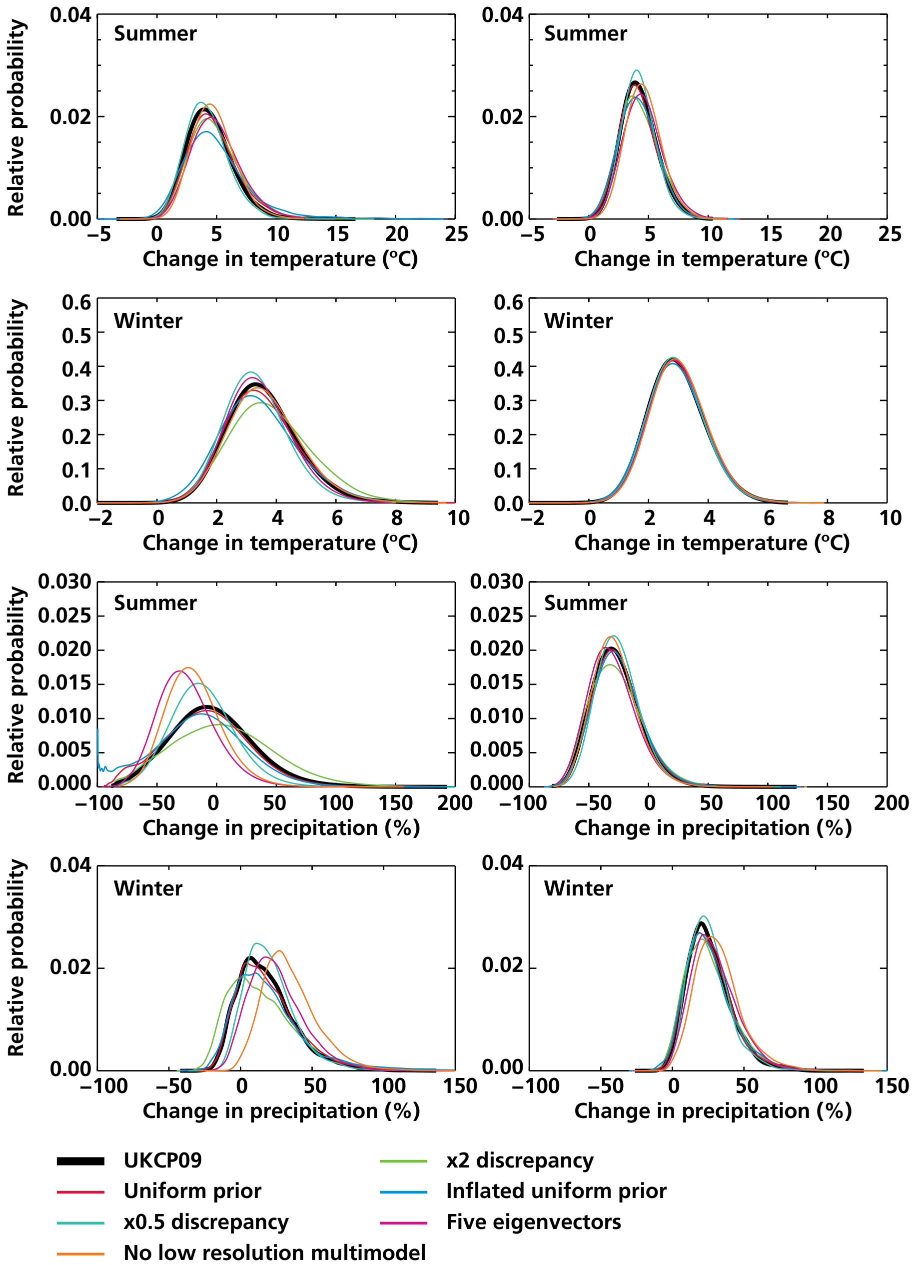

Figure A2.1: Probability distributions from six sensitivity tests (coloured) compared to UKCP09 results (black). The tests were done for summer and winter, for absolute changes in mean temperature (°C), and percentage changes in mean precipitation, for 2070–2099 relative to 1961–1990. Results are presented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

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

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

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

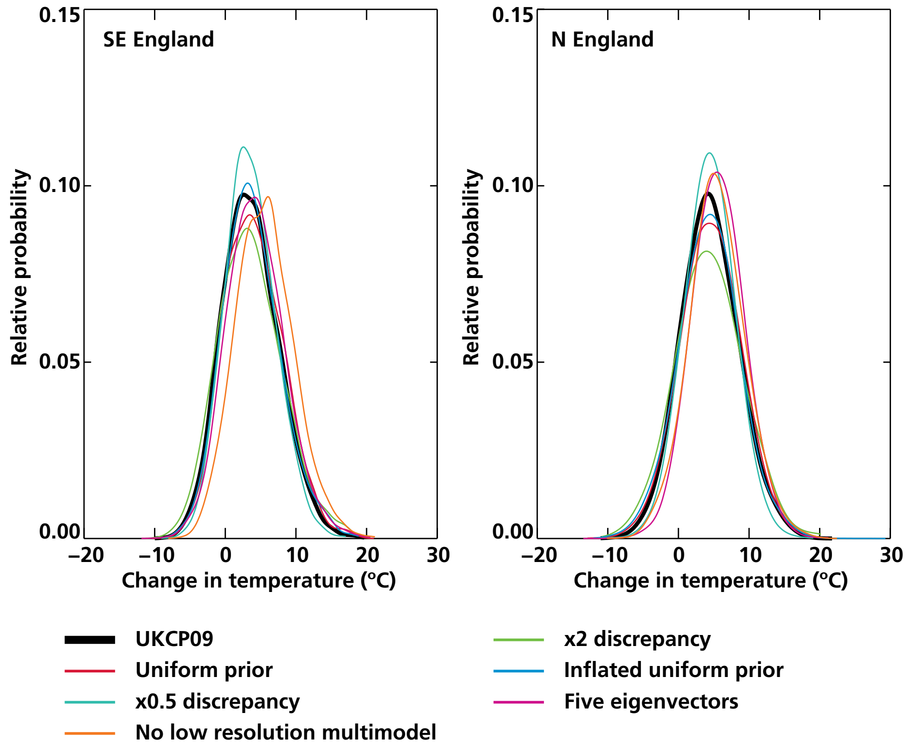

Figure A2.2: Posterior probabilistic projections from six sensitivity tests (coloured) compared to UKCP09 results (black), for summer changes in a typical warmest day of summer (°C), defined as the 99th percentile of daily maximum temperatures during June to August. Changes are shown for the global climate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

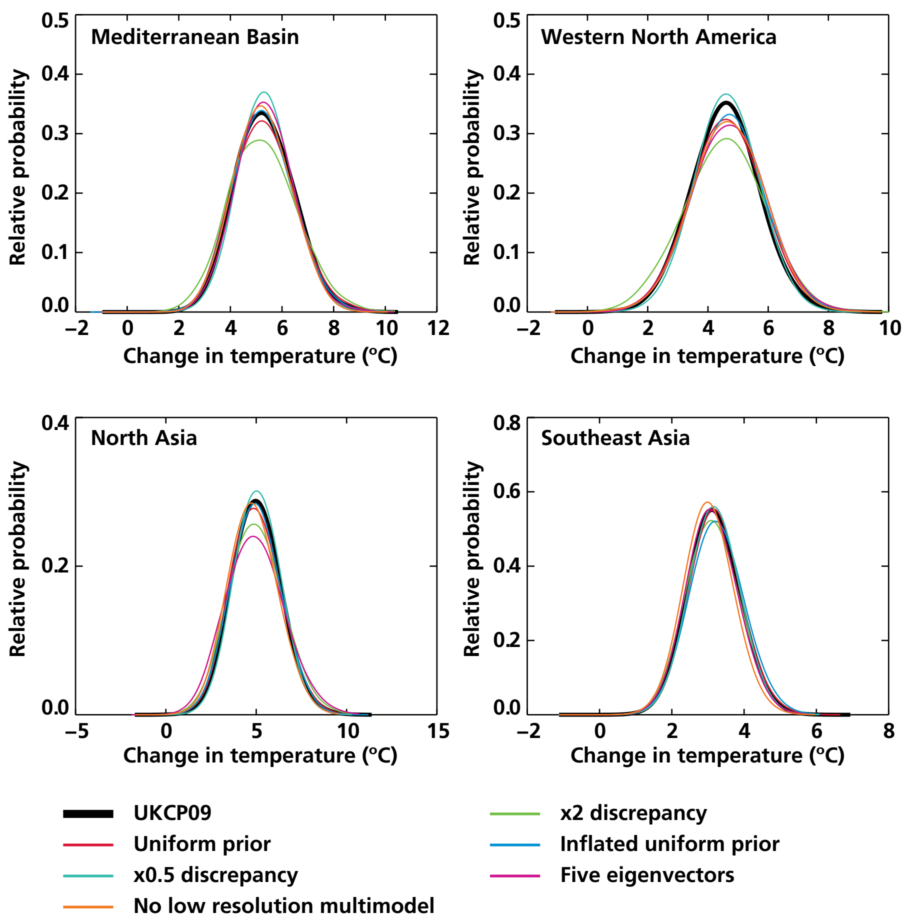

Figure A2.3: Posterior probabilistic projections from six sensitivity tests (coloured) compared to UKCP09 results (black), for summer changes in average temperature (°C) for 2070–2099 relative to 1961–1990, over a number of regions defined by Giorgi and Francisco (2000). Sensitivity tests are as described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

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

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

A2.3 Comparison of UKCP09 methodology against alternative approaches

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

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

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

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

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

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

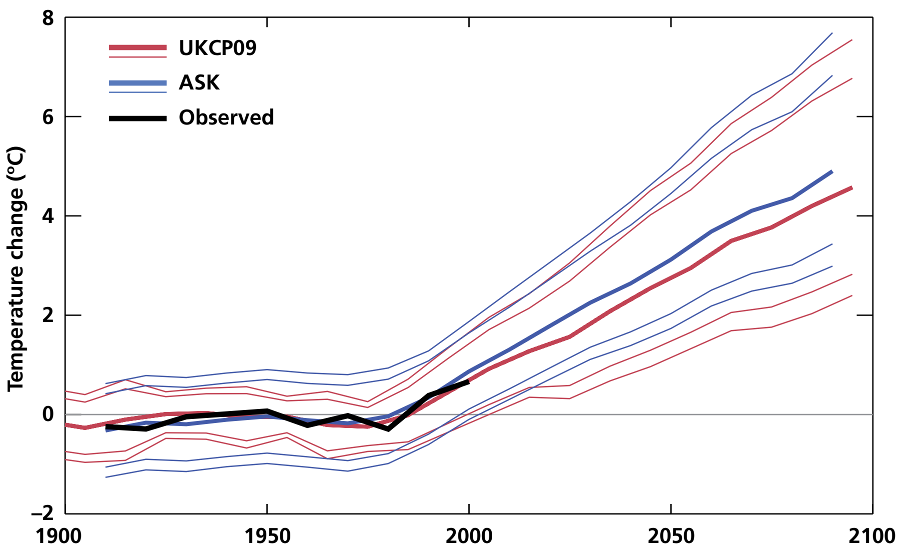

Figure A2.4: Comparison of probabilistic climate projections for changes in 10-yr annual mean 1.5 m temperature (°C) in response to SRES A1B (i.e. UKCP09 medium) emissions. Changes shown are for Northern Europe, relative to 1906–2005, from two methods: UKCP09 (red) and an updated version of Stott *et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

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

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

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

A2.4 Contributions to uncertainty in the UKCP09 projections

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

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

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

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

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

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

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

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