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A demonstration of the uncertainty in projections of UK climate change resulting from regional model formulation

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Abstract Regional climate models (RCMs) are now commonly used to downscale climate change projections provided by global coupled models to resolutions that can be utilised at national and finer scales. Although this extra tier of complexity adds significant value, it inevitably contributes a further source of uncertainty, due to the regional modelling uncertainties involved. Here, an initial attempt is made to estimate the uncertainty that arises from typical variations in RCM formulation, focussing on changes in UK surface air temperature (SAT) and precipitation projected for the late twenty-first century. Data are provided by a relatively large suite of RCM and global model integrations with widely varying formulations. It is found that uncertainty in the formulation of the RCM has a relatively small, but non-negligible, impact on the range of possible outcomes of future UK seasonal mean climate. This uncertainty is largest in the summer season. It is also similar in magnitude to that of large-scale internal variations of the coupled climate system, and for SAT, it is less than the uncertainty due to the emissions scenario, whereas for precipitation it is probably larger. The largest source of uncertainty, for both variables and in all seasons, is the formulation of the global coupled model. The scale-dependency of uncertainty due to RCM formulation is also explored by considering its impact on projections of the difference in climate change between the north and south of the UK. Finally, the implications for the reliability of UK seasonal mean climate change projections are discussed.

1 Introduction

Uncertainty in projected climate change arises from a number of sources (e.g., Cubasch et al. 2001): (1) the formulation and accuracy of the general circulation model (GCM); (2) the magnitude of anthropogenic emissions; and (3) the temporal and spatial impact of natural variations internal to the climate system. However, in order to provide projections of local climate change required by the impacts community and policy makers, a further tier of

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complexity is required. This is the addition of high-resolution detail, with one of the most utilised methods being the nesting of high resolution regional climate models (RCMs) within the GCMs (e.g., Giorgi et al. 2001; Leung et al. 2003). Thus a fourth source of uncertainty is introduced, which is the reliability with which such models are able to downscale global projections to national and finer scales.

This study aims to provide an initial estimate of the relative importance of the uncertainty arising from RCM formulation, and compare it with the other sources of uncertainty noted above. Our focus is on the United Kingdom and Irish Republic (hereafter UKIR), as an example of a region that is inadequately resolved by the current generation of GCMs but well resolved by RCMs. From a pragmatic viewpoint, it is hoped that this will contribute to guidance on the extent to which resources should be invested in multi-model ensembles of RCM integrations, rather than further enhancing the ensemble of GCM integrations. A further aim is to update published information on projections of seasonal mean climate change for UKIR, and their uncertainties (Hulme et al. 2002; Giorgi et al. 2004).

2 Data

The data for this study are derived from two sources. First, the EU PRUDENCE project (Christensen et al. 2002) has pooled a coordinated set of model integrations to produce a large matrix of RCM data. (Note that all acronyms used this paper, including modelling institutes, are defined in Appendix A.) These data enable the evaluation of uncertainty due to either RCM formulation alone, GCM formulation alone (but see below), emissions uncertainty, or uncertainty due to internal variations of the climate system. The matrix of data used in this study is shown in Table 1. Each control integration simulates the period 1960–1990, and each scenario integration simulates 2070–2100 using either the SRES A2 or B2 emissions scenarios (Nakicenovic et al. 2000). The majority of models are driven by a Met Office high-resolution ($1.25^\circ \times 1.875^\circ$) global atmospheric GCM (HadAM3H or HadAM3P), which in turn is driven by observed SSTs for the control integrations, or with HadCM3 SST anomalies added for the scenario integrations (HadCM3 is a Met Office global coupled model, with horizontal resolution $2.5^\circ \times 3.75^\circ$). The RCM integrations driven by the DKRZ/MPI global coupled model ECHAM4/OPYC are driven directly by these data, without the intermediate step of a high-resolution atmospheric GCM. Also, small ensembles of integrations were carried out for the DMI and Met Office RCMs, whereby each RCM ensemble member takes its boundary data from different members of the atmospheric GCM ensemble, and these in turn take their SST anomalies from different members of the coupled model ensemble. Last, all RCM data have been interpolated to a common 0.5° grid, preserving each model's coastline as far as possible.

These data can be used to estimate (a) the uncertainty due to RCM formulation by comparing the climate change responses in 9 different RCMs all forced by common boundary data from a single GCM (the 1st and 4th rows of Table 1); (b) the uncertainty due to projected emissions rates by comparing the response to the A2 and B2 scenarios averaged over 5 RCMs; and (c) the uncertainty due to *large-scale* internal climate variations by comparing the responses between 3 Met Office RCM simulations and between 3 DMI RCM simulations each nested within an ensemble of integrations generated by the GCM (so that differences between these RCM ensemble members are primarily due to differences between the GCM ensemble members). Table 2 provides a quick reference to this information and defines the abbreviations used in the figures.

Table 1 Ensemble size of RCM experiments used in this study. The first column shows the emissions scenario used, the second column the GCM used to drive the RCM, and remaining columns list the RCMs. 'AM3H' and 'AM3P' are the Met Office atmospheric GCMs HadAM3H and HadAM3P, respectively, both driven by the coupled GCM HadCM3. 'ECH4' is the DKRZ/MPI coupled GCM ECHAM4/OPYC. Other acronyms are defined in Appendix A

Scenario	GCM	DMI	ETH	GKSS	ICTP	KNMI	MO	MPI	SMHI	UCM
Cntl	AM3H	3	1	1	1	1	1	1	1	1
Cntl	AM3P						3			
Cntl	ECH4	1							1	
A2	AM3H	3	1	1	1	1	1	1	1	1
A2	AM3P						3			
A2	ECH4	1							1	
B2	AM3H								1	1
B2	AM3P						1			
B2	ECH4	1							1	

Table 2 Summary of the four sources of uncertainty

Abbreviation	Source of uncertainty	Data used to estimate this uncertainty
RCM	RCM formulation	9 different RCMs forced by the common boundary data of a single GCM (from the PRUDENCE database)
Internal	Large-scale internal climate variations	Two 3-member RCM ensembles forced by boundary data from GCM ensembles using the SRES A2 scenario (from the PRUDENCE database)
Emissions	Projected rates of anthropogenic emissions	5 different RCMs each forced by the SRES A2 and B2 scenarios (from the PRUDENCE database)
GCM	GCM formulation	7 GCMs forced by the SRES A2 scenario (from the IPCC database)

However, in order to estimate the uncertainty due to the formulation of the driving GCM, the PRUDENCE data provide only two RCMs forced by two different GCMs (see Table 1 for full details). Ideally, data are required from an experiment set whereby one (or more) RCM(s) have been forced by a larger and more representative sample of GCMs. Unfortunately such experiments have not yet been carried out, and so an alternative approach is adopted here of utilising data directly from GCMs. These data have been obtained from the Intergovernmental Panel for Climate Change (IPCC) Data Distribution Centre (DDC), from which 7 models are available forced by the SRES A2 scenario: the CCCma model CGCM1, the CCSR/NIES model, the CSIRO model Mk2, the DKRZ/MPI model ECHAM4/OPYC3, the GFDL model R15-a, the Met Office model HadCM3, and the NCAR model DOE-PCM. The same time periods as for the PRUDENCE RCM data were extracted. The disadvantage of this approach is that since the data have not been downscaled by an RCM the resulting uncertainty range is not strictly comparable with the other uncertainties that are computed. Nevertheless the UKIR averages for the Met Office and DKRZ/MPI GCMs are broadly similar to their downscaled companions from PRUDENCE (Appendix B), so it is judged that this approach is a better option than basing our assessment on the diminutive sample of PRUDENCE models driven by different GCMs.

3 Estimated uncertainties for UKIR averages

Figures 1 and 2 illustrate projections of late twenty-first century anomalies averaged over UKIR, for seasonal mean surface air temperature (SAT) and precipitation, grouped to demonstrate their sensitivity to each source of uncertainty. Thus, in this section we focus on the spatial scale of a few GCM grid boxes (~1000 km). The averaging region (land points only) is determined by the coastal topology of each model. Also shown is the standard deviation (SD) of the data within each group. Note that because sample sizes are rather small (due to obvious limitations in computing power), these enable only an approximate comparison of uncertainties, and should be interpreted as 'descriptive' rather than 'quantitative'. They are displayed primarily to aid more rapid assimilation of the uncertainties and to avoid the possibility of being misled by a purely visual interpretation. Four further caveats should also be noted. First, the uncertainty due to the emissions scenario will be biased slightly low (by about 15%), because more extreme scenarios (such as B1 and A1FI) are not included.[1] Second, the uncertainties due to the emissions scenario and to the GCM formulation will on the other hand be overestimated because they also include some variability due to internal climate anomalies. Third, it is assumed that the SDs of each of the three RCM-based groupings ('RCM', 'Internal' and 'Emissions') are independent of the choice of GCM(s) by which they are driven (i.e. only their mean depends on the driving GCM); this can only be supported (or refuted) as further experiments become available. Last, it is assumed that all models are equally reliable; additional analysis could for example seek to weight each model by its ability to reproduce current climate (c.f. Giorgi and Mearns 2002; Murphy et al. 2004).

For SAT, Figure 1 shows that uncertainty in UKIR average climate change, due to RCM formulation alone, is relatively small in all four seasons. It is similar to the uncertainty due to large-scale internal variations of the climate system, but somewhat smaller than that arising from the emissions scenarios, and considerably smaller than that arising from the formulation of the GCM. This is because a significant component of the RCM SAT response over UKIR is dependent on the lower tropospheric temperature response at the lateral boundaries (particularly the western boundary) and on the temperature response of the surrounding ocean. Both these factors are identically specified by the driving GCM that is common to

[1] The two emissions scenarios A2 and B2 should not be regarded as a *random* sample from a population of scenarios, but as two deliberate choices intended to span a part of the full range (one high scenario and one low scenario, with neither being extreme). Thus the estimated SD due to this source of uncertainty is more reliable than an estimate derived from a two point random sample. Furthermore, the A2–B2 range of UKIR climate change projections is estimated here with 'moderate' reliability since the response to each scenario is the mean of data from 5 randomly sampled models (*not* just the response of a single model).

Nevertheless, the choice of just two scenarios may introduce some bias to the SD due to emissions uncertainty, compared to an experimental suite in which all scenarios are used. At the global scale, this bias can be estimated using the data shown in Figure 9.13(b) of Cubasch et al. (2001), which illustrates the mean temperature response to a range of SRES scenarios. Thus, in the latter part of the 21st century, the SD of only the A2 and B2 global temperature anomalies is about 15% lower than the SD computed using all six illustrative SRES scenarios. If we then accept the first-order approximation that regional climate change scales linearly with global mean temperature (e.g., Mitchell et al. 1999; Mitchell 2003), it is apparent that the SD of UKIR climate change due to emissions uncertainty is also underestimated by around 15% due the particular choice of SRES scenarios.

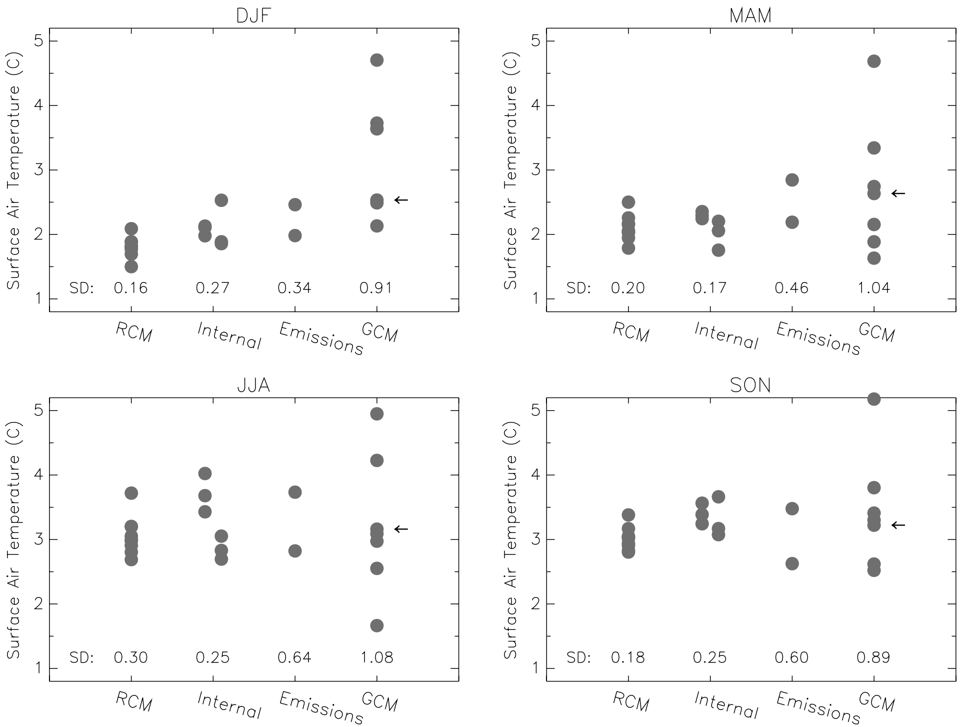

Fig. 1 Projected climate change anomalies for seasonal mean surface air temperature averaged over UKIR, computed as the time-mean differences between 2071–2100 and 1961–1990. Four groups of points are shown in each panel, the spread of each of which indicates the uncertainty due to a specified source: 'RCM' is RCM formulation, 'Internal' is large-scale internal anomalies of the coupled climate system, 'Emissions' is the emissions scenario, and 'GCM' is the GCM formulation. Note that 'Internal' contains two groups of points (at different locations on the *x*-axis) representing ensembles from different RCMs. See Section 2 of the text for further detail. 'SD' is the standard deviation of each group of anomalies, which in the case of 'Internal' is computed from the average of the two intra-ensemble variances. The arrow at the right-hand side of each panel indicates the HadCM3 anomaly

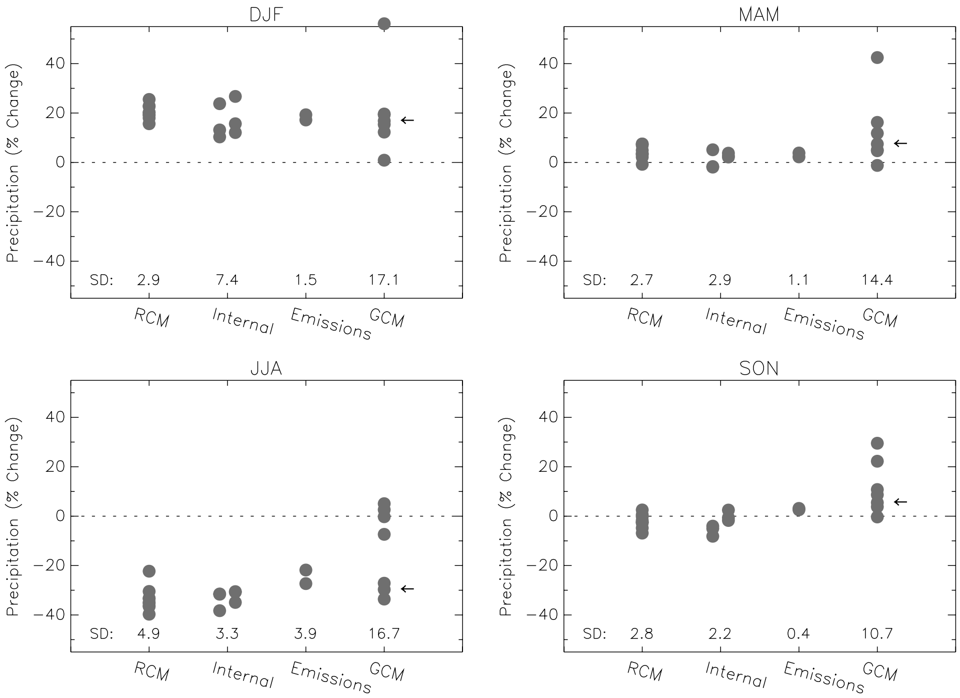

Fig. 2 As Figure 1, but for seasonal mean precipitation anomalies. UKIR average anomalies are computed in units of mm/day and then converted to a percentage of the appropriate model's 1961–1990 control climate

all RCMs in the first grouping of Figure 1, and hence there is little spread between them. However, some RCM uncertainty is nevertheless apparent, and its source lies in the variety of plausible formulations of model parameterizations that govern local feedback mechanisms and the local radiative response to greenhouse gases. Note also that these make a greater contribution to uncertainty in summer when the ambient flow is weaker, thus reducing heat advection from the surrounding ocean and lateral boundaries.

The actual projections for UKIR climate change are, not surprisingly, a warming in all seasons. However, the season of peak warming remains unclear. The first 3 groups in each panel of Figure 1 suggest that the warming anomaly will be largest in summer and autumn, but this merely reflects the seasonality of their driving model, HadCM3 (marked by the arrow in the right-hand grouping of each panel). The large contribution to uncertainty arising from the GCM formulation is emphasised by the result that these GCMs are almost equally split as to whether autumn, summer or winter will be the season with the largest warming. Uncertainty due to emissions may also be substantial (see caveats above), but probably less than that due to GCM formulation, and with associated projection errors that would be likely proportional between seasons.

For precipitation (Figure 2), the relative contributions of three of the sources of uncertainty – those due to RCM formulation, large-scale internal variations, and GCM formulation – are similar to that found for SAT. Thus, the first two contribute about equally, and the GCM formulation contributes more by a considerable margin. All are substantially larger than the sensitivity to the emissions scenario. The larger sensitivity of precipitation to differences in GCM formulation and internal variations of the GCM, compared to the emissions scenario, is well-known (see Raisanen 2001; Giorgi and Mearns 2002, for example). The larger contribution of the RCM formulation to precipitation uncertainty (compared to the contribution of the emissions scenario) can be explained by a greater dependence of precipitation (compared to SAT) on local physics and its reduced dependence on information transferred from the common lateral and ocean boundary data. Note also that the uncertainty due to RCM formulation again peaks in summer.

The sign of the seasonal mean precipitation changes portrayed by the experiments is most robust in winter, when 6 out of 7 GCMs predict that mean rainfall will be enhanced by at least 10%; this is consistent with the analysis of Hulme et al. (2002) and the single model analyses of Giorgi et al. (2004) and Rowell (2005). In summer, however, the uncertainty in GCM formulation suggests that 'no change' and 'notable drying' are both plausible outcomes, with 4 out of 7 models predicting an absolute change of less than 10%, and the remainder predicting a reduction of more than 25%. During the equinoctial seasons, and in the annual mean (Figure 3), rainfall is projected to be either close to present-day conditions, or to become wetter.

4 Estimated uncertainties at the sub-national scale

Here, we consider the impact of uncertainty due to RCM formulation at the finer spatial scales often required by users. Specifically, these are the scales of, or below, that of a single GCM grid box (of order 300 km). As an example, attention is focused on changes in the north-south difference in SAT and precipitation across the UK, defined here as the difference between climate change anomalies averaged over British land points north of 55 °N and south of 52.5 °N (each computed as percentage changes for precipitation). In this way the UK average response is excluded, filtering out the larger scale anomalies that have already been addressed in Section 3. Results are shown in Figure 4, and compared with the estimated uncertainty

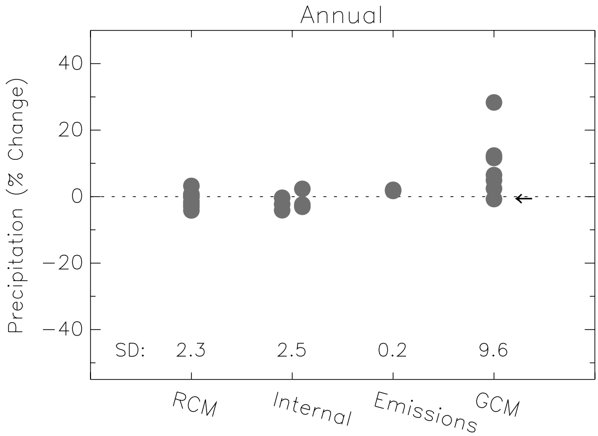

Fig. 3 As Figure 1, but for annual mean precipitation anomalies. UKIR average anomalies are computed in units of mm/day and then converted to a percentage of the appropriate model's 1961–1990 control climate.

arising from large-scale internal climate variations. Note however that these results are based on the large-scale forcing from only one global model, and so do not include the inter-GCM component of uncertainty. Due to the small spatial scales involved, this would require RCM integrations driven by several different GCMs to become available. Also, GCM data from the IPCC-DDC cannot be used in this case since the aim is to examine spatial scales that these models cannot resolve.

First consider the nature of the response of this 'difference index' to anthropogenic climate change. All models show that Scotland will warm less than southern England/Wales, and that this disparity is strengthened in summer (Figure 4a). This can be expected from the more maritime climate of the northern UK[2], and because the response of SAT over continental Europe is largest in summer in HadAM3H. For precipitation, Figure 4b shows that the RCMs agree that the percentage increase in winter will be lower in Scotland than in the southern UK. This is consistent with an increase in storm density over the northern UK in HadAM3H (R.E. McDonald personal communication, 2004), and that the majority of rain falls to the south of cyclonic centres. However the precise location of storm track anomalies on which this response depends is likely to be highly dependent on the driving GCM, implying much larger total uncertainty. In summer, the percentage decrease in rainfall is larger in the southern UK, but this may too be influenced by large scale features of the driving GCM which likely have an uncertain impact on UK summer rainfall (Rowell and Jones 2006).

Next, we consider the uncertainties shown in Figure 4, and compare these with those shown in Figures 1 and 2. Again, the summer season has the highest sensitivity to RCM formulation due to the larger role of RCM physics in the presence of weaker flow from the lateral boundaries. It can be seen that both the RCM and large-scale internal sources of uncertainty tend to be lower for SAT for the sub-national difference index, but generally higher for precipitation. Possible mechanisms for these scale-dependencies of uncertainty are discussed in Appendix C. Note, in particular, that such scale-dependency is likely to be

[2] This south-to-north negative gradient of warming anomalies over the UK is in the opposite sense to the global zonal mean response. At many other longitudes in winter (and at higher latitudes in summer) this gradient is dominated by a reduction in the snow-albedo feedback at higher latitudes. However, over the UK there is too little snow in the current climate for this to be important, and so instead the gradient of warming is determined by the shape of the land mass and the latitudes over which it is close to continental Europe.

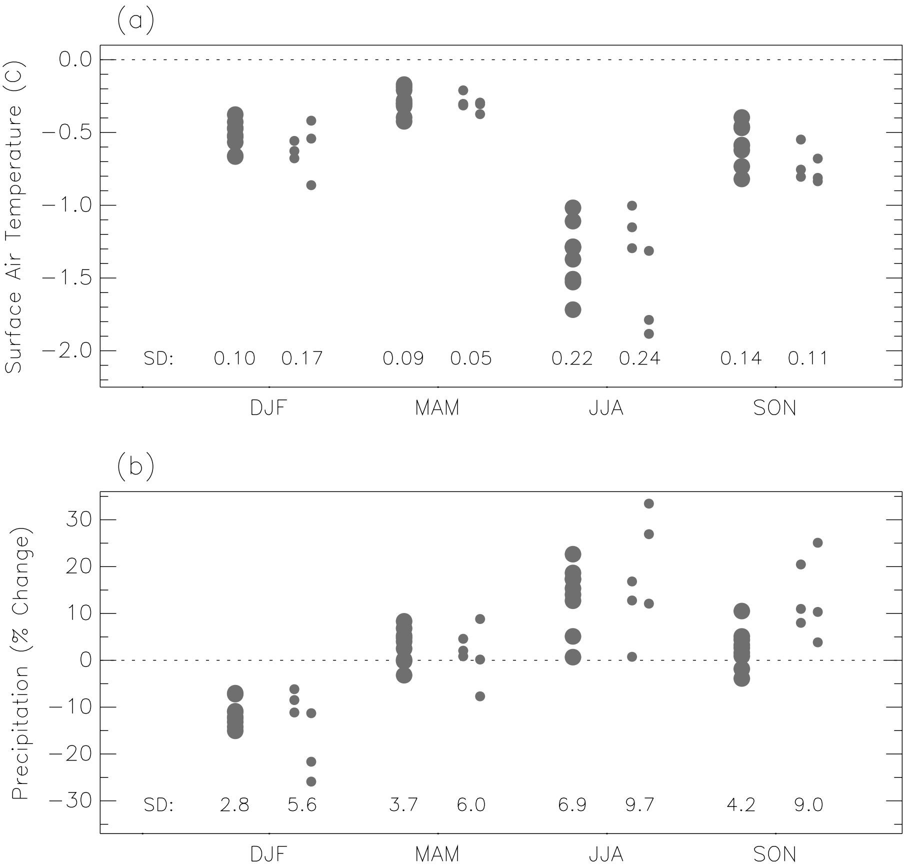

Fig. 4 Projected north-minus-south difference of seasonal mean climate change anomalies for the UK, under the A2 scenario, computed as time-mean differences between 2071–2100 and 1961–1990. See Section 4 of the text for further detail. (a) Surface air temperature, and (b) precipitation computed as the difference of percentage anomalies. For each season, two groups of points are shown, the spread of which indicates the uncertainty due to a specified source: the large circles are RCM formulation, and the small circles are large-scale internal anomalies of the coupled climate system. Note that the latter contains two groups of points (at different locations on the x-axis) representing ensembles with different RCMs. 'SD' is the standard deviation of each group of anomalies, which in the case of the smaller circles is computed from the average of the two intra-ensemble variances.

highly dependent on the indices and geographic region considered, so for other examples rather different results may be found.

Finally, to illustrate more clearly the impact that these sources of uncertainty can have on sub-national patterns of future climate anomalies, Figure 5 shows maps of the mean response over UKIR for summer precipitation. The variety of possible responses is clear, ranging from a near-uniform drying across UKIR to significant regional variations. This variety is due to differences in both the RCM formulation and the large-scale chaotic component of climate anomalies. Again we emphasize that the uncertainties due to the formulation of the driving global GCM, and due to anthropogenic emissions, are not included here.

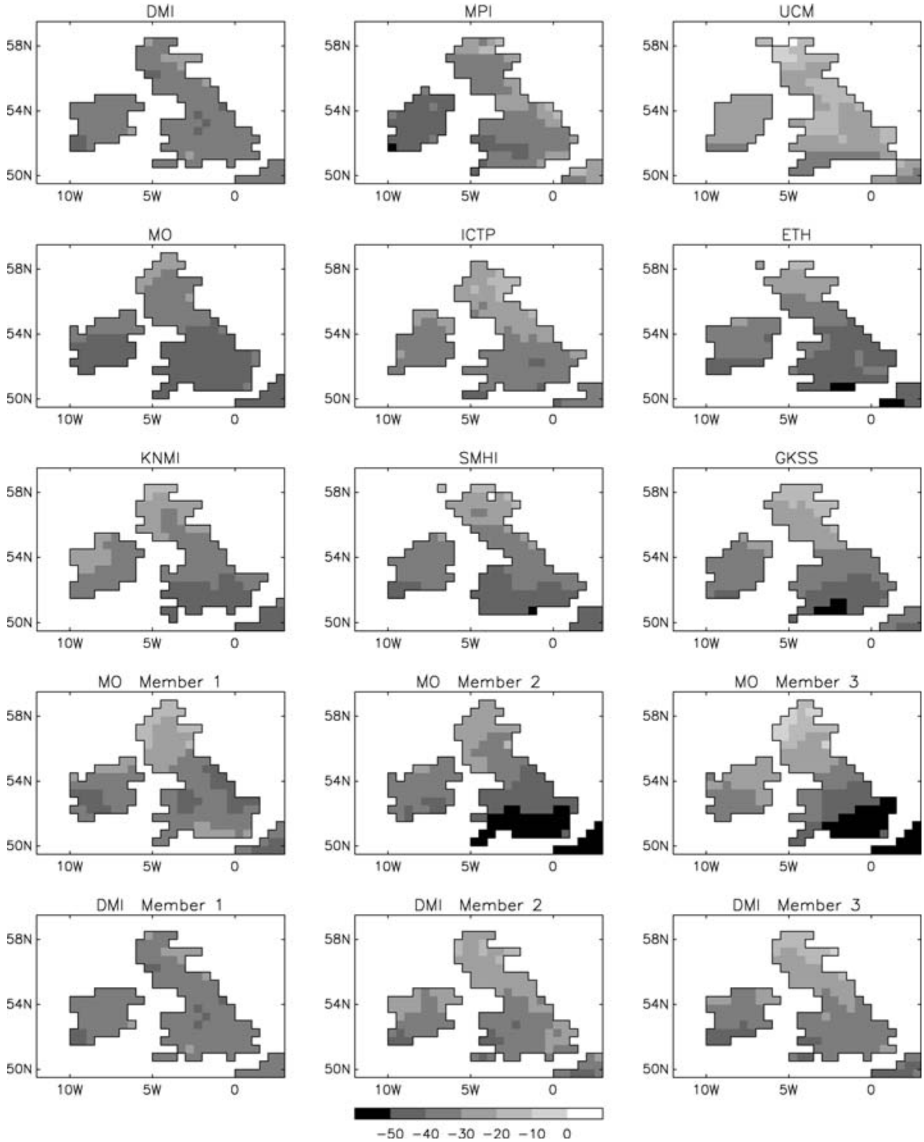

Fig. 5 Projected climate change anomalies of June–Aug mean precipitation over the UKIR under the A2 scenario. Computed as the time-mean difference 2071–2100 minus 1961–1990, as a percentage of the 1961–1990 mean. Three groups of data are shown: (1) The upper 9 panels show different RCMs driven by the same GCM (HadCM3 via HadAM3H); (2) the 4th row of panels are anomalies of the Met Office RCM driven by different ensemble members of the GCM (in this case, HadCM3 via HadAM3P); (3) the lowest 3 panels are anomalies from the DMI RCM driven by different ensemble members of the GCM. Within each group, the panels are ordered (from left-to-right, then top-to-bottom) according to the difference between their anomalies in the northern and southern UK (computed following Section 4).

5 Conclusions

The work presented here has extended previous assessments of future UKIR seasonal mean climate change (e.g., Hulme et al. 2002; Giorgi et al. 2004) by more closely integrating a description of projected anomalies with an initial estimate of all sources of uncertainty. To this end, the availability of the PRUDENCE data, along with that of the IPCC-DDC, has been essential.

A particular focus has been an assessment of the extent to which uncertainties in the regional models used for downscaling contribute to the reliability (or lack of reliability) of UKIR climate projections. This additional uncertainty may also be interpreted from a physical point of view (as well as the experimental point of view emphasised here), in that as finer scales are considered, additional phenomena and processes must be modelled, thus increasing the scope for disagreement amongst models. This source of uncertainty is therefore also relevant within a 'consistent' modelling framework, such as an RCM/GCM combination with identical physics, or a variable-resolution GCM such as described by Deque et al. (1998).

Although the sample of models available here is necessarily small, some broad conclusions may be drawn. First, the uncertainty due to RCM formulation is relatively small for average UKIR seasonal mean data. This results in differences between model responses (quoted here as twice their standard deviation) of approximately 0.3–0.6 °C for SAT and 5–10% of current climate for precipitation. This is of similar magnitude to the uncertainty due to large-scale internal variations of the global coupled climate system. For SAT, it is also less than the uncertainty arising from anthropogenic emissions at the end of the century, but for precipitation it is probably larger than this uncertainty. However, for both SAT and precipitation, and in all seasons, the dominant source of uncertainty is that arising from formulations of the structure and physics of the coupled GCMs. An additional finding at the UKIR-average scale has been that the uncertainty due to RCM formulation is probably largest in summer, which is consistent with a weaker ambient flow allowing a greater influence of the RCM physics. This larger influence of uncertainty due to the RCM is also likely to extend to other seasons over some regions, particularly where the ambient flow is weaker than that of the UK (reducing the influence of the GCM), or where the surface is more heterogeneous (e.g., steep mountains), or where the surface provides stronger feedbacks (through snow or soil moisture sensitivity).

The spatial scale-dependency of the uncertainty due to RCM formulation has also been considered, by examining spatial scales that the GCMs cannot resolve. For the example shown here – comparison of the UK average data with an index of the difference of climate change anomalies between the northern and southern UK – uncertainty appears to be lower at this finer (spatially filtered) scale for SAT, but higher for precipitation. Note however that these results may not generalise to other regions with different surface characteristics or to finer spatial scales.

The dominant role of uncertainty in the GCM formulation for UKIR climate change is emphasised by describing the UKIR predictions and their (lack of) consistency. For SAT, it is unclear which season will experience the greatest warming over UKIR, although it seems likely that the southern UK will warm more than the northern UK. For precipitation, there is often disagreement on even the sign of the projected change over UKIR, except in winter when most GCMs agree that UKIR average precipitation will increase by at least 10%. Such disagreements will remain until global modelling uncertainties can be narrowed. Understanding the mechanisms of regional climate change, and placing these in the context of the model's strengths and weaknesses, will continue to be informative (e.g., Carnell and Senior, 2002; Rowell and Jones, 2006).

Finally, to address the pragmatic question posed in the introduction, "To what extent should resources be invested in multi-model ensembles of RCM integrations, rather than further enhancing the ensemble of GCM integrations?", the results presented here suggest that it is indeed worthwhile investing in a range of plausible regional models to downscale climate change projections to the scales required by the impacts community. However (at least for seasonal time scales and roughly 1000 km spatial scales), the majority of resources should still be invested in developing and running a range of plausible GCMs. These models should of course include additional processes not currently incorporated (which will tend to increase uncertainty), and should also become more realistic in all other aspects of their physical and dynamical representation (which will tend to reduce uncertainty).

Appendix A: Acronyms used in this paper

CCCma – Canadian Center for Climate Modelling and Analysis
CCSR/NIES – Center for Climate Research Studies and National Institute for Environmental Studies (Japan)
CSIRO – Commonwealth Scientific and Industrial Research Organisation (Australia)
DKRZ – Deutsches Klimarechenzentrum (Germany)
DMI – Danish Meteorological Institute
ETH – Eldgenossische Technische Hochschule (Switzerland)
GCM – General Circulation Model
GFDL – Geophysical Fluid Dynamics Laboratory (USA)
GKSS – Forschungszentrum Geesthacht GmbH (Germany)
ICTP – International Centre for Theoretical Physics (Italy)
IPCC – Intergovernmental Panel for Climate Change
IPCC-DDC – IPCC Data Distribution Centre
KNMI – Koninklijk Nederlands Meteorologisch Instituut (Netherlands)
MO – Met Office (UK)
MPI – Max-Planck-Institute for Meteorology (Germany)
NCAR – National Centre for Atmospheric Research (USA)
PRUDENCE – Prediction of Regional scenarios and Uncertainties for Defining EuropeaN Climate change risks and Effects (a European Union project)
RCM – Regional Climate Model
SAT – Surface Air Temperature
SD – Standard Deviation
SMHI – Swedish Meteorological and Hydrological Institute
SRES – Special Report on Emissions Scenarios, Nakicenovic et al. (2000)
UCM – Universidad Complutense de Madrid (Spain)
UKIR – United Kingdom and Irish Republic

Appendix B: Suitability of IPCC data to estimate UKIR averages

The statement that: "UKIR averages for the Met Office and DKRZ/MPI GCMs are broadly similar to their downscaled companions from PRUDENCE" is supported by the following calculations. First, UKIR average climate anomalies (2071–2100 minus 1961–1990) were computed for the two GCMs, as well as for the DMI and SMHI RCMs driven by both GCMs (these being the only RCMs driven by both GCMs; Table 1). Next, the annual mean bias in the GCM anomalies (relative to the RCM anomalies) was assessed, showing that although the bias of the low resolution data is small, both GCMs fall slightly outside the range of the two RCMs. Specifically, for SAT, the annual mean GCM warming is overestimated by the Met Office GCM by 0.3 °C (compared to the nearest RCM), and underestimated by the DKRZ/MPI GCM by 0.2 °C. For precipitation, the GCMs overestimate the anomaly of the nearest RCM by 3% and 5% for the Met Office and DKRZ/MPI GCMs respectively. Nevertheless, the key point here is that these biases are all smaller than most of the inter-GCM differences shown in Figures 1 and 2. The similarity of the GCM and RCM seasonal means can be summarised by correlating the GCM UKIR seasonal anomalies with the averages of the RCM seasonal anomalies. For the Met Office GCM, this measure of similarity exceeds 0.99 for both variables, and for the DKRZ/MPI GCM they are 0.72 and 0.88, for SAT and precipitation respectively. Thus the broad shape of the seasonal cycle of downscaled climate anomalies is captured by both GCMs. The lower correlations for the DKRZ/MPI data may indicate that the PRUDENCE RCM integrations derive from a different ensemble member of the GCM to that made available to the IPCC-DDC.

Appendix C: Mechanisms for scale-dependency of RCM uncertainty and large-scale internal uncertainty

Four mechanisms may be proposed to explain the scale-dependencies of uncertainty shown by comparing Figure 4 with Figures 1 and 2:

1. If a climate change anomaly field is spatially homogeneous, then its response to changes in RCM formulation or to the boundary data is also more likely to be spatially homogeneous. In the context of the data analysed in Section 4, the homogeneity of the mean climate change anomaly field may be estimated as: the mean anomaly of the UK difference index divided by the mean anomaly of the UK average, both computed using the ‘RCM’ data groups in Figures 1 and 4. For SAT, this is on average about 0.25, whereas for precipitation it averages about 0.75 (using absolute ratios in each case). This greater homogeneity for SAT may partly explain why the ratio of the uncertainties is also lower for SAT than precipitation.
2. The spatial dependency of the uncertainty due only to RCM formulation will be affected by the interaction of physical processes with the orography and coastal topology, and by which processes dominate for a particular variable and region. Where the formulation of the most influential parameterisation schemes is less well constrained, then interaction with small scale surface features will tend to increase uncertainty at small spatial scales. This would be the case for precipitation, which is influenced (for example) by the interaction between the modelling of precipitation and the UK coastline and orography.
3. The uncertainty due to large-scale internal variations could also be spatially dependent, whereby small scale anomalies may be particularly sensitive to changes in boundary data. Such changes would include the location of synoptic systems at the lateral boundaries, as well as large-scale circulation anomalies and heat and moisture profile anomalies.
4. Chaotic variations *within* the domain of the RCM will also contribute to the spatial-dependency of all sources of uncertainty. However, it seems likely that their contribution to uncertainty here is small, because their random nature will have little net influence on

30-year seasonal averages, and because the domain of RCMs is deliberately chosen to avoid 'excessive' internal freedom (e.g., Jones et al. 1995; Denis et al. 2002).

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