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M1.3 Preliminary assessment of the perturbed parameter approach to representing model uncertainty in centennial climate predictions. Recommendations to the ENSEMBLES project concerning the design of the production ensemble system.

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PU	Public	
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M1.3: Preliminary assessment of the perturbed parameter approach to representing model uncertainty in centennial climate predictions. Recommendations to the ENSEMBLES project concerning the design of the production ensemble system

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Conclusions and Recommendations to ENSEMBLES Project

We may conclude the following from studies which use the Hadley Centre model:

1. The perturbed physics ensemble spread in equilibrium climate sensitivity is similar to that found in studies which use observational constraints to produce probabilistic estimates of that quantity, although ensemble distributions are sensitive to the method of perturbation;
2. The perturbed-physics ensemble spread in the transient climate response is similar to that found in the current multi-model ensemble run for the IPCC Fourth Assessment Report (AR4), although the ENSEMBLES subset of models under-represents uncertainty with respect to the perturbed-physics ensemble;
3. The leading-order drivers of uncertainty in atmospheric and surface feedbacks are associated with clouds. The ensemble spread in cloud feedback shows a large degree of overlap between the perturbed-physics and multi-model ensembles, although there are some detailed differences.

Hence we recommend (with our most important recommendation being the 5th bullet point):

1. The use of the perturbed physics approach is extended in the ENSEMBLES project using the Hadley Centre model. In particular, perturbations to other processes relevant to climate change should be made, including physical ocean processes and processes associated with other chemical and biological feedbacks in the Earth System;
2. The perturbed-physics approach is used by other ENSEMBLES partners to further assess the validity of the approach;
3. In studies using output from multi-model ensembles, use of a limited set of models may seriously under-represent uncertainty with respect to that found in perturbed physics ensembles. The ENSEMBLES project may choose to facilitate the use of the widest possible range of models in such studies;
4. Detailed comparisons of the drivers of uncertainty and the regional patterns of climate change in perturbed-physics and multi-model ensembles are required;
5. Perturbed-physics ensembles with the Hadley Centre climate model are capable of providing the main underpinning component of the ENSEMBLES production ensemble system for centennial predictions.
6. Work should be initiated to combine information from perturbed physics ensembles, multi-model ensembles and observational constraints to produce probabilistic predictions on the centennial time scale.

Introduction

Perturbed parameter or perturbed physics ensembles are generated by running versions of a climate model in which uncertain parameters are changed with respect to their standard settings and kept fixed throughout the model experiment (Murphy et al., 2004; Stainforth et al., 2005). (While, in general, we have chosen to simply perturb parameters in a number of physical parameterisation schemes in version three of the Hadley Centre model (HadCM3), there are also a number of instances of perturbations to switches in which non-standard sections of code are activated. Nonetheless, we still refer to these as physics perturbations. See Murphy et al. (2004) for more details.) The motivation for perturbed physics ensembles is two-fold. Firstly we wish to easily generate large ensembles of simulations in order to quantify uncertainty in climate predictions that arise from both physical and biological processes and feedbacks, and their interactions. Secondly, we must be able to specify the underlying distribution of models from which our ensemble is drawn (our *prior* assumptions). The latter may seem like a fairly academic point, but can have a leading-order impact on the predictions we produce from the ensemble. Even in studies which seek to minimise the influence of prior assumptions (e.g. Piani et al., 2005), the ensemble has a central role to play in calibrating relationships between global-mean and impact-relevant local variables. Hence it is important to quantify the influence of parameter choices on those relationships.

The defining feature of an ensemble is the spread or variance it captures in the forecast variable of interest. In ensemble weather and seasonal forecasting, it is possible to calibrate the perturbation technique to sample the correct forecast spread by examining the performance of the ensemble system over a number of verification cycles (an activity underway using the perturbed-physics approach in WP1.4 and 1.5). In centennial climate prediction this is, for practical reasons, impossible. Hence when designing a perturbation technique, it is impossible to formally tune the perturbations to produce some “correct” forecast spread. The task is rather to produce a spread consistent with our current understanding of uncertainties in climate system processes and the effects of natural climate variability. Nevertheless, a number of evaluation techniques may be applied in assessing the ensemble design. We may;

1. compare the spread in a particular forecast variable with the spread computed from some completely independent method, perhaps one based on applying observational constraints in a very simple climate model, or
2. compare the spread in a particular forecast variable with the spread from an ensemble generated in a completely different way e.g. the multi-model ensemble, or (in a similar vein)
3. compare the physical drivers of uncertainty with those found in an ensemble generated in a different way.

For the purpose of this report we focus on the assessment of global mean temperature under both equilibrium and transient conditions, these being recognised as fundamental benchmarks of the magnitude of centennial climate change.

Assessment of Climate Sensitivity

Figure 1 shows histograms of climate sensitivity, the equilibrium global-mean temperature change in response to a doubling of CO_2, from three perturbed physics ensembles produced with HadSM3 (the version of HadCM3 in which the atmosphere is coupled to a simple mixed layer ocean). Also shown are a number of independent estimates of the mean and uncertainty in this quantity from studies which attempt to constrain it using different observational records. Broadly speaking, the perturbed physics ensembles are similar to the estimates from observations, which builds confidence in the perturbed physics approach. (Here we examine only un-weighted distributions. In studies which have introduced weighting and other statistical techniques to produce PDFs, the leading-order characteristics of the ensemble remain intact, although differences are evident, particularly at the upper limit.) However, the details are important. In the case where model parameters are only perturbed one-at-a-time, only one ensemble member is capable of sampling the high sensitivities admitted by the observational studies, and the histogram is strongly peaked around the sensitivity of the standard (unperturbed) model version (3.4K in this case). This suggests that simultaneous perturbations and interactions between uncertainties in physical processes are important in sampling both the low and the high tail. In addition, the sampling strategy or prior assumptions can clearly influence the histograms and therefore the final predictive PDFs; as they do also in the case of the observationally constrained predictions (Frame et al., 2005). Hence it is important to consider the impact of those assumptions in any predictions. In other words, we need to quantify the uncertainty in the uncertainty of our predictions.

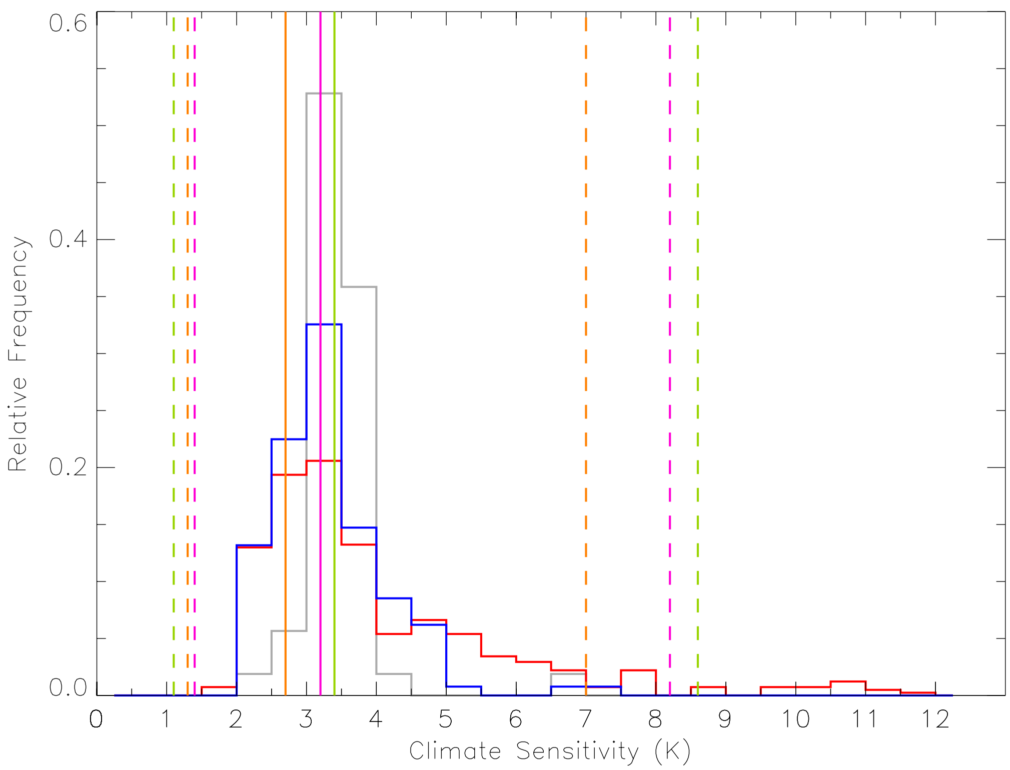

Figure 1: Un-weighted histograms of climate sensitivity from three perturbed physics ensembles. The grey curve is from the 53-member study of Murphy et al (2004) in which 29 parameters are perturbed one-at-a-time. The blue curve is from the 128-

member study of Webb et al (2006) in which the same 29 parameters are perturbed simultaneously. The red curve is from the 1148-member study of Stainforth et al (2006) in which 6 parameters are perturbed simultaneously. Histograms can be compared with PDFs of climate sensitivity produced independently from observations; pink lines from Gregory et al (2002); orange lines from Frame et al (2005) and green lines from Hegerl et al (2006). Solid lines show the median value of climate sensitivity from those studies and the dashed lines show the 5th and 95th percentiles.

Assessment of Transient Climate Response

While climate sensitivity provides a useful benchmark in assessing uncertainty, the more impacts-relevant quantity is the rate of climate change over the next few decades. This requires the use of ensembles of coupled climate models with dynamical ocean components. Figure 2 shows a comparison of a 17-member perturbed physics ensemble (with only atmosphere, surface and sea-ice parameters perturbed - Collins et al., 2006) with the current multi-model ensemble run for AR4, under a simplified scenario of CO_2 increase. This scenario largely isolates differences between physical feedbacks in models rather than differences that may result from using different implementations of forcing scenarios. The range of TCR (the 20-year average global-mean temperature change centred on the time of CO_2 doubling) is similar in the two ensembles suggesting that the perturbed physics approach is broadly capable of sampling the range of feedbacks associated with time-dependent climate change. Again though, the details are important. Only one member of the multi-model ensemble exhibits a TCR value greater than 2.2K and the ranges would not agree if this model had not been submitted to the multi-model archive. Similarly, the ranges do not agree when taking the (formal) ENSEMBLES subset of models.

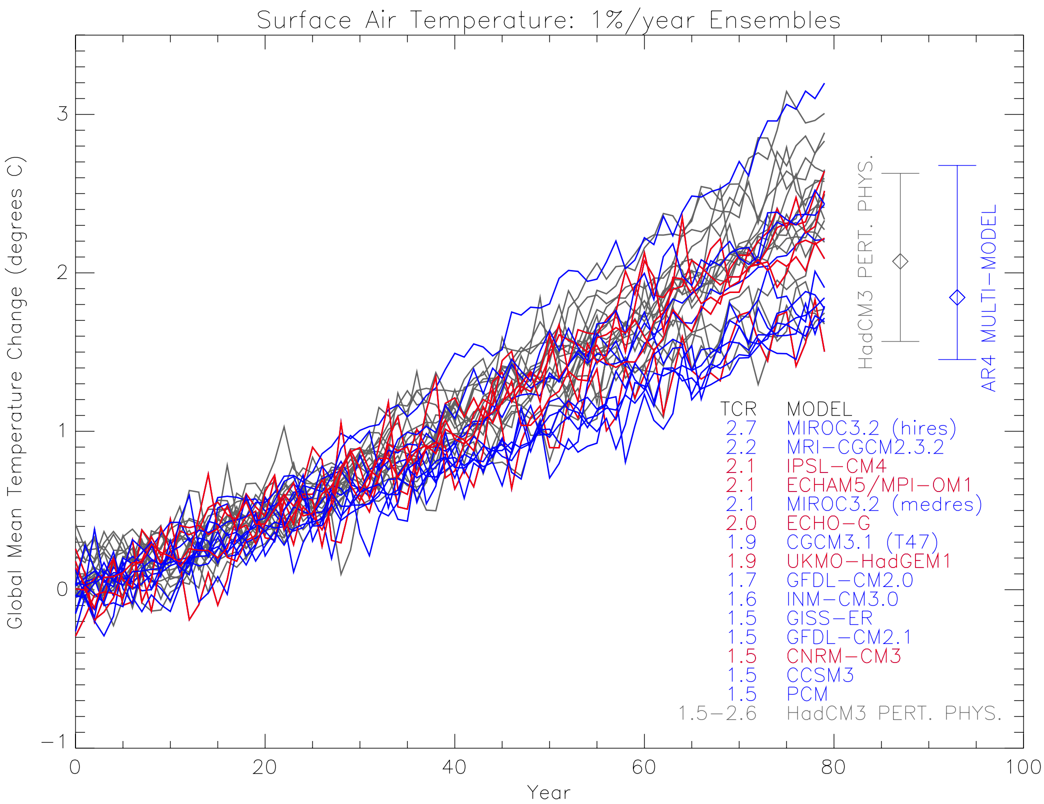

Figure 2: Global-mean temperature anomalies in experiments in which CO_2 is increased at a rate of 1% per year compounded. Anomalies are computed with respect to the corresponding control experiments with fixed CO_2. The grey lines are from HadCM3 experiments (Collins et al., 2006) with perturbations made to parameters and schemes in the atmosphere-surface-sea-ice component of the model. The coloured lines are from multi-model experiments with red lines highlighting the models which are formally part of ENSEMBLES.

Assessment of the Leading-Order Driver of Uncertainty

The above simple examination of global-mean temperature change is an important first step, but may mask differences between different ensembles in terms of their physical drivers of uncertainty. Webb et al (2006) have performed an extensive comparison of the leading-order driver of uncertainty - cloud feedbacks - between a perturbed physics and multi-model ensemble. They find that in the 128-member simultaneous-perturbation ensemble (figure 1) there is an 80% or greater overlap between the long-wave and short-wave components of the global mean cloud feedbacks between the perturbed physics and multi-model subset examined (see table 1 and Webb et al. (2006) for more details). In addition, they find that uncertainties in feedbacks associated with low-clouds explain much of the variance in total cloud feedbacks, but that in the multi-model subset, this is driven by uncertainty in positive cloud feedback, whereas in the perturbed-physics ensemble, it is driven by uncertainty in negative cloud feedback. Thus again, differences in the detailed nature of the feedbacks are important, and could lead to larger regional differences between the alternative ensembles than are seen in the globally averaged changes. It is important, therefore, to assess in more detail the drivers of regional changes in perturbed physics and multi-model ensembles, and to consider methods of combining information from the two types of ensemble (where possible) in order to obtain the best possible expression of the range of possible future changes.

	Total feedback	Total cloud feedback	Short-wave cloud feedback	Long-wave cloud feedback
Perturbed physics overlap with CFMIP multi-model	93%	91%	82%	100%
CFMIP multi-model overlap with perturbed physics	93%	85%	100%	41%

Table 1: Percentage “overlap” of ensemble spread in various feedback parameters between a perturbed physics and multi-model ensemble. The overlap is defined as the range of feedback parameter lying between, for example, the maximum value of the parameter from one ensemble and the minimum value of the parameter from the other. It is expressed in row 2 as a percentage of total spread in the multi-model ensemble and row 3 as a percentage of the total spread in the perturbed physics ensemble. Hence in row 2, column 3, the perturbed physics ensemble has a spread in total cloud feedback which is 91% of that found in the multi-model ensemble.

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