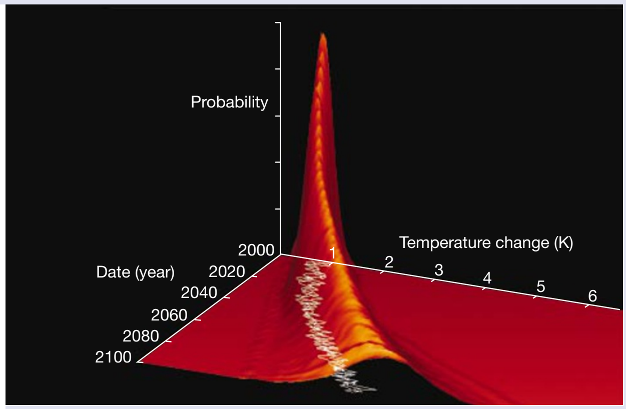
Box 1
Towards objective probabilistic climate forecasting
Myles R. Allen & David A. Stainforth

A climate forecast is intrinsically five-dimensional, spanning space, time and probability. Mainstream climate modelling has, so far, sacrificed probabilistic resolution almost completely in favour of the other four dimensions[1]. Correcting this imbalance requires a new approach. Hitherto, forecasts have explored uncertainty in initial conditions[2,3] (see Box 1 Figure opposite) as well as the impact of altering boundary conditions, such as adopting different scenarios of future concentrations of greenhouse gases[4]. For many variables, however, the main uncertainty in multi-decade climate prediction is not in the initial state nor in the external driving, but in the climate system's response[5]. Where this issue has been addressed with atmosphere–ocean general circulation models (AOGCMs) it is primarily through unconstrained 'ensembles of opportunity' based on comparisons between different models with no direct reference to observations[4,6]. These, we have argued, are likely to provide a misleadingly small (over-optimistic) impression of forecast uncertainty[7].

At the most basic level, the community needs to agree on what is meant by a 'correct' estimate of risk in climate forecasting. A probabilistic climate forecast (for example, of the risk of global precipitation increasing by more than 10% by 2050) cannot be checked against observations as can a probabilistic weather forecast. If a two-day weather forecast is wrong at the 5% level much more than 5% of the time, then something is amiss with the forecasting system. If a 50-year climate forecast is 'wrong' at the 5% level, we could simply have been unlucky. This apparent difficulty with verification has led to the view that estimates of uncertainty based on expert opinion (for example, the range for climate sensitivities used by ref. 8) are as good as any other[9]. This leaves the field open to the charge of subjectivism.

Objectively, we need to ask: 'given the observations available now, what range of forecasts might we have obtained had we started again from scratch many times over and made completely independent sets of decisions about model formulation and resolution?' A probabilistic forecast can only be said to have converged when including additional models is unlikely to make much difference to the forecast distribution of a particular variable. But there are complications. For example, we have no way of defining how 'close' two models are solely in terms of their formulation[7], so we cannot design a representative sampling strategy over 'all possible AOGCMs' even if we had the resources to do so. In practice, therefore, a probabilistic forecast must begin with a very large ensemble of possible models, obtained by varying parameter values, parameterization schemes, resolution and entire model components, and extracting a sub-sample weighted according to the different models' ability to simulate recent observed climate change. A probabilistic forecast based on this sub-sample will have converged if its spread is determined primarily by the constraint of consistency with observations and not by the choice of models within the original ensemble — this is the crucial distinction between a constrained ensemble and an unconstrained ensemble of opportunity.

For some variables, probabilistic forecasts may be converging already. Given the emergent constraints relating past to future greenhouse warming that seem to hold across all available climate models, the distribution of forecast global-mean temperature changes in Fig. 1 is determined not by the choice of model(s), but by uncertainty in how much recent warming can be attributed to CO_2 increase. This uncertainty is due primarily to other signals and internal variability in the observed climate record. It will reduce as the signal strengthens[5], but it may not change much as models improve. We would argue that this is both more robust (less subject to short-term revision) and more reliable (acceptable to non-specialists as a basis for action) than a forecast based on expert opinion.



Box 1 Figure The three-dimensional surface shows a forecast probability distribution of a one-dimensional quantity (global-mean warming above pre-industrial), accounting for uncertainty in the climate response, while the lines show the (smaller) impact of initial condition uncertainty in an ensemble of model simulations. Data courtesy of P. Stott (Met Office) and J. Kettleborough (Rutherford Appleton Laboratory)[5], based on the IPCC SRES A2 scenario.

When will we be able to say that forecast changes in the hydrologic cycle have converged enough to be trusted? We made a tentative estimate of the distribution of global-mean precipitation change in Fig. 2, primarily to show that distributions based only on the spread of current AOGCMs should not be trusted. To extend this to regional changes, we need to repeat the analysis behind Fig. 1 with a full-scale AOGCM. Figure 1 required many hundreds of integrations to explore just three uncertain parameters in a two-dimensional climate model[10], and there are hundreds of such uncertainties in an AOGCM. The chaotic nature of an AOGCM means that many of the techniques used in shorter-range forecasting to select perturbations[11] are not directly applicable to the climate problem[12]; it also means that several simulations will be needed to assess the impact of every perturbation to the model's formulation.

Thus, objective probabilistic forecasts of regional changes in rainfall and other climate variables will require numbers of simulations several orders of magnitude larger than the CMIP-2 experiment, the largest ensemble of AOGCM simulations undertaken to date. New approaches utilizing distributed computing and the emerging electronic 'grid' may provide a way forward[13,14], and readers interested in participating in such an initiative[15] may wish to contact us on http://www.climate*prediction*.net.

Dave Stainforth is at Atmospheric, Oceanic and Planetary Physics, Department of Physics, University of Oxford, Clarendon Laboratory, Parks Road, Oxford OX1 3PU, UK (e-mail: d.stainforth1@physics.ox.ac.uk)

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