Analysis of the impact of a stochastic physics parameterization on the seasonal forecasting of the North Atlantic Oscillation

Alberto ARRIBAS HERRANZ

Met Office, UK
Ensemble Forecasting Research Group
alberto.arribas@metoffice.com

ABSTRACT

In the past decade, ensemble forecasting has proved to be a successful way of dealing with the uncertainty that limits the accuracy of weather and climate forecasts. However, most ensemble systems have generally paid more attention to the uncertainty in the initial conditions (IC) than to the model error, even thought it is now fully recognised that the representation of the uncertainty related to the use of imperfect models is unavoidable. Here we present a stochastic physics scheme developed to represent the uncertainty arising from sub-grid scales. The impact of this scheme on the climatology of the model and its potential for seasonal forecasting are analyzed. It is shown that the scheme is able to impact the seasonal forecast of the North Atlantic Oscillation (NAO) with a neutral effect on the model's climatology.

Keywords: Ensemble forecasting, stochastic physics, model error, seasonal forecasting, North Atlantic Oscillation

Análisis del impacto de una parametrización física estocástica en la predicción estacional de la oscilación del Atlántico Norte

RESUMEN

Durante la pasada década, la predicción numérica utilizando ensembles ha demostrado su utilidad para tratar la incertidumbre que limita la precisión de los pronósticos meteorológicos y climáticos. Sin embargo, aunque está totalmente reconocido que la representación de la incertidumbre relacionada con el uso de modelos imperfectos es inevitable, la mayoría de los sistemas de predicción por ensembles diseñados hasta la fecha han prestado generalmente más atención a la incertidumbre debida a las condiciones iniciales que a la debida a los errores de los modelos. Aquí presentamos un esquema estocástico de perturbación de las parametrizaciones físicas desarrollado para representar la incertidumbre debida a las escalas sub-rejilla. El impacto de este esquema en la climatología del modelo y su potencial para la predicción estacional son analizados. Como se muestra, el esquema tiene un impacto en la predicción estacional de la Oscilación del Atlántico Norte (NAO, según sus siglas inglesas) con un efecto neutral sobre la climatología del modelo.

Palabras clave: Predicción por conjuntos, física estocástica, error del modelo, predicción estacional, Oscilación del Atlántico Norte.

SUMARIO: 1. Introduction. 2. System description. 3. Analysis of the results. 4. Discussion and conclusions. 5. References.

1. INTRODUCTION

The importance of the representation of model error for seasonal forecasting can be explained by the fact that, whereas the uncertainty in the initial conditions

is only present at the beginning, the uncertainty due to model error is injected throughout the whole simulation. But, as recognised in a recent assessment of the status of global ensemble prediction (Buizza et al. 2004), the representation of model errors is though to be an even greater challenge than simulating initial value related errors.

In terms of model formulation, there are two main sources of uncertainty: first of all, only imperfect models are available, and second, the resolution of these models is limited. The place where both factors more clearly come together is in what is known as physical parameterizations (i.e. the representation of the effects of processes occurring at unresolved scales using comparatively simple deterministic functions of the resolved variables). In any of them, the value of a large number of empirical-adjustable parameters and thresholds present is somewhat arbitrary, either because of being based on incomplete physical knowledge of the process or because of having been tuned to give optimal results for a test case that is not necessarily representative of more general applications (Yang and Arrit 2002). Another downside of conventional or deterministic parameterizations is that, by returning something like a mean parameterized quantity, computed from the relevant large-scale variables, they neglect the unpredictable fluctuations of the small-scale processes. The major problem is that, even if unresolved scales only describe a small fraction of the total variance of the system, neglecting it can, through the upscale of energy, lead to gross forecast errors (Palmer 2001). Therefore, a proper representation of sub-grid scale variability is needed in order to improve the seasonal forecast of large scale phenomenon (e.g. NAO).

Most of the research completed up to date accounted for the model error uncertainties through the use of different model parameterizations or a multi-model approach (Houtekamer et al. 1996; Hou et al. 2001; Mylne et al. 2001; DEMETER 2003). A slightly different approach, using a range of plausible values for some parameters in different schemes, was followed by Yang and Arrit (2002) or in the Quantifying Uncertainty in Model Prediction project (QUMP; Murphy et al. 2003) for climate prediction. In general, all these studies coincided in showing an improvement in the skill of the system (or a better estimation of the uncertainty associated to the forecast) when account for model error was introduced. But, as explained by Hansen (2002), a good multi-model ensemble should consist of a series of model attractors that systematically bound the real-system attractor. Unfortunately, the real-system attractor is unknown, hindering the construction of multi-model systems.

A different approach is to develop explicit stochastic parameterizations. This could have the advantage of allowing the forecast ensemble to explore important nearby regions of phase space that the deterministic parameterization would not reach. Interestingly, in spite the idea of stochastic parameterizations was suggested at least thirty years ago (Lorenz 1975), fewer attempts have been done in this direction. The ECMWF pioneered this approach by including a stochastic perturbation to the net effect of parameterized physical processes in their ensemble prediction system (Buizza et al. 1999). ECMWF forecasts were improved with respect to ensemble spread and rms error of the ensemble mean (Buizza et al. 1999). Lin and Neelin (2002) introduced a stochastic component to the convection scheme by using a first-order autoregression model and their results show that, by adding the stochastic scheme, the GCM simulates

part of the low-frequency convective variance normally underestimated by GCMs. Bright and Mullen (2002) extended this approach to the Convection and Planetary Boundary Layer schemes of the fith-generation Pennsylvania State University-National Center for Atmospheric Research Mesoscale Model (MM5) showing a slight increase in forecast skill. A more complex approach was developed by Gray and Shutts (2002) through their «Stochastic Convective Vorticity» (SCV) scheme. Their results over a set of case studies showed that the scheme was able to produce realistic perturbations (Gray and Shutts 2002) and preliminary tests within an ensemble showed an increase in the spread of the system (J. Delnholm-Price, personal communication).

In this study we combine the SCV with a new Random Parameters scheme (RP) with the aim to create a more complete stochastic physics scheme for the Met Office Unified Model (UM). By combining both, we attempt to better explore the uncertainty arising from the unresolved sub-grid scales and, therefore, to improve the representation of the total variance of the system. This, in turn, could result in a better forecast of large-scale patterns such as the NAO, which are of fundamental importance for the seasonal forecasting in the North Atlantic region (Rodwell and Folland 2002).

This paper is organized as follows: the system and experiments are described in section 2. The analysis of the results, including a verification of the current climate and the analysis of the impact of the stochastic scheme is presented in section 3. Finally, conclusions are presented in section 4.

2. SYSTEM DESCRIPTION

The stochastic physics scheme employed in these experiments consists of the combination of two different schemes: the Stochastic Convective Vorticity and the Random Parameters schemes.

2.1. THE STOCHASTIC CONVECTIVE VORTICITY (SCV) SCHEME

The main aim of the SCV scheme (Gray and Shutts 2002) is to represent a Potential Vorticity (PV) anomaly dipole similar to the one typically associated to a Mesoscale Convective System (MCS) in a GCM. As shown in observational studies (Bartels and Maddox 1991), MCSs possess an upper level anticyclone, associated with the cirrus outflow or anvil, and also a smaller scale mid-level cyclonic vortex near the freezing level. However, given that MCSs may be only partially resolved in the model, the PV dipole generated by them may not be well represented. Consequently, the GCM may not transfer as much of the subgrid diabatic heating into resolved balanced motions as would be suggested from high resolution modelling studies (Gray 2001). It has been also shown that PV anomalies associated with MCSs could have a significant impact on the forecast evolution, especially when located close to baroclinic areas (Beare et al. 2003).

In the SCV scheme the PV dipole is formed by two vortices, one mid-level cyclone representing the positive PV anomaly and one upper-level anticyclone

representing the negative PV anomaly, the scales of which are determined using a randomised function. Because the application of a PV anomaly through a PV inverter would make the scheme prohibitively expensive, a simpler approach, just modelling the vorticity part of the PV anomaly, was used. Also, it appears from Gray (2001) that the vorticity is more important in perturbing the forecast than the stratification, so this simplification is not expected to be detrimental to the overall impact of the scheme.

Schematically, the upper-level anticyclone is of depth d_a, centred at height z_a and consisting of a zero PV core of radius a. The mid-level cyclonic vortex is of depth d_c, centred at height z_c and is of radius ηa, where η is some constant between 0 and 1. Therefore, we have six parameters, a, d_a, d_c, z_a, z_c, and η that determines the size, shape, position and magnitude of the vorticity dipoles. In implementing a stochastic scheme all six could be given some form of random element but, given that the size of the MCS, a, is clearly the parameter which has the largest range in the atmosphere and in order to simplify the SCV scheme for initial implementation only a will vary stochastically. As suggested by Shutts (1987), the parameter a is related to the value of CAPE (Convective Available Potential Energy) according to the following formula:

$$a = c\,\frac{\sqrt{\text{CAPE}}}{f} \tag{1}$$

Where c is a non-dimensional constant containing the random element of the scheme, and linked to the convection scheme by making it proportional to the magnitude of the diagnosed convective rain rate. A more complete description of the SCV scheme can be found in Gray and Shutts (2002).

2.2. THE RANDOM PARAMETERS (RP) SCHEME

Unfortunately, because of our incomplete knowledge of the atmospheric and oceanic processes, the simplification of the equations that need to be solved or the limited computing resources, only imperfect models are available, and the physical parameterizations are the best example of this imperfectness. In any of them a large number of empirical-adjustable parameters and thresholds are given values somewhat arbitrary. Our aim in the RP scheme is to account for the uncertainty associated to these empirical parameters and, also, to simulate the nondeterministic processes that are not explicitly accounted for by the different parameterizations. Thus, each parameter value is calculated using a first-order auto regression model (Wilks 1995) as given by:

$$P_t = \mu + r(P_{t\pm1} \pm \mu) = \varepsilon \tag{2}$$

Where P_t is the parameter value at time t, μ is the mean value of the parameter, r is the autocorrelation of P and ε is the stochastic shock term.

Table 1. Parameters affected by the RP scheme. The Physics parameterization to which parameter belongs is indicated in the central column. The minimum and maximum values that bound each parameter´s value in the RP scheme are shown in the right column, together with the standard value in the UM

Parameter	Scheme	Min/ std*/Max values
Entrainment Rate Coefficient	Convection	2 / 3 / 5
Cape timescale (closure)	Convection	30 / 30 / 120 (min)
Critical Relative Humidity	Large Scale Cloud	0.6 / 0.8-0.85 / 0.9
Cloud to rain conversion threshold (land)	Large Scale Cloud	1E-4 / 8E-4 / 1E-3
Cloud to rain conversion threshold (sea)	Large Scale Cloud	5E-5 / 2E-4 / 5E-4
Parameter controlling ice fall speed (CI)	Large Scale Cloud	17 / 25.2 / 33
Flux profile parameter	Boundary Layer	5 / 10 / 20
Neutral mixing length	Boundary Layer	0.05 / 0.15 / 0.5
Gravity wave constant	Gravity wave drag	7.5E4 / 7E4 / 1.3E4
Froude number	Gravity wave drag	2 / 2 / 4

A total of 10 parameters from 4 different physical parameterizations are included in the 2004/05 version of the scheme. In order to avoid unrealistic values, each parameter is bound by a minimum and maximum value as estimated by experts in each field (Table 1). The stochastic shock term, ε, is sampled from a uniform distribution between $\pm (P_{max} - P_{min})/3$, and the autocorrelation r has been given a value of 0.90. Because no knowledge exists a priori of ε and r values, both were determined empirically after some limited tuning of the RP scheme. Finally, the parameters' values are the same for all grid points (i.e. the spatial correlation is 1).

2.3. EXPERIMENTS DESCRIPTION

Two 3-year simulations, a *control* run and a run including *stochastic physics* scheme, were completed using the HADGAM1 version of the Met Office Unified Model. HADGAM1 is an atmospheric only model evolved from HADCM3, the model used operationally by the Hadley Centre until 2003. The horizontal resolution is 3.75×2.5 degrees (lon-lat) with 38 levels in the vertical. SSTs were prescribed using observed data.

Although three years is too short for a full quantitative analysis of climate differences between the two runs, it is long enough to spot any significant systematic changes that the presence of the stochastic scheme may cause.

3. ANALYSIS OF THE RESULTS

To evaluate how well both simulations reproduced climate we used the Climate Prediction Index (CPI; Sexton et al. 2002). The CPI measures how well a climate model
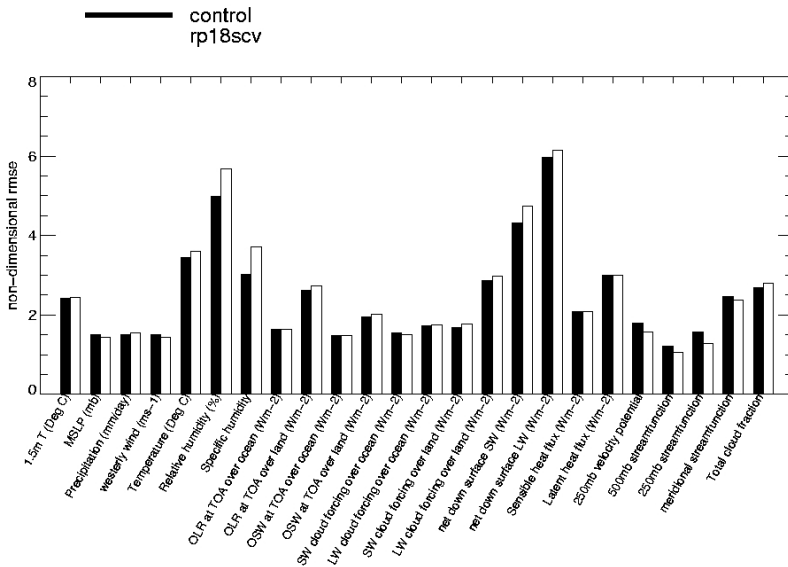
Figure 1. Climate prediction index values for all analyzed variables (x-axis) in the control and stochastic (RP18SCV) runs.

reproduces various aspects of the climate system such as atmospheric radiation and clouds, atmospheric dynamics, the hydrological cycle and surface fluxes. A complete list of all variables used can be found on x-axis in Figure 1.

For each modelled seasonal means (DJF, MAM, JJA, SON) each variable is compared against the appropriate observational or reanalysis data set using a normalised version of root-mean square error. This statistic penalises bias, differences in the spatial variances of the observed and modelled means and poor patterns correlations. The closer the CPI values to 0 the better.

The CPI values for both simulations are similar, 2.461 for the control run and 2.534 for the stochastic physics run, values that can be both considered very good (typical values for the HADCM3 were around 3.0 depending on the configuration). The total CPI value for the control run is slightly better than the stochastic run, mainly due to the contribution from the relative and specific humidity components of the CPI (see Figure 1). This is caused by the impact of the stochastic scheme on the «critical relative humidity» parameter (it seems that the minimum value for this variable inside the RP scheme is too low), something that could be tuned in future versions of the scheme to produce better results. However, there are other variables in which the stochastic run is outperforming the control run, especially in the «dynamical» variables, such as, 250mb velocity potential or the different stream function components.

An example of how similar both simulations are is shown in Figure 2, where the 3-year average values of mean sea level pressure (PMSL) during the DJF season are presented. As it can be seen, there are little differences between both simulations, which
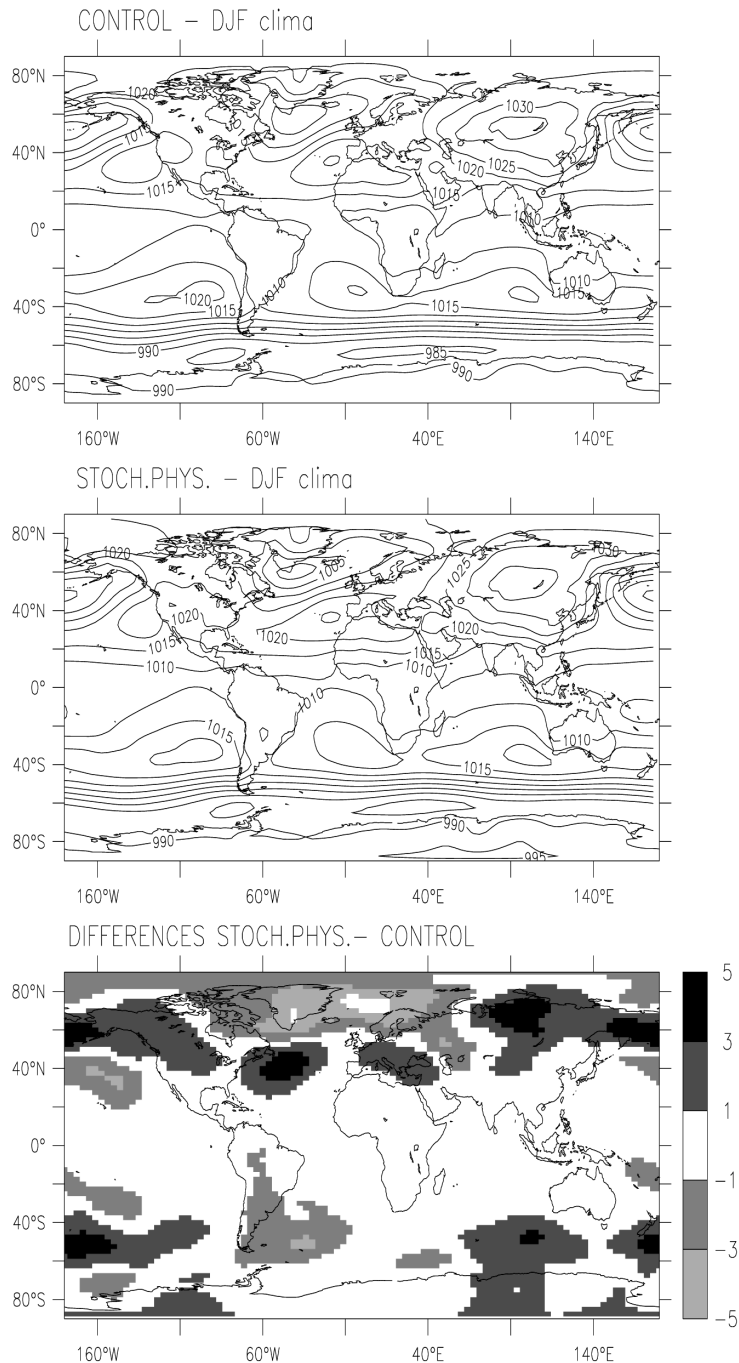
Figure 2. Climatological (3-year) mean of seasonal (DJF) PMSL for the control
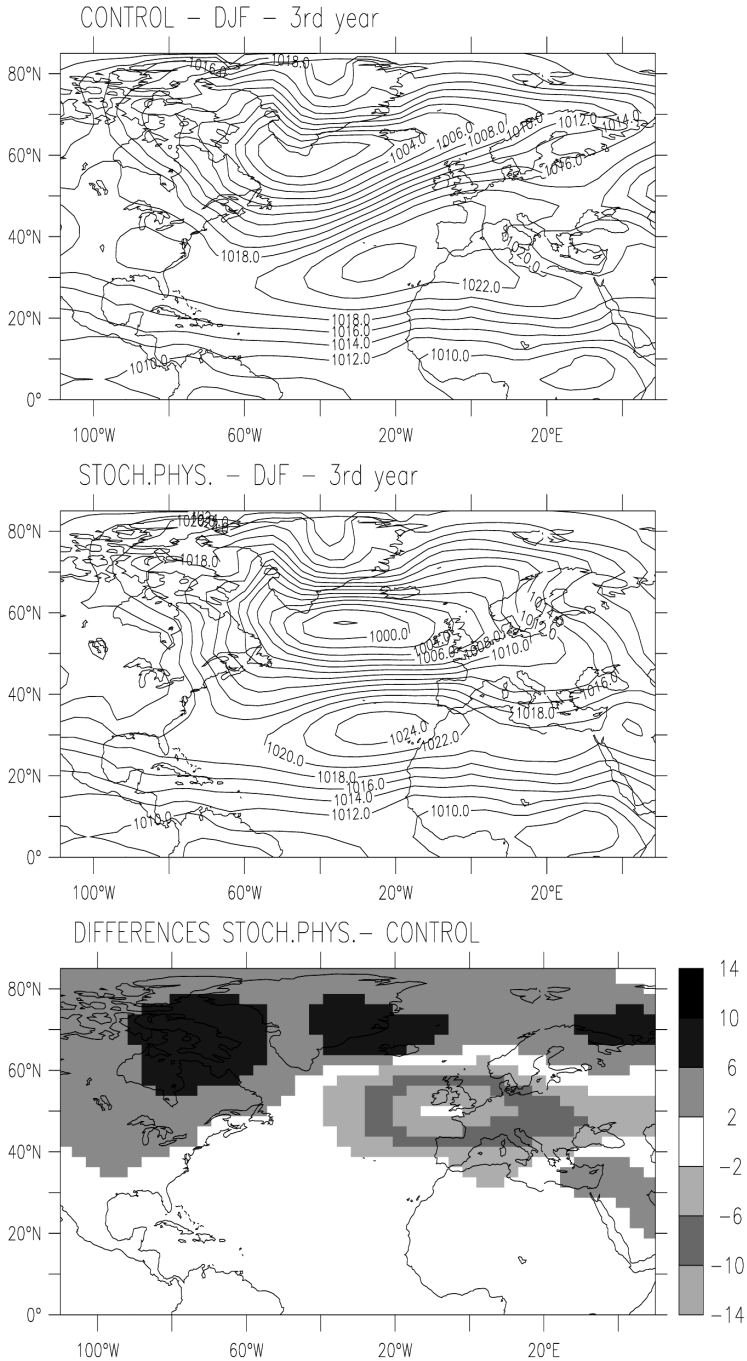(top) and stochastic (center) runs. Differences are plotted in the bottom figure.

Figure 3. PMSL seasonal (DJF) mean at year 3 for control (top) and stochastic (center) runs. Differences are plotted in the bottom figure.

also agree well with climatological distributions (e.g. ECMWF 15-year reanalysis, not shown). Therefore, we can conclude that both simulations are correctly representing the current climate and that the stochastic scheme is not having a noticeable impact (either positive or negative) on the model climate. This is very encouraging, especially considering that we are comparing the stochastic scheme against a well tuned control version of the model.

Having ascertained that the stochastic scheme is having a neutral impact on the model's climate, we still need to verify if, as intended, it is capable to impact the forecast evolution on seasonal time-scales. One way of addressing this is to analyse the seasonal differences between both simulations. If the scheme is successfully feeding back the sub-grid scale variability onto the resolved flow we should be able to find significant differences (i.e. larger than in the climate means) between the control and the stochastic runs. Figure 3 shows the PMSL fields for DJF at year 3. The top panel corresponds to the control run, the middle one to the stochastic physics run, and the differences between both are shown in the bottom panel. As it can be seen, differences are substantial. In fact, each run is simulating a different phase of the NAO. Thus, whereas the control run is simulating a positive NAO phase, with stronger winds crossing the Atlantic Ocean on a more northerly track, the stochastic physics run is simulating a negative NAO phase, with winds following a more west-east pathway.

4. DISCUSSION AND CONCLUSIONS

In this work the RP+SCV stochastic scheme has been shown to be able to perturb forecasts on a seasonal timescale whereas having a neutral impact on the model's climatology. Our analysis shows that, even when the initial and boundary conditions (SSTs) are kept unchanged, the inclusion of sub-grid scale variability may have a substantial impact on the large-scale flow characteristics such as the NAO. A plausible hypothesis is that the RP+SCV scheme is seeding disturbances in the synoptic scales resolved by the model, where they amplify by extracting energy from the large-scale background flow as proposed by Tribbia and Baumhefner (2004).

This suggests that an explicit representation of model error (caused by unresolved or unknown processes) is unavoidable in ensemble systems designed for seasonal forecasting.

5. REFERENCES

BARTELS, D. L. & R. A. MADDOX (1991). Midlevel cyclonic vortices generated by mesoscale convective systems. *Mon. Wea. Rev.,* 119, 104-118.

BEARE, R. J.; A. J. THORPE & A. A. WHITE (2003). The predictability of cyclones: non-linear sensitivity to localised potential vorticity perturbations. *Quart. J. Roy. Meteorol. Soc.,* 129, 219-237.

BUIZZA, R.; M. MILLER & T. N. PALMER (1999). Stochastic representation of model uncertainties in the ECMWF EPS. *Quart. J. Roy. Meteorol. Soc.,* 125, 2887-2908.

BUIZZA, T.; P. L. HOUTEKAMER, Z. TOTH, G. PELLERIN, M. WEI & Y. ZHU (2004). Assessment of the status of global ensemble prediction. Submitted to *Mon. Wea. Rev.*

BRIGHT, D. R. & S. L. MULLEN (2002). Short-range ensemble forecasts of precipitation during the southwest monsoon. *Wea. Forecasting*, 17, 1080-1100.

DEMETER (2003). http://www.ecmwf.int/research/demeter.

GRAY, M. E. B. (2001). The impact of mesoscale convective system potential vorticity anomalies on numerical weather prediction forecasts. *Quart. J. Roy. Meteorol. Soc.,* 127, 73-88.

GRAY, M. E. B. & G. J. SHUTTS (2002). A stochastic scheme for representing convectively generated vorticity sources in general circulation models. APR Turbulence and Diffusion Note No. 285. Met Office, UK.

HANSEN, J. A. (2002). Accounting for Model Error in Ensemble-based state estimation and forecasting. *Mon. Wea. Rev.,* 130, 2373-2391.

HAMILL, T. M. & S. J. COLUCCI (1997). Verification of Eta-RSM short-range ensemble forecasts. *Mon. Wea. Rev.,* 125, 1312-1327.

HOU, D., E. KALNAY & K.K. DROEGEMEIER (2001). Objective verification of the SAMEX'98 ensemble forecasts. *Mon. Wea. Rev.,* 129, 73-91

HOUTEKAMER, P. L.; L. LEFAIVRE, J. DEROME, H. RITCHIE & H. L. MITCHELL (1996). A system simulation approach to ensemble prediction. *Mon. Wea. Rev.,* 124, 1225-1242.

LIN, J. W. B. & J. D. NEELIN (2000). Influence of a stochastic moist convective parameterization on tropical climate variability. *Geophys. Res. Lett.,* 27, 3691-3694.

LORENZ, E. N. (1975). Climate predictability. The physical basis of climate modelling, W.M.O. GARP Pub.Ser., 16, 132-136.

MURPHY, J.; D. BARNET, D. SEXTON & M. WEBB (2003). Quantifying uncertainties in the response of mean climate and extreme events to a doubling of carbon dioxide: The relative contributions of modelling errors and natural variability. Report to DEFRA, 14/2/03, Hadley Centre, The Met Office, UK.

MYLNE, K. R.; R. E. EVANS & R. T. CLARK (2001). Multi-model multi-analysis ensembles in quasi-operational medium-range forecasting. *Quart. J. Roy. Meteorol. Soc.,* 128, 361-384.

PALMER, T. N. (2001). A nonlinear dynamical perspective on model error: A proposal for non-local stochastic-dynamic parametrization in weather and climate prediction models. *Quart. J. Roy. Meteorol. Soc.,* 127, 279-304.

RODWELL, M. J. & C. K. FOLLAND (2002). Atlantic air-sea interaction andseasonal predictability. *Quart. J. Roy. Meteor. Soc.,* 128, 1413-1443

SEXTON, D.; D. BARNET, J. MURPHY, G. S. JONES & M. WEBB (2002). Measuring the quality of HadSM3 simulations and its impact on the uncertainty of climate sensitivity. Report to DEFRA, 14/3/02, Hadley Centre, The Met Office, UK.

SHUTTS, G. J. (1987). Balanced flow states resulting from penetrative, slantwise convection. *J. Atmos. Sci.,* 44, 3363-3376.

TRIBBIA, J. J. & D. P. BAUMHEFNER (2004). Scale interactions and atmospheric predictability: An updated perspective. *Mon. Wea. Rev.,* 132, 703-713.

WILKS, D. S. (1995). Statistical methods in the atmospheric sciences – an introduction. International Geophysics Series. Vol 59, Academic Press, New York, USA

YANG, Z. & R. W. ARRIT (2002). Tests of a perturbed physics ensemble approach for regional climate modelling. *J. Climate.*