1.1 IMPACT OF A STOCHASTIC PERTURBATION SCHEME ON NCEP GLOBAL ENSEMBLE FORECAST SYSTEM

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1. INTRODUCTION

Effort has been made to represent model uncertainties since 1990s. Toth and Kalnay (1995) deliberately inflate the ensemble perturbations during the integration to increase the ensemble spread. Multi-model and multi-model version approaches are employed in both operational systems (e.g. Houtekamer et al., 1996) and experimental tests (e.g. Stensrud et al. 2000 and Hou et al. 2001). On the other hand, the use of stochastic noise to represent unpredictable small-scale variability, in the form of stochastic physics with the ECMWF ensemble forecast system (Buizza, et al, 1999) and the stochastic backscatter applied to the UK Met Office model (Frederiksen and Davies 1997), appear to have beneficial effect on forecast skills and synoptic variability. Based on these considerations, research is being conducted at EMC/NCEP to develop a practical and effective stochastic parameterization scheme within NCEP's Global Ensemble Forecasting System (GEFS). The scheme is based on random combinations of the tendencies of the ensemble perturbations and referred as a Stochastic Perturbation Scheme (SPS). The experiments with a simplified version of SPS (Hou, Toth and Zhu 2006, HTZ hereafter) show encouraging results. Since 2006, GEFS has been running under the Earth System Modeling System (ESMF) environment and this makes it possible to employ the scheme in the operations with a more realistic version. This paper presents the results of experiments with SPS at operational environment and discuss the impact of the scheme on the GEFS model output.

2. FORMULATION OF THE SCHEME

The general framework with stochastic presentation of model related uncertainties is to add a stochastic forcing term S to the conventional tendency T, for each member *i* of the ensemble system, i.e.,

$$X_i = T_i + S_i \qquad (1)$$

The stochastic formulation of the ECMWF ensemble system (Buizza et al. 1999) links stochastic forcing S to regions in the atmosphere where conventional subgrid parameterization is active (Palmer, 2001). A different approach is adopted in the current scheme by linking the stochastic forcing term S to the total conventional forcing T (including the grid scale and subgrid scale parameterizations). It is assumed that the conventional tendencies of the ensemble perturbations

$$\boxed{P_i = T_i - T_0}$$

provide a sample of realizations of the stochastic forcing. Therefore, the S terms are formulated by various combinations of the P vectors, i.e.,

$$\boxed{S_i \sim \sum_j w_{i,j} P_j}$$

where i and j are the index denoting the ensemble members and the summation is taken over all N ensemble members j=1, N.

With the simplified version of the scheme (HTZ), two approximations are made. Firstly, the scheme is applied every 6 hours and the conventional tendency T_i is approximated by 6h finite differences. Secondly, the combination of the P vectors for a particular member i, is replaced by a single Pj vector randomly selected from the P vectors excluding j=i. While keeping the first approximation, the scheme is improved by randomly combine all of the P vectors. This is realized by a procedure similar to Ensemble Transform (ET) technique but applied to ensemble perturbation tendencies (instead of the ensemble

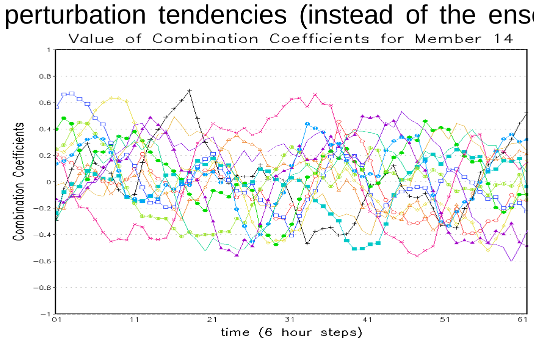

Fig.1 Examples of the temporal variation of the combination coefficients wi,j. N=14 is assumed and shown are the 14 curves for i=14 and j=1 to 14.

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perturbations) successively (not only at the initialization of the integration).

To illustrate the procedure, S and P, as well as w, are expressed as functions of time t and written in matrix form, i.e.

$$\underset{M\times N}{S(t)} = \underset{M\times N}{P(t)}\ \underset{N\times N}{W(t)} \qquad (2)$$

Where M is the number of grid points and N the number of ensemble members. The elements of Matrix W are the random weights used to combine the ensemble tendency perturbations and the Appendix describes the algorithm used to generate these coefficients. Each $w_{i,j}$ varies like a random walk imposed on a periodic function and some examples are shown in Fig. 1.

Once the combination coefficients $w_{i,j}$ are specified, the stochastic perturbation scheme is executed by periodically (every 6 hours) halting the integrations and modifying the model state X_t by

$$X_i^{'} = X_i + \gamma_t \sum_{j=1}^{N} w_{i,j}(t)\left\{\left[(X_j)_t - (X_j)_{t-6h}\right] - \left[(X_0)_t - (X_0)_{t-6h}\right]\right\} \qquad (3)$$

where the coefficient γ_t represents a global rescaling factor to reduce the stochastic forcing perturbations to a representative size. As shown in Fig.2, the ESMF software allows for concurrently running all ensemble members (including the control) and periodically modifying each model state X_i by using information from all other members.

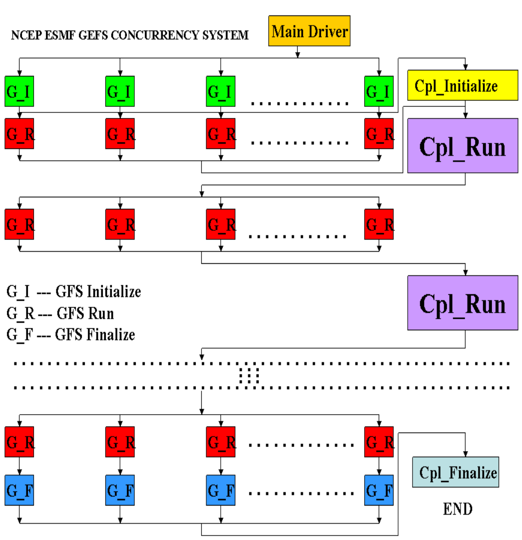

Fig.2 A flow chart showing GEFS forecast component under ESMF environment. All of the ensemble members (including the control), each shown as a vertical column, are running concurrently. The blocs G_I, G_R, and G_F represent procedures to start, run and finish the GFS model integrations. The model state modification is performed by the Cpl_Run procedure, while Cpl_Initiate and Cpl_Finalize serve as supporting subroutines of the Cpl module.

The model perturbations, or stochastic forcing terms generated with this scheme are for all of the model variables and they are at approximate balance. The perturbations have structures of random noise and their variances (and kinetic energy) have flow-dependent geographic patterns.

3. IMPACT OF THE SPS SCHEME

The SPS scheme is tested for two periods, Aug. 16 to Sep. 30, 2006 (AS) and Dec. 30, 2006 to Jan. 29 2007 (DJ), representing northern hemisphere warm and win cold season, respectively. GEFS operational configuration with N=14 members, T126 horizontal resolution and 28 vertical levels, is used and Ensemble Transform (ET) is employed to generate the initial conditions (Wei et al., 2008). The integration was conducted with the stochastic parameterization scheme (SPS) and without it, with identical perturbations in the initial conditions and the results are compared to show the impact of the scheme.

3.1 *Ensemble Mean and Spread*

In fig.3, the mean error (ME or bias, solid lines near the bottom of the panel) and the root mean

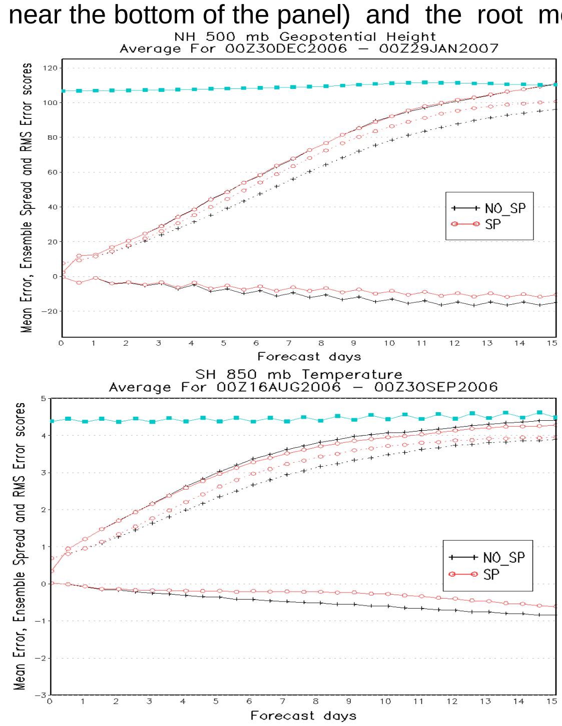

Fig.3 ME(solid curve in the lower halff of each panel) and RMSE (solid above 0) of ensemble mean forecast, and the ensemble spread (dashed), for Northern Hemisphere 500hPa height (upper panel) and Southern Hemisphere 850hPa temperature (lower panel) averaged over AS, as functions of forecast lead time. The red and black lines are for the ensemble with and without SP, respectively.

square error (RMSE, the other solid curve) of the ensemble forecast, as well as the ensemble spread (dashed) are plotted for the ensemble mean forecast with (red) and without (black) SP, for 500hPa height and 850hPa temperature. With the SP scheme, the spread is significantly increased. Although an increase in spread itself is not an indicator of forecast improvement, the associated reduction in the number of outliers does provide a mechanism for better interpretation of the forecast at the current level of forecast errors. Although RMSE is not reduced consistently, the reduction in ME is seen in both height and temperature, over all 3 domains (NH, SH and Tropics) and 2 seasons (AS and DJ). As shown in HTZ, Mean Absolute Systematic Error (MASE) is also reduced when SPS is used. Also note that ME and MASE are measures of systematic errors. For lead time longer than 2 days, systematic error is significantly reduced. It is interesting to point out that SPS tends to reduce negative ME of height and temperature, but not positive ME. This has significant implications in tuning the scheme and will be discussed in section 4.

3.2 *Ensemble Based Probabilistic Forecast*

Similar to the results shown in HTZ, probabilistic forecast verification scores are calculated for the ensembles with and without the stochastic perturbation scheme. Fig. 4 shows the results for the reliability (solid) and resolution (dashed) component of the Brier Skill Score (BSS). The former is reduced (leading to an increase in BSS) for the forecasts of 2 days or longer lead time, while the latter remain unchanged.

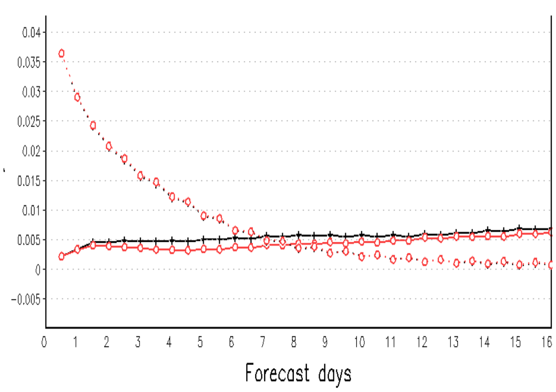

Fig. 4 Reliability (solid) and resolution (dashed) components of Brier Skill Score) as functions of lead time, averaged over AS period. The red and black curves are for ensembles with and without SPS, repectively.

As In HTZ, Ranked Probability Skill Score (RPSS) is calculated and the results show that the improvement induced by the SPS scheme is initially small and increases with time (not shown).To further demonstrate the impact of the scheme on the ensemble distribution, Continuous Ranked Probability Score (CRPS) is also computed. CRPS is the integral of the Brier Score of all possible threshold values for a continuous predictand averaged over the test data. It is reduced to Mean Absolute Error (MAE) for a deterministic-style (single) forecast. The corresponding skill score (CRPSS) is calculated for each grid point with a reference forecast based on the climatological distribution. As shown in Fig.5, the stochastic perturbation scheme led to significant improvement in the ensemble distribution and ensemble based probabilistic forecast.

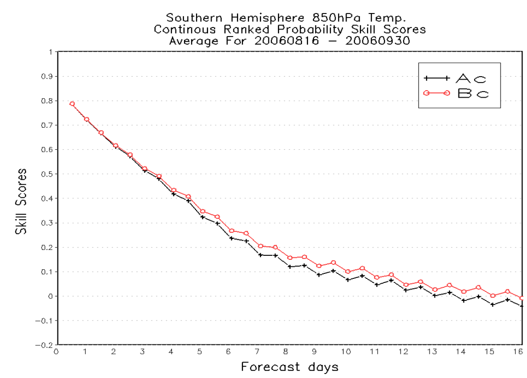

Fig. 5 CRPSS, as a function of lead time, for 850hPa temperature, averaged over Sothern hemisphere and AS. The red and black curves are for ensembles with and without SP.

4. A SIMPLE RESCALING METHOD

Preliminary experiments suggests that the impact of SPS on the mean error of the ensemble mean forecast and ensemble spread is proportional to the rescaling coefficient γ_t in Eq.(3), or the size of the perturbations. However, as mentioned in section 3.1, SPS only reduces negative ME. Therefore, the specification of γ_t is very important to maximize the benefit and avoid negative impacts associated with SPS. In the previous section, this parameter is empirically specified as a function of the forecast leading time only and taking the following form

$$\gamma_0(t) = 0.1 \qquad \text{If } t<120\text{h}$$

$$\gamma_0(t) = 0.1 - (0.1 - 0.02)\frac{t - 120h}{384h - 120h} \qquad \text{If } t>120\text{h} \tag{4}$$

As the added stochastic perturbations tend to reduce only negative ME, which has different values in the two hemispheres and have seasonal variations, Eq.(4) is not the optimal choice and fine tuning of the coefficient is necessary. A simple tuning method is tested and presented in this section.

Fig. 5 shows daily variation of ME over northern and southern hemispheres from Aug. 16 2006 to Aug.15, 2007, for the GEFS operational forecast of 500hPa height at day 9. Seasonal variations are clear in both hemispheres and they are roughly out of phase. The maximum is around Jan. 1 over the southern hemisphere and July 1 over the Northern Hemisphere, consistent to the results for the previous years. To incorporate this seasonal cycle into the tuning of γ_t, it is assumed that

$$\gamma_t = \gamma_1 \gamma_0 \qquad (5)$$

and

$$\gamma_1 = 1.0 + A \sin(\theta) \sin \frac{2\pi (d - 91)}{364} \qquad (6)$$

where θ is latitude, d the Julian day, and A an adjustable amplitude. Note that A=0.0 reduces (6) to (4) and A=0.2 is used in this section.

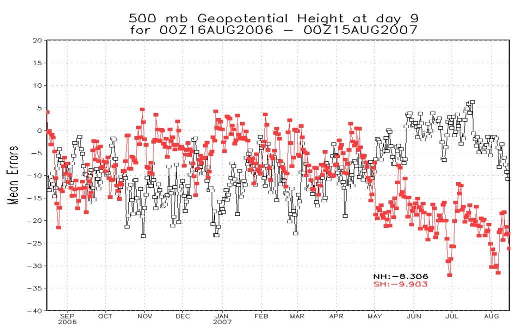

Fig.6 Daily variation of mean error in GEFS operational 9-day forecast of 500hPa height, averaged over the Northern (black) and Southern (red) Hemisphere, showing the seasonal cycle and the phase difference between the two hemispheres.

Fig. 7 compares the RPSS score of 500hPa forecasts over the Southern Hemisphere averaged over DJ. Note from fig.6 that ME is characterized by small negative or even positive values for this period. When γ is specified by (4), over correction of ME is applied and this may hurt the ensemble based probabilistic forecast (red curves). Reducing the perturbation size over by using (6) (the green curve) led to higher RPSS scores. More complicated formulation of this coefficient, presumably, varying with longitude and following the real value of the recent ME values, may further improve the forecast and require careful investigations.

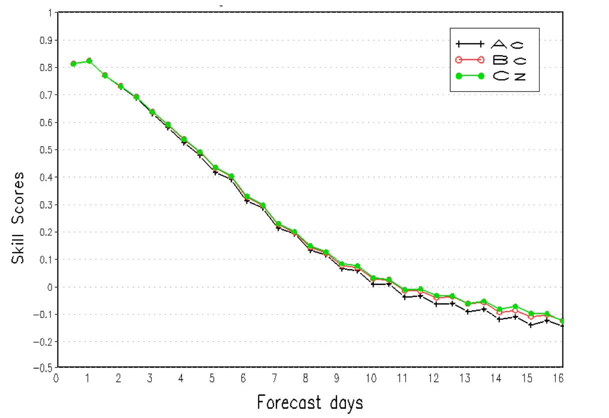

Fig. 7 RPSS, as a function of lead time, for 500hPa height, averaged over Sothern Hemisphere and DJ. The black curve is for the forecast without SP, while red and green for forecasts with SP formulated using (5) and (6), respectively.

5. SUMMARY AND SUGGESTIONS

A stochastic parameterization scheme is developed based on the tendencies of ensemble perturbations. The scheme is tested with NCEP Global Ensemble Forecast System and it can be practical under the ESMF environment. The results of recent experiments confirmed the tentative conclusions from previous experiments based on a simplified version of the scheme (HTZ). Specifically, it is demonstrated that

(1) The stochastic scheme can significantly improve ensemble forecast with increased spread and reduced systematic errors in the ensemble mean;

(2) For probabilistic forecasts, the stochastic scheme can significantly improve RPSS, BSS and other scores; In addition, it is shown in this study that Continuous Ranked Probability Skill scores (CRPSS) can be significantly improved.

It is also revealed that the size of the stochastic perturbations, or the coefficient γ, should vary in time and space. A simple method in specifying this parameter is proposed and tested. The method allows γ to vary with latitude and season, based on the seasonal variation of domain averaged model error (ME) in 500hPa height over the two hemispheres. It led to more improvement in the forecast, compared with a globally specified γ. However, more research is required in tuning the scheme to maximize the benefit of the stochastic perturbation scheme and avoid negative impacts.

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APENDIX: GENERATION OF THE W MATRIX

In eq.(2), because P is orthogonal, an orthonormal matrix W can ensure that S is also orthogonal. In a M-dimensional space, the N orthgogonal P-vectors are rotated to generated N orthogonal S-vectors. Therefore, the problem is reduced to specifying the orthonormal matrix W as a random function of time. W is specified at t=0 as a random but orthonormalized matrix, by filling it with independent Gaussian random numbers and then applying Gram-Schmidt orthonormalization. Random proper rotations are then applied in an N-dimensional space to the W matrix at each time the scheme is applied, i.e.,

$$W(t) = W(t-1)\ R_0(t=0)\ R_1(t)$$

where R denotes a matrix of dimension NxN, which is a random perturbation of the identity matrix. The subscripts 0 and I denote two such rotations, with the former specified at t=0 and the fixed for all t, and the latter randomly specified at each time t. The variation of W specified this way can be viewed as a random rotation (R_1) imposed on a steady rotation R_0. Similarly, its elements, or the random combination coefficients $w_{i,j}$ vary like a random walk imposed on a period function. By specifying the amount of the rotation in R_0 and R_1, one can control the variation of these coefficients. Some examples are shown in Fig. 1.

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