4.5 A STOCHASTIC PARAMETERIZATION SCHEME WITHIN NCEP GLOBAL ENSEMBLE FORECAST SYSTEM

Dingchen Hou*, Zoltan Toth and Yuejian Zhu
Environmental Modeling Center/NCEP/NOAA, Camp Springs, Maryland

1. INTRODUCTION

Current operational ensemble forecast systems have a common shortcoming: the ensemble spread is significantly less than root mean square error of the ensemble mean forecast (Buizza et al, 2004). For the NCEP Global Ensemble Forecast System (GEFS), there is also significant bias in the mean forecast. Specifically, the mean error averaged over the northern or southern hemispheric extratropics for the 500hPa height and 850hPa temperature can be over 10m and $1°C$, respectively, in medium range forecasts. These deficits are mainly due to the inadequate representation of model uncertainty. In the operational GEFS system, model related uncertainties are neglected.

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). However, the attempt to include model uncertainty in GEFS, represented by the two available cumulus parameterization schemes lead to insignificant improvement in the forecasts of the atmospheric circulation variables (Hou et al. 2004). 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 GEFS. The results from some experiments with the scheme are reported in this paper.

* Corresponding author address: Dingchen Hou, Environmental Modeling Center/NCEP/NOAA,W/NP2 NOAA WWB #207, 5200 Auth Road, Camp Springs MD 20746; email: dingchen.hou@noaa.gov.

2. FORMULATION AND CHARACTERISTICS

The stochastic formulation of the ECMWF ensemble system (Buizza et al. 1999) links stochastic forcing to regions in the atmosphere where conventional subgrid parameterization is active (Palmer, 2001). A different approach, similar to the "stochastic backscatter", is adopted in the current scheme. With this approach, the stochastic forcing is linked to the total conventional forcing (including the grid scale and subgrid scale parameterizations). In addition, the stochastic forcing is sampled from the differences in the conventional tendency between the ensemble members and the control forecast and the scheme is applied every 6 hours. With subscripts i and j representing one of the N ensemble members, i=1,2,…,N, 0 the control forecast and t the time after the initialization of the integration, the conventional model equation

$$\dot{X}_i = T_i$$

is replaced by

$$\dot{X}_i = T_i + \alpha_i \left\{ \frac{\left[(X_j)_t - (X_j)_{t-6h} \right] - \left[(X_0)_t - (X_0)_{t-6h} \right]}{6hr} \right\}$$

for t=k x 6hr, k=1,2,3,….., where the coefficients α's represent rescaling of the stochastic forcing perturbations to a representative size in each of the 3 domains of northern hemisphere extratropics (NH), southern hemisphere extratropics (SH) and the tropics (TR), using 500hPa kinetic energy as the norm. Note that α's can be positive, negative or 0, and they sum to unity:

$$\sum_i \alpha_i = 0 .$$

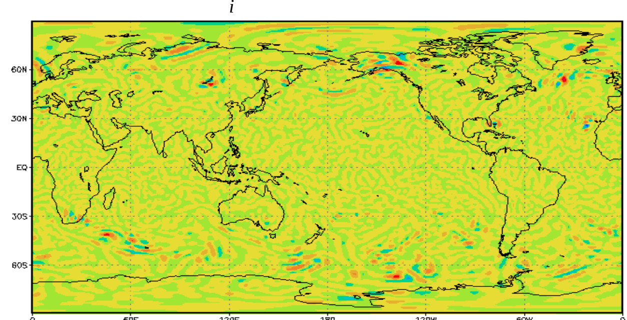

Fig.1 An example of stochastic forcing terms for vorticity near 500hPa, valid at t=18h in the forecast initialized at 00Z, Sep. 25, 2004.

The model perturbations, or stochastic forcing terms generated with this scheme are for all of the model variables and they are at approximate balance. As shown as an example in fig.1, the perturbations have structures of random noise and their variances (and Kinetic Energy) have a flow-dependent geographic pattern.

3. EXPERIMENTS AND RESULTS

The scheme is tested for the month of October 2004, using the GEFS operational configuration (N=10 or 5 pairs of bred perturbations in the initial conditions) valid for the period. Daily 00Z 15 day forecast is initialized with a higher resolution (T126) and truncated to a lower one (T62) at t=180h. An experiment with the stochastic parameterization scheme (SP) and another, with identical perturbations in the initial conditions but integrated without SP in the model, are conducted.

3.1 *Outliers*

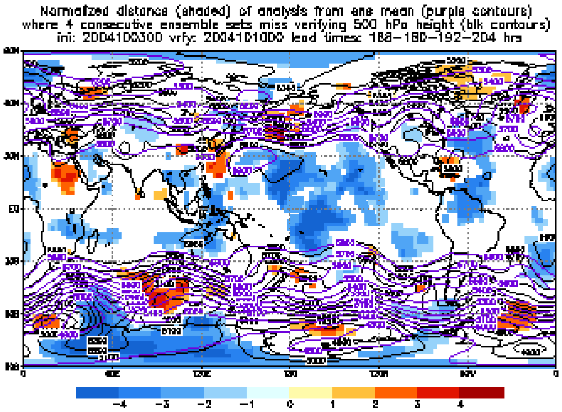

Fig2. Distribution of outliers for 192h 500hPa forecast from the ensemble with SP.

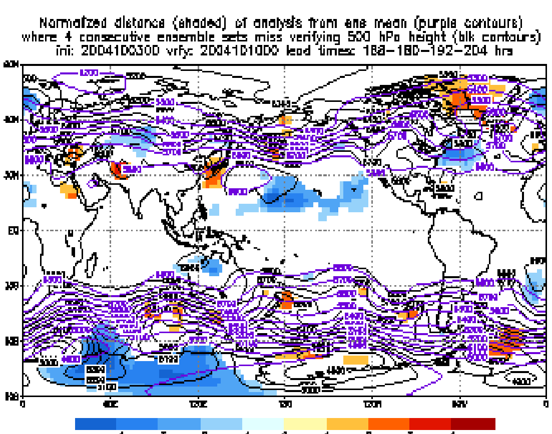

Fig3. Distribution of outliers for 192h 500hPa forecast from the ensemble without SP.

A dramatic impact of the stochastic parameterization scheme is to reduce the number of outliers, or the grid points at which the verifying analysis falls outside the range of the ensemble member forecasts. Figs.2 and 3 show a randomly-selected example of 500hPa height ensemble forecasts, with the areas of outliers shaded with cold color (blue) for negative forecast bias and warm color (yellow to brown) for positive bias. Without SP (fig.2) there are extensive areas of outliers with cold bias dominating. When SP is included (Fig.3), the area (or number) of outliers is significantly reduced, both in the tropics and in the extrtropics.

3.2 ***Ensemble Mean and Spread***

The result in section 3.1 can be generalized with statistics or verification scores of the ensemble mean forecast, and the ensemble spread, both averaged for the whole month, shown in Fig.4.

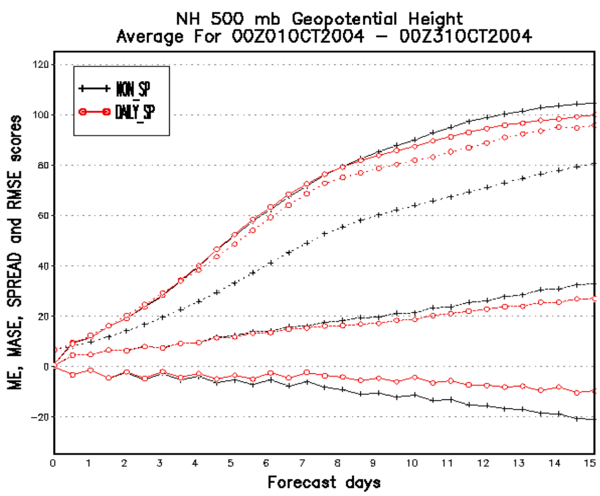

Fig.4 Ensemble spread, ME, MASE and RMSE of 500hPa height ensemble mean forecast, averaged for October, 2004, as functions of forecast lead time. The red and black lines are for the ensemble with and without SP, respectively.

In fig.4, the ensemble spread (dotted lines), mean error (ME or bias, solid lines near the bottom of the panel), root mean square error (RMSE, solid lines near the top of the panel) and mean systematic error (MASE, the dashed lines in the middle of the panel) are plotted for the ensemble mean forecast with (red) and without (black) SP. With the SP scheme, the spread is significantly increased and is roughly the same magnitude as RMSE. Although an increase in spread 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 and MASE is seen in all 3 domains. ME and MASE are measures of systematic errors and this can be seen from their definitions

$$ME = \overline{\langle f - a \rangle} = \langle \overline{(f - a)} \rangle$$

$$MASE = \overline{\left| \langle (f - a) \rangle \right|}$$

where the angle bracket and the overbar indicate temporal and domain average, respectively. For lead time longer than 2 days, systematic error is significantly reduced. For 15 days forecast, the reduction is about half in ME and 15% in MASE.

3.3 *Comparison with Bias-correction*

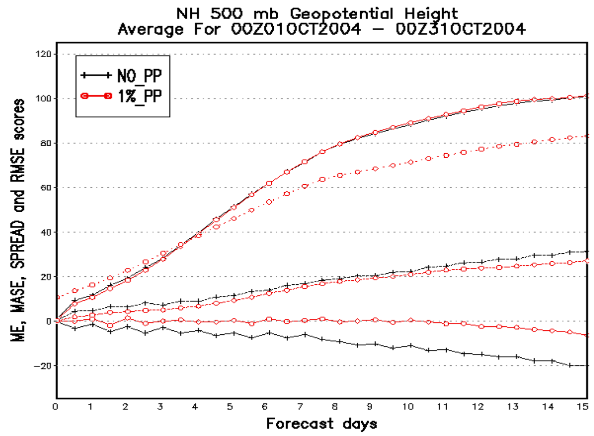

Fig.5 Ensemble spread, ME, MASE and RMSE of 500hPa height ensemble mean forecast, averaged for October, 2004, as functions of forecast lead time. The red and black lines are for the ensemble with and without bias correction, respectively. No SP is applied.

It is well-known that systematic error can be reduced with a post–processing procedure, i.e., bias correction. This involves estimating the bias at each grid point and subtracting it from the forecast. With a dependent training period and using temporal mean error as the estimated bias, the temporal mean of ME and MASE can be 0. Practical bias-correction schemes should be based on independent training period and less effective than this optimal scheme. For the GEFS, such practical schemes are developed using an adaptive (Kalman Filter Type) algorithm (Cui et al. 2005). The algorithm is applied to the operational forecast and the verification scores of the corrected (red) and uncorrected (black) forecasts are shown in Fig.5, which can be compared with Fig.4. The bias corrected forecast have its ME close to 0 for lead time up to 10 days, but the reduction in MASE is modest. For short lead time (1-7 days), the systematic error reduction is more effective with the bias-correction scheme than with SP. On the other hand, SP is more effective than the bias correction for the longer lead time (7-15 days). This difference between the two schemes is easy to understand from their formulations. The bias correction is guided by recent observation (analysis) which is close to the forecast for shorter lead time, while SP works through modifying the model tendency and its effect will be accumulated as the integration continues.

3.4 *Probabilistic Forecast*

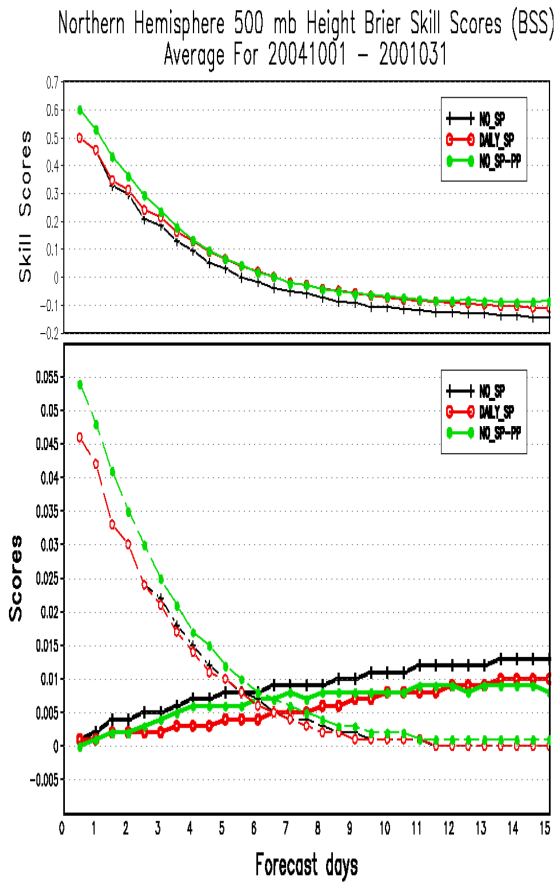

Fig. 6 Brier Skill Scores (BSS, upper panel) and its reliability (solid, lower panel) and resolution component (dashed, lower panel) as function of lead time, averaged for October, 2004. The red, black, and green lines are for ensembles with SP, without SP, and without SP but after optimal bias correction.

Figs. 6 shows the Brier Skill Score (BSS) in the upper panel and its reliability (solid lines) and resolution (dashed lines) components in the lower panel, for the ensemble forecast with SP(red), without (black) SP, and its optimally bias-corrected products (green). Note that an improved forecast will have higher BSS, which in turn, requires lower reliability component and/or higher resolution component. With SP, significant increase in BSS starts at day 2. From day 4 to day 11, the BSS score of the SP experiment is roughly the same as that of the optimally bias-corrected forecast from the experiment without SP, and even higher for day 7 to day 9. The lower panel reveals that the improvement of probabilistic forecast is mainly from the reduction in the reliability component, which is much larger than that in the optimal bias-correction between day 2 and day 10. On the other hand, SP does not increase the resolution component of BSS and slight degradation is seen between day 2 and day 10. For the bias correction scheme (not shown), all of the 3 scores are between the black and green lines, indicating BSS improvement due to both decrease in reliability component and increase in resolution.

For the Ranked Probability Skill Score (RPSS, not shown), the SP forecast is always between the forecast without SP and its optimally bias corrected products, and the improvement is initially small and increase with time.

4. TENTATIVE EXPLAINATION

The nature of stochastic parameterization schemes predicts that they have the following potential benefits (e.g., Palmer, 2001): (1) more complete representation of model uncertainty; (2) reduction in systematic error, due to noise-induced drift and (3) more accurate estimate of internal climate variability. The first benefit is obvious. The reduction in systematic error is also seen in sections 3.1-3.3. The improvement in probabilistic forecast may indicate more accurate estimate of internal climate variability. As a stochastic parameterization scheme describes the collective effect of unresolved scales on the resolvable scale, but not the exact evolution of such motions, it is expected to improve forecast reliability instead of forecast resolution.

5. SUMMARY AND SUGGESTIONS

The results of this study can be summarized as following:

(1) A stochastic parameterization scheme is developed base on the tendencies of ensemble perturbations and it is practical and effective with the NCEP GEFS system;

(2) The stochastic forcing terms added to the model are balanced, flow-dependent and showing both random noise structures and geographic patterns;

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

(4) For probabilistic forecasts, the stochastic scheme can significantly improve RPSS and BSS scores;

(5) Compared with a post processing procedure, the stochastic scheme improves BSS more effectively, but mainly by reducing its reliability component;

(6) Compared with a post processing procedure, the effect of the stochastic scheme in reducing systematic error is less effective in week1 but equally or more effective in week2 forecast.

6. ACKNOWLEDGEMENTS

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