Quantifying the Predictability of Low-Resolution Medium-Range Weather Forecasts

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LONG-TERM GOALS

To predict the probability distribution function (pdf) of medium range weather forecast errors as accurately as possible.

OBJECTIVES

Objective 1: To compare the Bishop et al.'s (2001) recently developed Ensemble Transform Kalman Filter (ET KF) ensemble generation technique against the breeding of growing vectors (BGV) technique (Toth and Kalnay, 1993, 1997) in a GCM.

Objective 2: To quantify the limits of an ET KF ensemble that *does not* explicitly account for model error to predict forecast error variance in a GCM.

Objective 3: To identify and remove (a) model error bias, (b) model error that correlates with variations in key parameters controlling the model's parameterizations of unresolved processes and (c) model error that correlates with deviations of the model trajectory about the climatological mean. (NWP failure to predict cold air damming due to poorly resolved topography is a fine example of a systematic model error that would correlate with the deviation of the model trajectory about the climate mean.)

Objective 4: To create and test an ensemble generation scheme that accounts not only for the loss of predictability due to initial condition error but also for the loss of predictability due to model error.

APPROACH

The above aims are motivated by the fact that in current operational ensemble prediction systems, e.g., the singular vector method (Buizza and Palmer 1995; Molteni et al. 1996) adopted by the European Centre for Medium-Range Weather Forecasting (ECMWF), the breeding method (Toth and Kalnay 1993,1997) used at National Centers for Environmental Prediction (NCEP), the ratio of ensemble variance to forecast error variance diminishes with time form the 3 day to 10 day forecast lead time. Work by Houtekamer et al. (1996) and Smith (2001) makes it clear that a major reason for this

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deficiency in ensemble forecasts is the presence of model error. As such, model error is a major issue in quantifying predictability.

To build up stable statistics for model error, one needs to examine many years worth of data. The limitations of the computing resources we expect to obtain for this study thus forces us to restrict our study to the predictability characteristics of a model with considerably lower resolution than the models typically used for NWP.

WORK COMPLETED

Considerable progress has already been made in achieving Aims 1 and 2. Xuguang has developed numerical tools to run T42 CCM3 ensemble forecasts off the NCEP/NCAR reanalysis data set on 4 PCs each with dual 933 MHz processes running Linux. She has already begun using these tools to compare the performance of ensemble perturbations during the 2000 Boreal summer (JJA) generated using the breeding method (Toth and Kalnay, 1997) with ensemble perturbations generated using the recently developed ET KF ensemble generation technique.

In this new ET KF ensemble generation scheme, forecast perturbations listed as columns in the matrix $\mathbf{Z}^{\mathbf{f}}$ are transformed into analysis perturbations $\mathbf{Z}^{\mathbf{a}}$ by a transformation matrix $\mathbf{T}$, that is, $\mathbf{Z}^{\mathbf{a}}= \mathbf{Z}^{\mathbf{f}}\,\mathbf{T}$. These analysis perturbations are then added to the analysis to give the initial conditions for the subsequent ensemble forecast. The transformation matrix $\mathbf{T}$ is chosen in order to ensure that the covariance matrix associated with the transformed perturbations $\mathbf{F}^{a} = \mathbf{Z}^{\mathbf{a}}\,\mathbf{Z}^{\mathbf{aT}}$ would be precisely equal to the true analysis error covariance $\mathbf{P}^{at}$ if $\mathbf{F}^{f} = \mathbf{Z}^{\mathbf{f}}\,\mathbf{Z}^{\mathbf{fT}}$ were precisely equal to the true forecast error covariance matrix $\mathbf{P}^{ft}$.

In the breeding technique, all of the forecast ensemble perturbations are transformed into analysis perturbations by multiplying each of them by a constant factor whose magnitude is less than one. Thus, in its simplest form, the breeding technique takes no account of variations in observational density nor does it account for the fact that data assimilation schemes reduce error in directions corresponding to large forecast error variance more than directions corresponding to small forecast error variance (cf Daley, 1991). Because the breeding method’s transformation from forecast perturbations to analysis perturbations reduces perturbation amplitude in all directions by the same factor, directions corresponding to slowly growing errors maybe removed from the ensemble perturbation subspace.

Indeed, if the atmosphere went into a quasi-stationary state, all bred perturbations would eventually take on the characteristics of the fastest growing eigenvector of the perturbation dynamics propagator associated with the quasi-stationary basic state. In this case, all of the perturbations would be approximately parallel to each other and there would be little point in having more than one or two ensemble members.

In contrast, the ET KF transformation of forecast perturbations into analysis perturbations accounts for variations in observational density. Furthermore, consistent with filtering properties of an optimal data assimilation scheme, it ensures that perturbation amplitude is reduced more in directions corresponding to large forecast error variance than it is in directions corresponding to small forecast error variance. These considerations led to the following hypotheses.

Hypothesis 1. The variance of initial ET KF ensemble members would better reflect inhomogeneities in analysis error due to inhomogeneities in the observational network than the corresponding variance of initial bred mode ensemble members.

Hypothesis 2. The spectrum of eigenvalues of the forecast error covariance matrices produced by the ET KF ensemble will be much flatter than the corresponding spectrum of eigenvalues produced by the bred-mode ensemble; i.e. the ET KF ensemble will produce ensemble spread in many more directions than the bred-mode ensemble.

Hypothesis 3. Bred-vector forecast errors are more highly correlated than ET KF ensemble members.

RESULTS

To test these hypotheses, Xuguang ran an 8 member ET KF T42 CCM3 ensemble for the 2000 Boreal summer and compared the characteristics of this ensemble with the characteristics of an 8 member bred mode ensemble over the same period. For the ET KF ensemble generation scheme, it was assumed that the observational network consisted solely of rawinsondes released every 12 hours. For both the breeding and ET KF techniques, Dee's (1995) maximal likelihood parameter estimation theory was used to ensure that 12 hr ensemble perturbation magnitude was consistent with 12 hr forecast error at rawinsonde sites. Fig. 1 compares the seasonal mean vertically averaged ensemble wind variance of ensemble members at the analysis time for the breeding technique (Fig. 1a) and the ET KF technique (Fig. 1b). First, note that initial perturbation amplitude in the observation scarce southern hemisphere is much larger for the ET KF than it is for the breeding technique. Second, note that despite the high concentration of rawinsondes over the Eurasian continent, initial bred perturbation amplitude is locally maximized in this region. In contrast, ET KF initial perturbation amplitude is quite small in this region. These characteristics of Fig. 1 are consistent with hypothesis 1.

Gross characteristics of Fig. 1 that are not clearly consistent with hypothesis 1 are that localized concentrations of rawinsonde observations such as those in South Africa and South America had no perceptible effect on mean ET KF initial ensemble perturbation amplitude. Moreover, we are concerned that while there is a local mid-latitude minimum in perturbation amplitude over rawinsonde dense North America, initial perturbation amplitude seems unrealistically high. Since with an ensemble of only 8 members there is a limited number of observation density characteristics towards which the ET KF perturbations can adjust, presumably these aspects of the ET KF ensemble analysis variance would be reduced if a larger ensemble were used. Tests are currently under way to test this presumption.

Fig. 2 compares the seasonal mean spectrums of eigenvalues of the ensemble based 12 hr forecast error covariance matrices for the bred-mode ensemble and the ET KF ensemble.

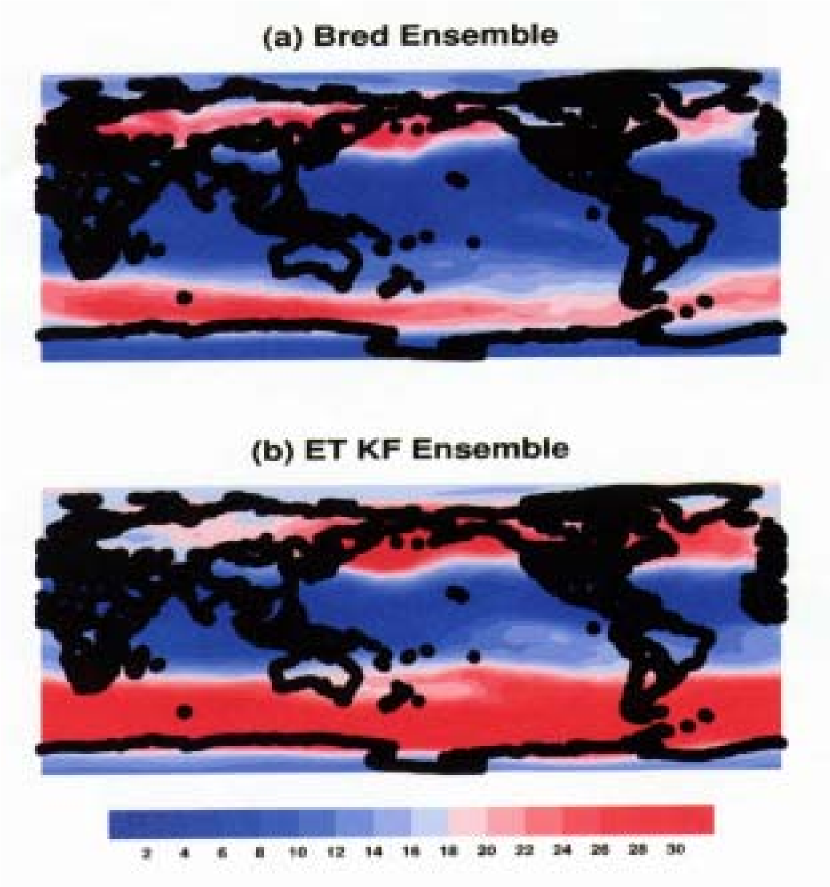

Fig. 1 Seasonal mean vertically averaged ensemble wind variance

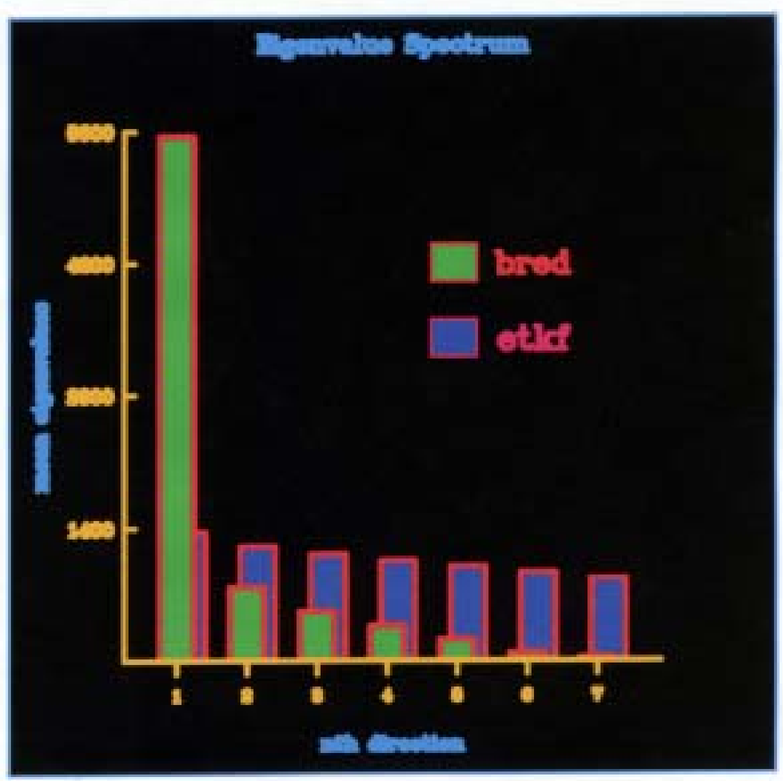

Figure 2. Mean ETKF and BGV eigenvalues

In confirmation of hypothesis 2, Fig. 2 shows that the spectrum of ET KF eigenvalues is much flatter than the bred-mode eigenvalues. In other words, while there are large amounts of ensemble forecast variance present in all seven orthogonal directions of the ET KF ensemble nearly all of the bred-mode ensemble forecast variance is contained in a single direction.

In confirmation of Hypothesis 3, the average error correlation of T42 forecasts of 2m temperatures at northern hemisphere mid-latitude rawinsonde sites for ET KF and breeding members was found to be 0.79 and 0.91, respectively. Presumably, the relatively large error correlations found for both techniques is due to model error.

IMPACT/APPLICATIONS

At NRL Monterey, research is being conducted to improve FNMOC's (bred vector) ensemble forecasting capabilities. Because of the positive results found in our preliminary tests, the ETKF ensemble generation scheme and other schemes will be tested at NRL to determine their suitability for transition into operations at FMNOC. Zoltan Toth and Mohzeng Wang of the National Centers for Environmental Prediction (NCEP) are also preparing to test versions of the ETKF ensemble generation scheme to determine its suitability as a replacement to their current bred vector scheme.

TRANSITIONS

NCEP, in collaboration with former Post-doctoral fellow Sharanya Majumdar, graduate student Brian J. Etherton and undergraduate student Jonathon Moskaitis, is currently applying the ETKF to a combined ECMWF/NCEP ensemble to determine were aircraft should fly in the ongoing NOAA Winter Storms Reconnaissance program.

RELATED PROJECTS

The NSF grant ATM-98-14376 "Adaptive Sampling with the Ensemble Transform Kalman filter" enabled tests of the ability of the ETKF to predict reductions in forecast error variance due to targeted observations. See http://www.met.psu.edu/dept/faculty/bishop.htm and http://orca.rsmas.miami.edu/~majumdar/ for details.

SUMMARY

In order to more accurately represent the uncertainty in weather forecasts a new, computationally inexpensive method has been devised for generating multiple forecasts whose differences reflect weather forecast uncertainty. Our tests indicate that the method is superior to the breeding technique that is currently used by the federally funded civilian and Naval weather forecasting agencies.

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