J1.12 ENSEMBLE-BASED “PRE-EMPTIVE” FORECASTS

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1. INTRODUCTION

A new technique is developed for issuing rapid forecasts, based on incoming observations and available ensemble forecasts. It is entitled a “pre-emptive forecast”, since it pre-empts an operational analysis/forecast that assimilates these observations. In addition to its potential practical use in issuing rapid storm warnings (using mesoscale ensembles and observations), the pre-emptive forecasting technique can also be used as a computationally cheap framework to test an ensemble-based data assimilation scheme with complex models. If the pre-emptive technique is to be practicable, its skill must be consistently (i) comparable to that of the model forecast, and (ii) higher than that of any other forecast available at the time the pre-emptive forecast is made. We present some simple tests using global models and synthetic observations.

2. THEORY

Pre-emptive forecasts are based on the Ensemble Transform Kalman Filter (ET KF) data assimilation scheme (Bishop *et al.* 2001). Using available ensemble forecasts to provide the background fields and background error covariance estimates, incoming observations are used to transform the ensemble into one that provides an improved estimate of the state of the atmosphere, given the new information. A pre-emptive forecast is then made by performing the same transformation on the ensemble forecasts valid at any later time.

A pre-emptive analysis $\mathbf{x}^a(t_j)$ is made at time t_j by blending new observations (denoted by the vector $\mathbf{y}$ with linearized operator $\mathbf{H}$ and diagonal error covariance matrix $\mathbf{R}$) with a background field $\mathbf{x}^f(t_j)$. The background field is the best estimate of the atmospheric state prior to assimilating the new observations (we use the mean of a short-range ensemble initialized at some time t_{j-1}). The background error covariance matrix $\mathbf{P}^f(t_j)$ is approximated by the outer product of the matrix of transformed ensemble perturbations $\mathbf{Z}(t_j)$, in the form

$$\mathbf{P}^f(t_j) \quad = \quad \mathbf{Z}(t_j)\,\mathbf{Z}^T(t_j)\,. \tag{1}$$

Typically, the raw ensemble perturbations from a short-range forecast (represented by $\mathbf{X}(t_j)$) are transformed into the matrix $\mathbf{Z}(t_j)$ using information from the standard (routine) observational network, and a statistical rescaling (such as that of Dee 1995) to ensure that the magnitudes

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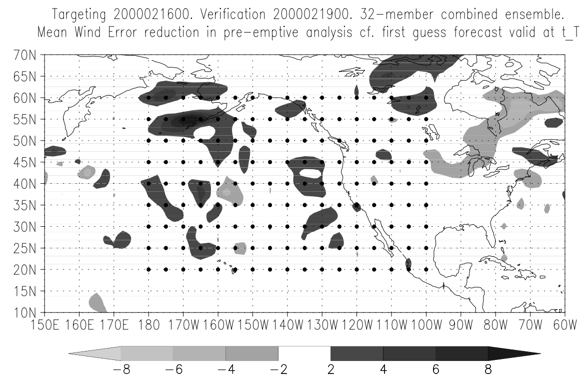

FIG. 1: Improvement in pre-emptive analysis compared with the background forecast, produced by wind pseudo-observations taken at 153 gridpoints.

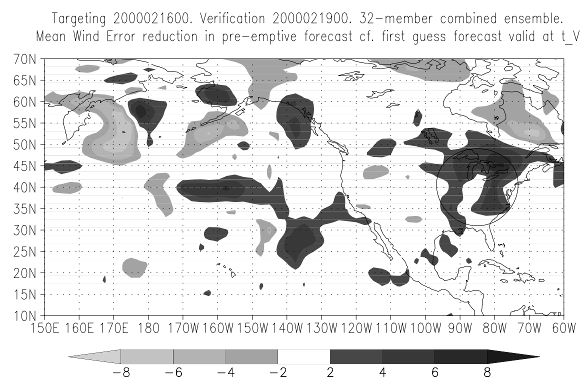

FIG. 2: Improvement (dark shading) in the corresponding pre-emptive forecast compared with the background forecast. Light shading refers to a degradation.

of background error variances estimated by the ensemble are realistic. By first calculating the eigenvectors $\mathbf{E}(t_j)$ and eigenvalues $\boldsymbol{\beta}$ of the matrix $\mathbf{H}^*\,\mathbf{P}^f(t_j)\mathbf{H}^{*\,T}$ (where $\mathbf{H}^* \equiv \mathbf{R}^{-\frac{1}{2}}\,\mathbf{H}$), the pre-emptive analysis can be rapidly produced in the form

$$\begin{aligned}\mathbf{x}^a(t_j) \quad &= \quad \mathbf{x}^f(t_j) + \mathbf{H}^{*\,c}\,\mathbf{E}(t_j)\,\boldsymbol{\beta}\,(\boldsymbol{\beta}+\mathbf{I})^{-1}\,\mathbf{E}^T(t_j) \\ &\quad\quad \times \left\{\mathbf{y}^* - \mathbf{H}^*\,\mathbf{x}^f(t_j)\right\}.\end{aligned} \tag{2}$$

To make a pre-emptive forecast valid at some future time $t \geq t_j$, the term $\mathbf{H}^{*\,c}\,\mathbf{E}$ in (2) is replaced by $\mathbf{Z}(t)\,\mathbf{B}\,\boldsymbol{\beta}^{-1/2}$ ($\mathbf{B}$ is a transformation matrix), and the background field is given by $\mathbf{x}^f(t)$. Hence, the pre-emptive forecast is a linear combination of ensemble perturbations valid at the desired time. Via serial observation processing (Bishop *et al.* 2001), pre-emptive forecasts can be updated quickly for additional incoming observations.

3. PRELIMINARY RESULTS

Pre-emptive analyses and forecasts were produced for each of 30 forecast cases in the 2000 Winter Storm Reconnaissance (WSR00) program. A combined ensemble of ECMWF and NCEP MRF horizontal wind forecasts generated 24-36h prior to the pre-emptive analysis time, and a fixed block of 153 pseudo-observations (MRF analyses in this example) over the northeast Pacific Ocean were used. No other observational information at the analysis time was given. The improvement of one such analysis and forecast (case number 30), compared with the respective background fields, is shown in Figs 1 and 2 respectively. At the forecast time, the pre-emptive forecast produces a significant improvement over the background field, within the WSR00 verification region.

The skill of each of the 30 pre-emptive forecasts, compared with the respective background fields and MRF forecasts (initialized at the observing time) within the selected verification regions, is displayed in Figs 3 and 4 respectively. While the pre-emptive forecast usually did not attain the skill of the operational NCEP MRF forecast (it only performed better in 4/30 cases), it was often more skillful than the background field (20/30 cases). The tests were also performed using an ECMWF ensemble initialized 12h prior to the pre-emptive analysis time. In 20/30 of the WSR00 cases, the pre-emptive forecast was more skillful than the background field, and in 8/30 cases it was more skillful than the MRF initialized at the analysis time.

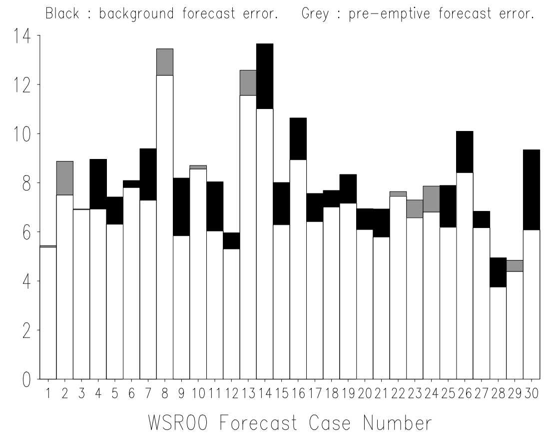

FIG. 3: Pre-emptive forecast errors versus background forecast errors, averaged within the verification region.

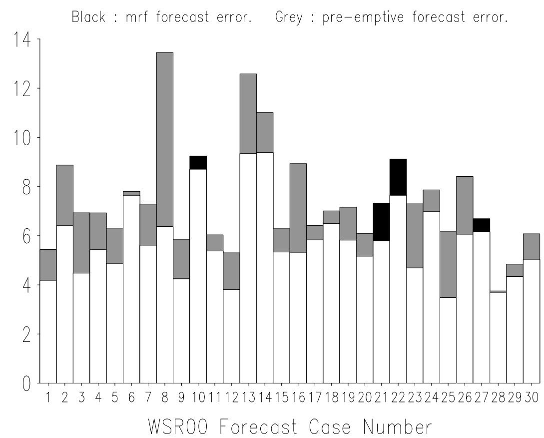

FIG. 4: Pre-emptive forecast errors versus errors of the MRF forecast initialized at the 'pre-emptive analysis time'.

4. CONCLUSIONS AND FUTURE WORK

Preliminary results demonstrate that the pre-emptive forecasting strategy holds promise as a rapid forecasting technique. However, considerable effort is still required to produce pre-emptive forecasts whose skill is systematically comparable to that of a model forecast initialized at the same time. The skill of the pre-emptive forecast is constrained by the ability of the ensemble to capture the important error structures, the number and quality of the observations, and deficiencies in the ET KF (such as rank deficiency, and linearity assumptions). Nevertheless, we expect the skill of pre-emptive forecasts to improve with refined (and rescaled) error covariance specifications, more multi-model ensemble members, and assimilation of real observations.

The version of the ET KF that most consistently produces successful pre-emptive forecasts can then be used to extend the current operational implementation of the ET KF adaptive observing strategy at NCEP (Majumdar *et al.* 2001). Further, it can be used to tackle predictability issues, such as the capability of observations to reduce errors in certain directions of analysis and forecast error.

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