Testing Linear Diagnostics of Ensemble Performance on a Simplified Global Circulation Model

Ethan Nelson and Dr. Istvan Szunyogh Department of Atmospheric Sciences, Texas A&M University, College Station, TX

Ensemble weather forecast systems are used to account for the uncertainty in the initial conditions of the atmosphere and the chaotic dynamics of models. It has been previously found that forecast performance of an ensemble forecast system is inherently flow dependent; it predicts potential patterns of forecast error more reliably than the magnitudes of error. A low-resolution global circulation model is implemented to calculate linear diagnostics in the vector space of the ensemble perturbations. Our goal is to assess the ability of the linear diagnostics in predicting ensemble performance. The anticipated outcome of our research is the development of improved post-processing techniques to enhance the forecasts and an improved interpretation of the ensemble forecasts.

Introduction

The accurate prediction of weather can save both lives and money. Despite the atmosphere being an infinite dimensional dynamical system, finite dimensional models are able to simulate most processes that determine the weather. Forecast errors are the result of the chaotic nature of the atmosphere, uncertainty of initial conditions, and imperfections of the model. Ensemble forecast systems generate probabilistic estimates of the present and future states of the atmosphere in an attempt to account for these errors. Each ensemble member has its initial conditions slightly perturbed to account for uncertainty. Satterfield and Szunyogh (2010 *a* and *b*) found that ensembles provide a more reliable prediction of the space of uncertainties, S_1 , than the actual magnitude of the forecast errors. Our experiment replaces the model used in the previous study with SPEEDY, a simplified global circulation model. We apply the linear diagnostics detailed in Satterfield and Szunyogh (2010 b).

Methods

•Model: SPEEDY Model (e.g. Molteni 2003 and Kucharski, et al. 2006) •Data Assimilation: Local Ensemble Transform Kalman Filter (Hunt, et al. 2007) •Truth: National Centers for Environmental Prediction (NCEP) Global Forecast System (GFS) •Ensemble size (K) : 40

Diagnostics

$$\underline{\text{Local Error Covariance Matrix}} \qquad \underline{\text{Forecast Error}} \\ x^{\prime(K)} = x^{(K)} - \overline{x} \qquad x^{t} = truth \\ \hat{P}_{l} = \frac{1}{K-1} \sum_{k=1}^{K} \left[x^{\prime(k)} (x^{\prime(k)})^{T} \right] \qquad \delta x^{t} = x^{t} - \overline{x} \\ V_{l} = trace(\hat{P}_{l}) \qquad TV_{l} = E[(\delta x)^{2}] \\ \end{bmatrix}$$

Experiment Design

Analyses are generated every six hours from 00Z 1 January 2004 to 12Z 29 February 2004. 120 hour forecasts are created using each analysis as the initial conditions and output every six hours. Diagnostics are run on all forecasts starting from 00Z 11 January 2004 to 12Z 15 February 2004 using a state variable transformation such that the square norm has unit energy. The local state vector used is defined in a 5 x 5 grid point cube; diagnostics are then spatially and temporally averaged with forecasts of similar lead times. Atmospheric "true state" is simulated as the NCEP GFS model integration from 00Z 1 January 2004 to 12Z 29 February 2004 with the operational analysis scheme.

Abstract

$$\frac{\text{Error Projection onto } \mathbf{S}_{l}}{u_{k}} = \lambda_{k} \left[\sum_{i=1}^{K-1} \lambda_{i}^{2} \right]^{-1/2}$$
$$\delta x^{t(l)} = \sum_{k=1}^{K-1} \left[(\delta x^{t})^{T} u_{k} \right]$$
$$TVS_{l} = E[(\delta x^{t(l)})^{2}]$$



Discussion and Future Work

The analysis covariance inflation is tuned for $V \approx TVS$ at analysis time (135%). At longer lead times, the difference between TV and TVS decreases, confirming Satterfield and Szunyogh's (2010 b) result; however, TV and TVS begin to level out sooner than V. Forecasts will be extended to investigate the behavior of the linear diagnostics at longer lead times up to fifteen days. A predictable evolution of the diagnostics at these longer times could lead to the development of an improved postprocessing technique enhancing ensemble forecasts. Additionally, the enhanced forecasts may result in an improved interpretation of ensemble forecasts.

<u>References</u>

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