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Grant: NOAA/NA040AR4310103: Estimation and potential correction of model errors

Goals:
-Use techniques from shadowing theory to estimate the effect of correcting for model error during nonlinear integration of a forecast model.
-Identify and correct the state-independent and state-dependent model errors associated with reduced dimension weather models.
-Estimate model errors for the NCEP operational model, interface with data assimilation project at Maryland.

Motivation: Numerical weather forecasting errors grow with time as a result of two contributing factors. First, atmospheric instabilities amplify small perturbations causing indistinguishable states of the atmosphere to rapidly diverge. Efforts to reduce *internal* error growth focus on choosing ensemble perturbations in a clever manner. Second, model deficiencies introduce errors during the model integration leading to *external* error growth. This external model error includes inaccurate forcings, unrealistic parameterizations used to simplify the physics, and sub-grid scale phenomena. The presence of model error impacts forecasting skill for both short and extended range predictions. As the methods of data assimilation and generation of initial perturbations become more sophisticated, compensation for model deficiencies is essential.

To evaluate the performance of a numerical weather model L, it is natural to ask how long a forecast trajectory will accurately describe the observed weather H. Model deficiencies of L in approximating H are in this context defined by the difference in tendency predicted by L and H for a given initial condition. Shadowing theory addresses the idea that some rather special systems H have the following property: given a $\delta > 0$, when system L is sufficiently close to H, each trajectory of H will be within δ of some trajectory of L for all time. In other words, each trajectory of H is δ-shadowed by a trajectory of L. These systems are called *hyperbolic*, the tangent space at each point along a trajectory is composed of expanding and contracting subspaces whose angle is bounded away from zero. In particular, the dimensions of these subspaces do not change from point to point. Shadowing trajectories are unlikely to exist for non-hyperbolic systems. The system describing the weather is almost certainly *not* hyperbolic and as a result, shadowing of the atmosphere fails quickly.

Progress: Fortunately, a successful forecast need not be an actual shadowing trajectory. Assimilating observations of H periodically, we may correct a forecast of L. The resulting pseudo-trajectories of L *can* remain close to H (for a reasonable definition of 'close'). Using a method of data assimilation similar to breeding, we have found pseudo-trajectories of a low-resolution model L (given by Emanuel and Lorenz '98) which shadow an H trajectory for orders of magnitude longer than true trajectories of L. We refer to these pseudo-trajectories as *stalking* solutions, they are essentially a time series of analysis states resulting from a data assimilation scheme. We have also found that the stalking time is predicted by a 1-D map of forecast error under expansion and contraction. The results will be submitted to Physical Review Letters this spring.

Ideally, we could identify pseudo-trajectories of L which remain close to H with only observations of H. In other words, we would like to make corrections to the forecast state based on an estimate of the external error. In an attempt to find such trajectories, we seek a state-dependent model error correction term, to be integrated into a forecast model.

Experiments have been carried out using Marshall and Molteni's 1993 global quasi-geostrophic model (L) and the NCEP reanalysis from 1980 through 2000 as the target H. We performed relaxation experiments by *nudging* the QG model forecast towards the NCEP reanalysis, essentially attempting to synchronize the two time series. Nudging is done by introducing a correction to the model forcing of the form $c(t) = [q\_reanalysis(t) - q\_model(t)]/\tau$ every 6 hours, where τ is the relaxation time scale. The time average, N, of c(t) is an estimate of the systematic model error. While nudging is a fairly simple method of data assimilation, it performs amazingly well. Despite the simplicity of both the QG model and the nudging scheme, the anomalous pattern correlation between q_reanalysis and q_model remains above 95% throughout the assimilation period, for a wide range of relaxation time scales τ. Correcting the forcing by the bias N increases forecast accuracy significantly (38%).

The time series of anomalous model error corrections, given by $c(t) - N$, provides a residual estimate of the linear state-dependent model error. The time covariance of an uncorrelated group of these residuals gives Empirical Orthogonal Functions representing their spatial variability, as well as Principal Components which illustrate variation in time. The time covariance of the corresponding model states are also expanded into EOF's and PC's. The PC corresponding to the dominant error correction EOF can then be written as a linear combination of the model PC's. During subsequent forecasts, the forecast state can be projected onto the experimental model states, giving the best representation of the original corrections in terms of the current forecast state. This method of identifying a state-dependent model error correction is similar to that proposed by Leith in 1978. The main difference is that Leith's method involves directly replacing the model forecast with the target data every 6 hours, while the nudging method corrects the forcing and involves no analysis of the forecast state. Both methods have been used to show that although the QG model has a large constant systematic error, it does not exhibit a state-*dependent* systematic error. We plan to report these results in a paper.

Future:
We are now using the far more realistic primitive equations SPEEDY model described by Molteni in 2003 which should allow us to identify a state-dependent model error. Once we develop and test the methodology on the SPEEDY model and determine how it benefits from the correction of the state-dependent error, we plan to implement similar methods for model corrections using the NCEP model. This effort is part of a larger project here at the University of Maryland to introduce a state-of-the-art Local Ensemble Transform Kalman Filter for data assimilation.