Evaluation of model error using data assimilation

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The principles of initiating an ensemble forecst (EPS) with ensemble data assimilation (EnDA) are reviewed. This allows an estimate of initial uncertainty consistent with the uncertainties due to the model and the available present and past observations. Maximum resolution of the EPS is achieved by using the best available and affordable deterministic model. Achieving reliability then requires an estimate of the errors in the deterministic model. The true state in model space is filtered to the model resolution. This means that the true evolution is stochastic, as it depends on information that is not present in the initial state. The error in a deterministic model is therefore also stochastic.

If the statistics of the model error are known, then a reliable forecast ensemble can be generated given a reliable analysis ensemble. In particular, a reliable prior ensemble can be generated for the next analysis cycle. If the statistics of the observation errors are also known, and represented by perturbed observations, then an analysis ensemble performed by updating a randomly chosen prior ensemble member using a random draw from the perturbed observations will also be reliable. This is because the true state is statistically indistinguishable from a random member of the prior ensemble, and the true state mapped to observation space is statistically indistinguishable from a randomly chosen set of perturbed observations. Thus no update is performed at the true state, and so the reliability of the analysis ensemble is assured whatever method of analysis update is used, and whether or not the statistics are Gaussian.

Since the model error is inherently unknowable *a priori* because it depends on unknown information, the statistics of model error can only be estimated from observations. Data assimilation provides a way of doing this which allows all observations to be used while properly allowing for observation error. Ideally this should take the form of a reanalysis. The weak constraint 4dVar method is designed to estimate the forcing term with the minimum variance which, when included in the model, allows the model to fit the observations to within observation error over an extended period. We can infer the statistics of the necessary forcing term by performing cycled weak constraint 4dVar with no background increments. This can only give the statistics of the model error over a sufficiently long period for the data assimilation to be fully spun up. It requires a prior estimate of the model error statistics, which should ideally be bootstrapped. If the forcing terms estimated from the assimilation can be regarded as a random draw from an archive of such increments, then the reanalysis trajectory will be staistically indistinguishable from a model trajectory forced with randomly chosen increments from the archive.

This idea is tested using the Met Office Unified Model with 40km horizontal resolution and 70 levels. An archive of model error forcing terms is generated using weak constraint 4dVar with no background term. An ensemble data assimilation and forecast system is then run with 10 members, perturbed observations, and strong constraint 4dVar. Randomly chosen model error forcing terms from the archive are added to the model trajectories. 6 hour forecasts from the system are then verified against randomly chosen members of the analysis ensemble. This is equivalent to verifying against the truth if the analysis is properly set up. The spread-skill relation is satisfied to within sampling error.

Results are presented for 6 day forecasts, which are found to be reliable based on the spread-skill relation. They are also presented for 10 year AMIP simulations verified against ERA-Interim analyses. These show large improvements over the control, primarily because the systematic errors are removed by the forcing terms. Some of the remaining errors are because our simulations should reproduce a Met Office reanalysis, which will not be the same as ERA-Interim due to differences in the two assimilation systems.

Additional results are presented which show that our system, when used only in forecast mode, outperforms the Met Office operational EPS. This is because the model error forcing is significant in all regions, while the stochastic physics used in the operational EPS is mostly restricted to the storm tracks. We also illustrate that the use of weak constraint 4dVar to estimate the model error forcing is important. Analysis increments calculated on the assumption that increments are only added every 6 hours are different in character, typically smaller and on smaller scales.

C. Piccolo and M.J.P. Cullen (2016) Ensemble Data Assimilation Using a Unified Representation of Model Error. *Mon. Weather Rev.,***144***, 213-224*
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