4.6 SIMULATION OF THE OBSERVATIONAL NETWORK USING AN ENSEMBLE KALMAN FILTER

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1. INTRODUCTION

The ensemble Kalman filter (Evensen 1994) provides a frame work for the description of the error statistics as they occur in a data-assimilation cycle. The error statistics at any phase of the cycle can be estimated from an ensemble of model states. If the different members of the ensemble are supplied with random realizations of the observational and modeling error (Mitchell and Houtekamer 2000), the ensemble statistics should be representative of the actual ensemble mean error. Our working hypothesis is that an appropriate statistical description of the sources of error can, and will, indeed be found. In that case, the ensemble Kalman filter can be used as a tool to simulate the impact of changes to the observational network. The improvement due to additional (hypothetical or real) data can then be estimated from the corresponding decrease in ensemble spread when two simulations with and without the additional observations are compared. Thanks to the large number of ensemble members (as compared to using a single realization) statistically significant conclusions could be obtained from the evaluation of a small number of cases.

2. A PERFECT-MODEL EXPERIMENT

We use the data-assimilation algorithm proposed by Houtekamer and Mitchell (2001) in the context of a dry low-resolution version of our center's primitive equation model (Côté et al. 1998). The model uses 21 levels in the vertical and a 144×72 horizontal grid. It is forced as in Held and Suarez (1994), but includes a realistic topography. As motivated in Houtekamer and Mitchell (1998), a pair of ensembles is configured so that the assimilation of data using one ensemble of short-range forecasts employs the weights calculated from the other ensemble of short-range forecasts. Here a pair of two 32-member ensembles is used. For an initial experiment, we use simulated reports from radiosondes and aircraft as well as satellite thicknesses. It is assumed that the forecast model is perfect.

It is observed that, even with this fairly basic observational network, very low error levels can be obtained. In fact, error levels are lower by an order of magnitude than those typically observed for operational data-assimilation systems when comparing with real data. The impact of the observations is much bigger at 0 and 12 UT than at 6 and 18 UT, which suggests that such low error levels could have been obtained using radiosonde observations only. This implies that, if our model is indeed perfect, the atmospheric flow can be determined accurately, given the current network of radiosondes and an ensemble Kalman filter with 2×32 members.

3. GROWTH OF ERRORS

The growth rates of errors, due to the internal dynamics of the model, have been determined for a number of generations of the ECMWF operational forecast model (Simmons et al. 1995). The growth rates are seen to increase as an unavoidable consequence of the development of a more active and realistic forecast model.

To determine growth rates for the model used here, a number of 14-day integrations were performed. No data were assimilated, so that the differences between ensemble members grew only in response to the model dynamics. After some initial adjustment, during which perturbations actually became smaller, the differences between the ensemble members were observed to grow at an unexpectedly modest rate. At no size of the errors were the growth rates comparable to the rate at which true forecast errors (i.e., when comparing an integration with verifying analyses) grow in our center's operational forecast model. The modest growth rate may well be responsible for the low simulated error levels in the perfect-model experiments. If errors do not grow at a realistic rate in our simulation, they will be unrealistically small and consequently one will arrive at overly optimistic

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conclusions about the quality of the forecasting system.

To analyze this further, growth rates were also computed for the model, with the same Held-Suarez forcing as before, on a 400×200 horizontal grid. This led to a significant, but insufficient, increase of the activity of the internal dynamics. A subsequent significant, but still insufficient, increase was obtained by replacing the Held-Suarez forcing with the physical parametrizations used in the operational model of our center. It is concluded that no model, available to us, is capable of simulating the growth of true forecast errors, if it is used with the perfect-model assumption. In other words: in order to obtain a realistic simulation of the error levels in a data-assimilation cycle, it will be necessary to account for the model-error component.

4. CONCLUSION

It was found that low-resolution dry dynamics account for only a fraction of the error growth processes in the numerical weather forecasts. It is necessary to introduce an additional error source term to account for model error (e.g., Dee 1995; Mitchell and Houtekamer 2000). Such a term will have to be carefully estimated using innovation statistics.

If indeed it is possible to obtain a realistic simulation of the errors in an environment with (i) radiosondes, (ii) a fairly simple forecast model, and (iii) a parametrized forecast model error, one may hope to be able to also evaluate the impact of different components of the observational network as originally intended.

The introduction of a well-calibrated model-error term, and the resulting realism of the background error statistics, is also of critical importance for the current project that aims at implementing an operational ensemble Kalman filter at the Canadian Meteorological Centre.

A more extensive report on these experiments can be found in Mitchell, Houtekamer and Pellerin (2001).

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