Inter-comparison of data assimilation methods including ensemble-based techniques and implications for real applications

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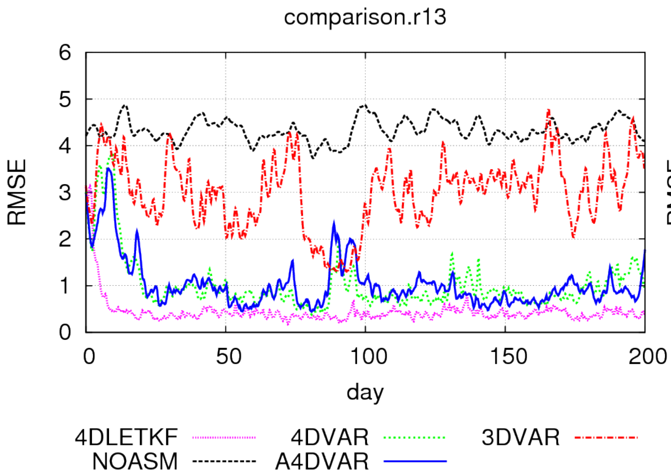
Recent development of computational resources with a huge number of multi cores facilitates implementation of the ensemble-based data assimilation techniques including ensemble Kalman filter and ensemble-based four dimensional variational methods for practical applications. To understand basic characteristics of ensemble-based data assimilation methods, we examine assimilation skills of two ensemble-based techniques: four dimensional local transformation ensemble Kalman filter (4DLETKF) and adjoint-free four dimensional variational (a4DVAR) scheme comparing them with the traditional 4DVAR and 3DVAR methods. Comparison is done in the framework of twin-data experiments with the Lorentz-96 model characterized by 40 degrees of freedom and the external forcing parameter of 8. Pseudo observation data are created by adding random noise with amplitude of 1 to the data sampled from a background (“true”) model run at 6-hour intervals. These data are assimilated into the model starting from an initial condition extracted from another (first guess) simulation. The data at 0, 6, 12 hours are assimilated for adjusting the initial condition for each 12-hour long assimilation window. In the case of dense observations (13 data points per sample), 4DLETKF effectively reduces RMSE below the noise level (left panel in Fig.1). Both 4DVAR and A4DVAR with carefully tuned background error covariance matrices show comparable skills with that of 4DLETKF. The best performance of 4DLETKF in Fig. 1 might be attributable to its superior ability of capturing the error covariance structure based on the ensemble simulation because a temporal variation of the ensemble spread is quite similar to that of RMSE. In contrast, in the case of sparse observations (7 grid points per sample, right panel in Fig.1), the skill of 4DLETKF deteriorates with a mean level of RMSE (4.3) larger than those of both 4DVAR (3.3) and A4DVAR (3.6), suggesting a requirement of more tuning LETKF parameters and/or relatively robust responses of 4DVAR/a4DVAR to sparse sampling. We present more details of the experiments and discuss possible implementation of the ensemble-based methods in operational ocean forecasting systems.

Figure 1. Time sequences of the root mean square error (RMSE) of reconstructing the true state during the 200-day assimilation period with dense (left) and sparse (right) sampling of the true state by observations.

Keywords: data assimilation, ensemble , 4DVAR, Kalman filter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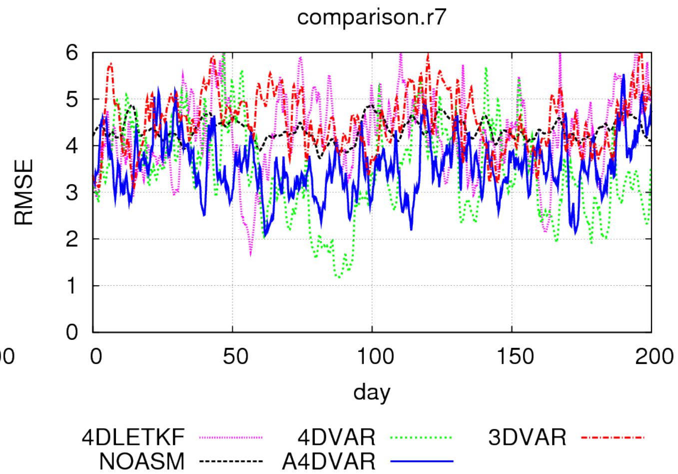
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RMSE
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4DLETKF
4DVAR
3DVAR
NOASM
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