Ensemble-Variational Data Assimilation Methods – Modelling and Diagnosis of Localized Covariances

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Most data assimilation (DA) methods use covariances to characterize the errors they are trying to correct. This enables them to spread the information from scattered observations to all the variables needed to define the analysis and start a forecast. In the ensemble Kalman filter (EnKF) the covariances come from an ensemble of forecasts, giving estimates which reflect both the meteorological situation, and the recent observing network. In applications like numerical weather prediction (NWP), the ensemble has to be very small (O(100)) compared to the degrees of freedom to be analyzed; the usual compensation is to localize the ensemble covariances. Modern NWP models have billions of degrees of freedom, so the effectiveness of localization at supplying the extra degrees of freedom while retaining the real feature in the ensemble covariance is key to the success of the DA algorithm.

Many EnKF algorithms directly localize the error covariance between the observation locations and model variables; this constrains the design of localization methods. Variational (Var) algorithms on the other hand manipulate model fields, making available operators for differentiation, variable transform, balance, scale-decomposition and smoothing. Var traditionally uses a time-averaged "climatological" error covariance estimate, but, using an "alpha control variable" [6], localised ensemble covariances can also be used in "Ensemble-Variational" (EnVar) DA. A combination of the two gives a hybrid method.

We explore the greater scope for sophisticated localization algorithms within hybrid-EnVar. As well as the original horizontal [4] and vertical, localization can be applied between variables, and in spectral space [1]. 4DEnVar methods [5] directly use the 4D covariance from an ensemble of trajectories, so 4D-localisation is also applied. On the other hand hybrid-4D-Var [2] localizes the 3D covariance and gets the time-dimension from its linear and adjoint models.

These methods have all been implemented as options in the Met Office's VAR system. This paper presents diagnostics of the effect of various localization methods on the implied covariances used. Trials of some of the DA systems are presented in a companion paper [3].

References

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