Data assimilation projects

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Introduction

The projects below are intended to illustrate the importance of different parts of the assimilation procedures and the effects when the usual assumptions do not hold. You should begin by choosing one of the projects and investigating the question as fully as possible, under different scenarios. From what you have learnt in the lectures, try to explain what you see happening.

If you complete one project in good time, you may combine it with another project. For example, you can look at the same question in both the ensemble Kalman filter and 4D-Var and compare the results, or you may wish to use one of the other assimilation schemes available. You can also combine two questions in the same assimilation scheme, for example looking at what happens when there is bias in both the observations and the model.

List of projects

Correlated observation error 1

Project 1 *Investigate the effect of correlated observation error in the ensemble Kalman filter.*

Project 2 *Investigate the effect of correlated observation error in 4D-Var.*

If two observations are made with the same instrument (for example a satellite instrument) then the errors between them may be correlated. In this project you can investigate the effect of this on the different assimilation schemes. Using either the ensemble Kalman filter or 4D-Var, change the program so that the same random noise is used to create the observation error for x, y and z (or just two of these). How does this affect the assimilation results? Consider what happens when the observation error covariance matrix is assumed to be diagonal and not.

Correlated observation error 2

Project 3 *Investigate the effect of time correlated observation error in the ensemble Kalman filter.*

Project 4 *Investigate the effect of time correlated observation error in 4D-Var.*

We usually assume that observational errors are uncorrelated in time, but this may not be the case for observations taken by a single instrument at different times. Using either the ensemble Kalman filter or 4D-Var, change the program so that a time correlation is introduced into the observational error. How does this affect the assimilation results?

Biased observation error

Project 5 *Investigate the effect of biased observations in the ensemble Kalman filter.*

Project 6 *Investigate the effect of biased observations in 4D-Var.*

In data assimilation we assume that the observation errors are unbiased. Try replacing the random observation error with a constant bias for one or more of the variables. What is the effect on the analysis?

Observation operators

Project 7 *Investigate the performance of 4D-Var when the model state is only partially observed.*

In the ensemble Kalman filter practicals, various observing networks were considered. The 4D-Var codes are set up so that all components of the state vector (x, y, z) are observed at the observation time, so that the observation operator is the identity. Change the 4D-var code so that only two components of the state vector are observed. How well is the other component retrieved by the assimilation? Compare the effect of using a diagonal and non-diagonal background error covariance matrix. Compare these with the ensemble Kalman filter results.

Importance of the linearity hypothesis in 4D-Var

Project 8 *Test the convergence of 4D-Var as the tangent linear hypothesis breaks down.*

Adapt the test routine *test_tl* to run the tangent linear model test for a given finite sized perturbation. By using the relative error as a measure of nonlinearity, investigate how well the tangent linear hypothesis holds for different size perturbations and for different time windows. Perform 4D-Var assimilations using these different time windows and perturbations. How does the rate of convergence and the accuracy of the solution relate to the nonlinearity of the problem?

Effect of model error in the data assimilation

Project 9 *Investigate the effect of model error in the ensemble Kalman filter. You may consider*
(a) random stochastic error;
(b) an error in the parameters;
(c) a bias error.

Project 10 *Investigate the effect of model error in 4D-Var. You may consider*
(a) random stochastic error;
(b) an error in the parameters;
(c) a bias error.

Usually the numerical model we use to assimilate is not an exact representation of the true system, but will contain model errors. We can investigate the effect of this in a simple assimilation experiments by using one version of the model to produce the 'truth' trajectory and the observations and using a different version of the model to assimilate. To add error to the assimilation model you may
(a) add a random forcing to one of the model equations;
(b) change one of the model parameters σ, β or ρ to be slightly different in the assimilation model;
(c) add a constant forcing to one of the model equations. How does this affect the analysis? If using the ensemble Kalman filter, examine the effect of different forms of the model error covariance matrix $\mathbf{Q}$. If using 4D-Var, you may want to try adding a model error term to the cost function.