The Data Assimilation Research Centre

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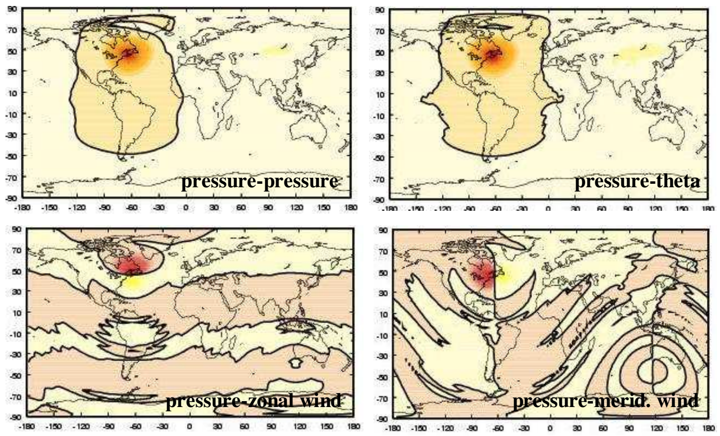
Background Error Modelling for the Atmosphere

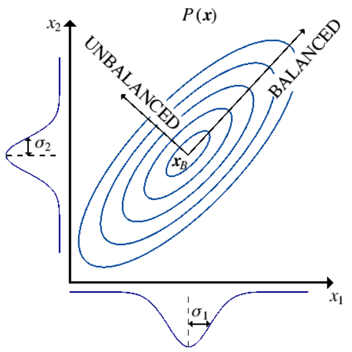
In data assimilation it is crucial to estimate realistically the errors in the background forecast. An incorrect error characterization can corrupt the analysis. All meteorological fields have local errors (variances) as well as non-local errors (covariances) due to long-range correlations within the same field and between different fields. As an example, the figure shows typically how a point error in pressure covaries with errors in other dynamical quantities.



The background error covariance matrix, B represents these errors, but it contains far too many pieces of information for even today's computers to hold. We are working to represent B as a physical model. The physics of nearly balanced fluids helps us to partition the errors into a number of components.

i. 'Balanced' errors reflect the leading modes of variability in the atmosphere. These represent mainly errors in the large scale weather systems, and are related to a 'potential vorticity' parameter. These errors have a large variance (stretched axis in the figure below).

ii. The residual errors represent uncertainties of the unbalanced (or 'gravity') modes (compressed axis). Unbalanced modes must be constrained more firmly than the balanced modes.



Simplified and linearized equation sets for atmospheric dynamics have balanced and unbalanced modes that are mututally uncorrelated. With the assumption that this property holds (approximately) in the atmosphere also, we can decompose B into a number of smaller matrices that can be dealt with. Getting right the partition between balanced and unbalanced modes is important. A correct characterization will help the assimilation system, while an incorrect characterization can hinder it.

Assimilation of Satellite Retrievals

Satellites measure the radiation emitted by the atmosphere and by the Earth. Users of remote sensing products are usually interested in profiles of meteorological quantities, which can be extracted from the raw measurements using an off-line inversion process. Profiles derived in this way are called retrievals and are computed along with the uncertainties in the quantities at each measurement level.

Actually, retrievals include a-priori information that does not come from the observations. A-priori information is needed to solve the inverse problem, which is otherwise ill-posed.

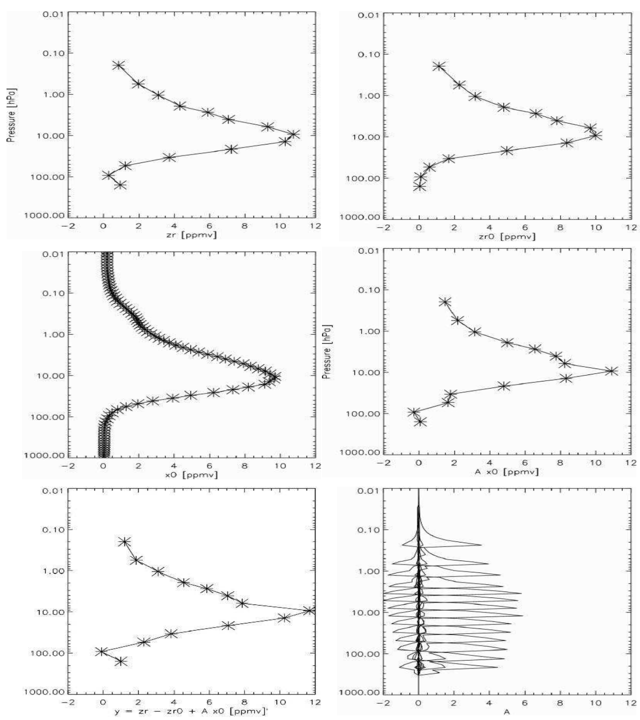
When the forward problem (of predicting the radiance given the profile) is exactly or nearly linear, the retrieval can be expressed as,

$$z_r - z_{r0} = \mathrm{A}(x - x_0) + \mathrm{G}\varepsilon$$

where z_r is the ordinary retrieved atmospheric profile, z_{r0} is the simulated retrieval from a simulated noise-free measurement using the forward model, A is the averaging kernel matrix, x_0 is the a-priori of the retrieval and $G\varepsilon$ is the retrieval error.

Shown in the panels below are these quantities for a specific MIPAS measurement, where $y = z_r - z_{r0} + \mathrm{A}\,x_0 = \mathrm{A}\,x + \mathrm{G}\,\varepsilon$ is uncorrelated with the a-priori used in the retrieval.

Assimilation of y instead of z_r leads to a more consistent estimate of the real atmospheric state.



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