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High resolution data assimilation guide

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1 Introduction

The purpose of data assimilation is to find a model state that gives the best match between the most recent model prediction and the observations that became available since. This state is called the analysis. It is the starting point for the Numerical Weather Prediction (NWP) model to calculate the forecasts. As computers become more powerful, more detailed NWP models are possible. As a consequence, this poses challenges not only to the model physics that should be able to describe meteorological features on smaller scales, but also to the observations that should cover all scales of interest at sufficient temporal resolution and the data assimilation system that should produce a detailed analysis.

In this document some of the problems regarding the assimilation of mesoscale observations into NWP models are addressed.

The report is intended for all who work on mesoscale data assimilation. The report is by no means exhaustive, nor will it answer all questions. In many cases only the challenges and caveats will be mentioned. User feedback is therefore more than welcome to keep this document up to date.

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2 Principles of data assimilation

From statistical interpolation theory, see e.g. *Daley* [1998] the analysis state vector \mathbf{a} is given by

$$\mathbf{a} - \mathbf{b} = \mathbf{B}(\mathbf{B} + \mathbf{O})^{-1}(\mathbf{o} - \mathbf{b}) \quad (1)$$

with \mathbf{b} the background state vector, \mathbf{B} the background error covariance matrix, \mathbf{o} the observation state vector, and \mathbf{O} the observation error covariance matrix. In general, the observations are uncorrelated, so $\mathbf{O} = \sigma_o^2 \mathbf{I}$, with σ_o^2 the observation error variance and \mathbf{I} the identity matrix.

Such a data assimilation system acts like a filter [*Hollingsworth and Lönnerberg*, 1986]. Suppose that \mathbf{e}_i is an eigenvector of \mathbf{B} with eigenvalue λ_i . Suppose further that $(\mathbf{a} - \mathbf{b})_i$ and $(\mathbf{o} - \mathbf{b})_i$ are the projections of $(\mathbf{a} - \mathbf{b})$ and $(\mathbf{o} - \mathbf{b})$ on \mathbf{e}_i . Then we have

$$\mathbf{B}(\mathbf{o} - \mathbf{b})_i = \lambda_i (\mathbf{o} - \mathbf{b})_i$$

$$(\mathbf{B} + \mathbf{O})(\mathbf{o} - \mathbf{b})_i = (\mathbf{B} + \sigma_o^2 \mathbf{I})(\mathbf{o} - \mathbf{b})_i = (\lambda_i + \sigma_o^2)(\mathbf{o} - \mathbf{b})_i$$


$$(\mathbf{B} + \mathbf{O})^{-1}(\mathbf{o} - \mathbf{b})_i = (\lambda_i + \sigma_o^2)^{-1}(\mathbf{o} - \mathbf{b})_i$$

and therefore

$$(\mathbf{a} - \mathbf{b})_i = \frac{\lambda_i}{\lambda_i + \sigma_o^2} (\mathbf{o} - \mathbf{b})_i \quad (2)$$

This implies that the data assimilation system acts as a low-pass filter with respect to the eigenvalues: eigenvectors of \mathbf{B} with eigenvalues larger than σ_o^2 are analyzed well, but those with eigenvalues smaller than σ_o^2 are suppressed in the analysis. The filter properties are thus determined by the background error correlations, which in turn depend on the NWP model under consideration.

The background error correlations are often parameterized. They are then referred to as structure functions. Note, however, that the term structure function is also used to denote correlations of spatial differences.

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3 2DVAR as data assimilation test bed

By the nature of the physical processes involved, wind measurements from a scatterometer are ambiguous, so additional information is needed to select the “best” ambiguity for a stand-alone wind product. This is called ambiguity removal. Various schemes have been proposed, and the KNMI scatterometer wind processors use 2DVAR, two-dimensional variational ambiguity removal (Vogelzang *et al.*, 2009).

2DVAR consists of two steps:

- (1) Make an analysis from the scatterometer observations and the ECMWF (or NCEP) background;
- (2) Select the ambiguity closest to the analysis (so 2DVAR could also be named “closest-to-analysis”)

The analysis is made using the methods of statistical interpolation, and the first step of 2DVAR is the same as 3DVAR or 4DVAR. Therefore 2DVAR can be used as a data assimilation test bed.

Figure 1 shows wind spectra of all data of January 2009 for ASCAT at 12.5 km grid size (blue curves), the ECMWF background on approximately 60 km grid size interpolated in time and space to the ASCAT measurements (red curves), and the 2DVAR analysis (green curves). results are shown for the zonal wind component u (left hand panel) and the meridional wind component v (right hand panel). The dotted black line shows a $k^{-5/3}$ spectrum at arbitrary level. Such a spectrum is predicted by Kolmogorov’s three-dimensional turbulence theory.

Figure 1 shows that the ECMWF background contains much less information than the ASCAT wind field at small and intermediate scales. This is partly caused by the fact that the background fields that were downloaded from ECMWF had a resolution of about 60 km, but also because the ECMWF model lacks detail in areas where valid scatterometer winds are measured. Figure 1 also shows that the 2DVAR analysis follows the background and fails to incorporate the small scale information in the ASCAT measurements. This must be a consequence of the filtering properties of 2DVAR, with small eigenvalues corresponding with eigenvectors that describe small detail.

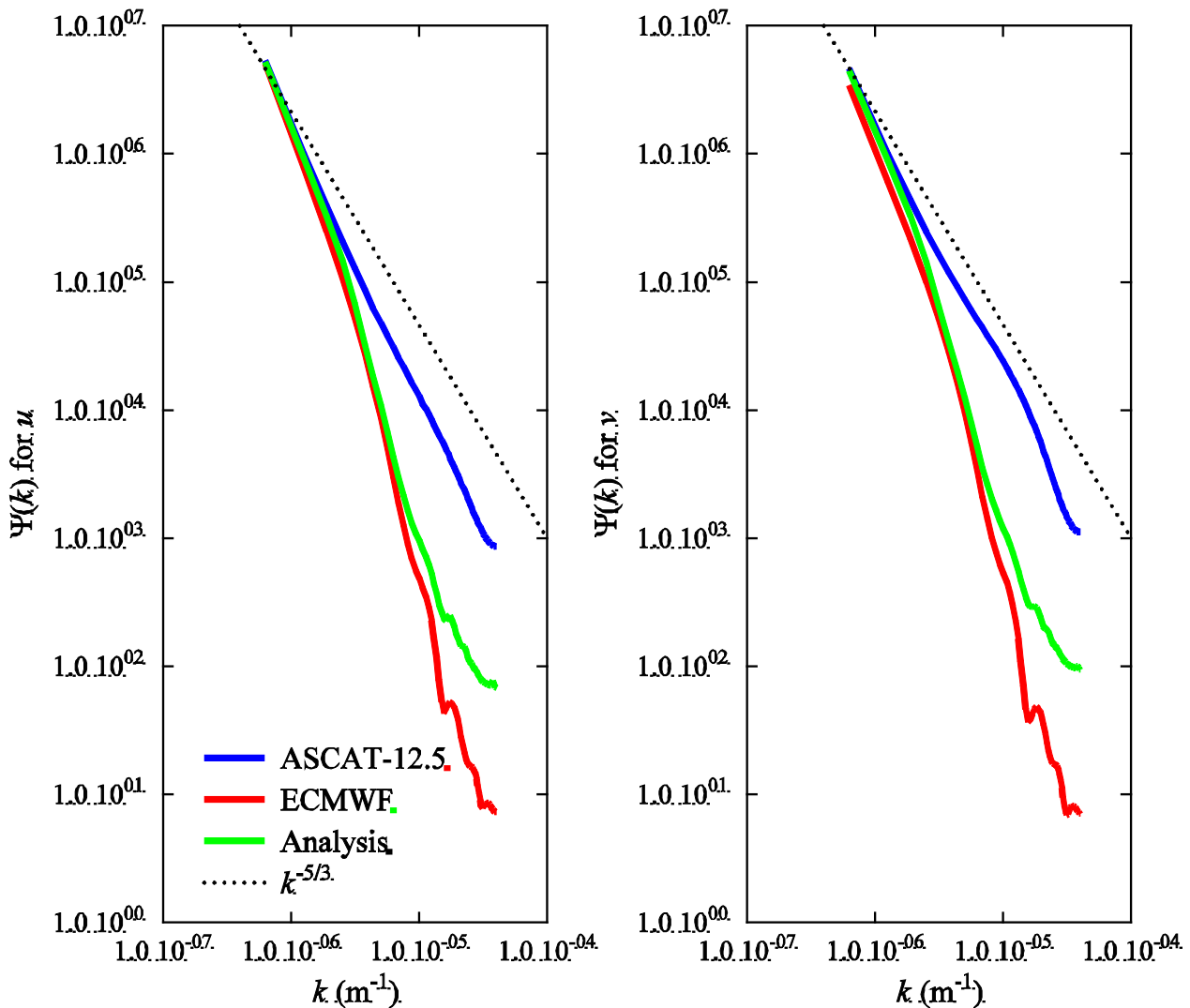


Figure 1 Wind spectra of ASCAT-12.5, ECMWF, and 2DVAR analysis.

2DVAR contains a number of parameters: the error variances of observations and background and the structure function parameters. When trying to improve 2DVAR there is little freedom in varying the error variances, as these are constrained by triple collocation. As an example figure 2 shows an ASCAT wind field on a 25 km grid on 17 November 2009 around 17:40 UT obtained with the default 2DVAR settings. Figure 3 shows the same area, but now with the structure function cutoff reduced to 100 km. As a consequence, ambiguity removal errors are visible in the northwestern part of the wind field.

Apparently, the short-ranged structure functions are not able to describe the inflow to the cyclone. The reason for this error is shown in figure 4: a spurious developing low near 25°S and 120°W.

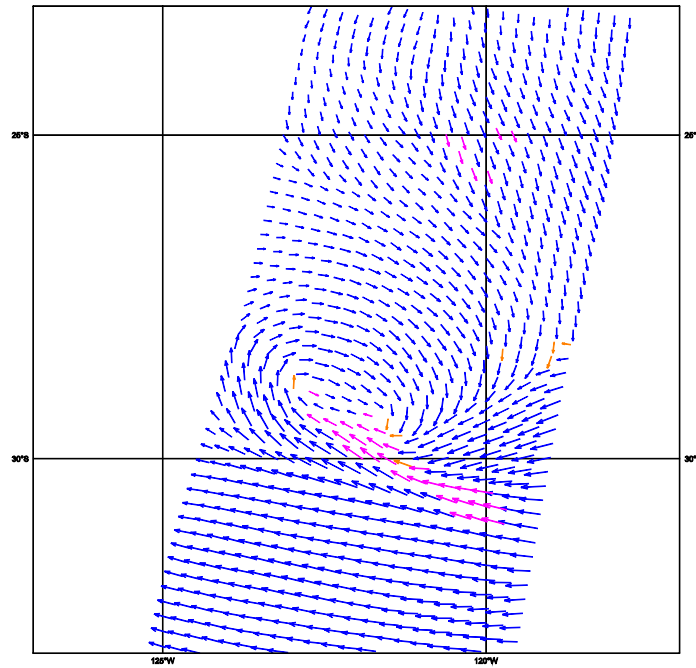


Figure 2 ASCAT-25 wind field on 17-11-2009 around 17:40 UT in the Southern Pacific. Purple arrows indicate cells that have the variational quality control set, orange arrows cells that have the MLE quality control set.

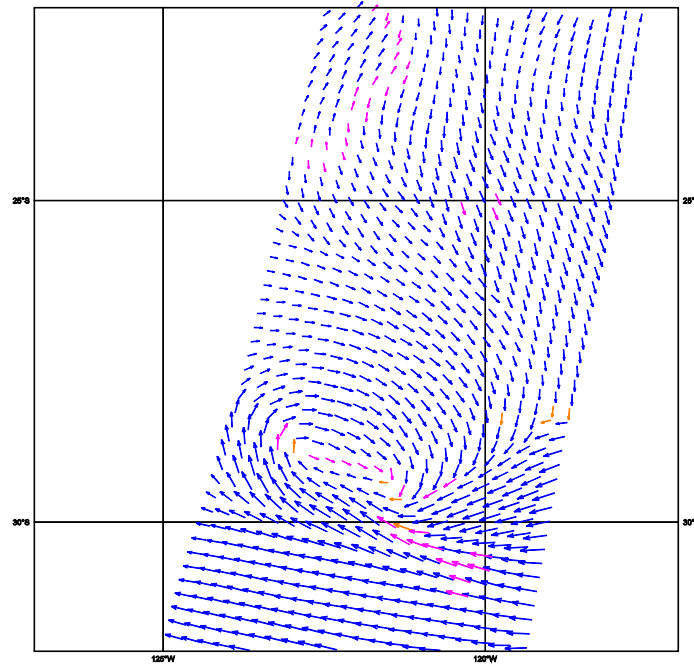


Figure 3 As figure 2, but obtained with a structure function cutoff of 100 km.

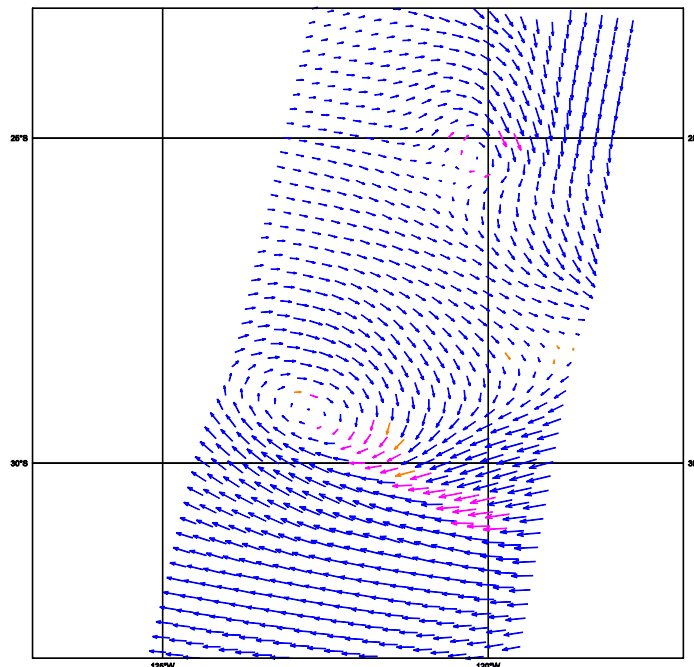


Figure 4 Background belonging to figures 2 and 3.

4 How to improve the analysis

In order to assimilate mesoscale features into a NWP model, one should use realistic values for the error variances and structure functions. Error variances of observations and background may be found using triple collocation [Vogelzang *et al.*, 2011]. Structure functions may be obtained in the following way: In the homogeneous and isotropic case the error autocorrelations for the longitudinal and transversal wind components, ρ_{ll} and ρ_{tt} , read [Daley, 1998]

$$\rho_{ll}(r) = -L_{\psi}^2(1-v^2) \frac{1}{r} \frac{d\rho_{\psi\psi}(r)}{dr} - L_{\chi}^2 v^2 \frac{d^2 \rho_{\chi\chi}(r)}{dr^2} \quad (3a)$$

$$\rho_{tt}(r) = -L_{\psi}^2(1-v^2) \frac{d^2 \rho_{\psi\psi}(r)}{dr^2} - L_{\chi}^2 v^2 \frac{1}{r} \frac{d\rho_{\chi\chi}(r)}{dr} \quad (3b)$$

with $\rho_{\psi\psi}$ and $\rho_{\chi\chi}$ the autocorrelations of the stream function and velocity potential. L_{ψ} and L_{χ} are length scales, and v^2 is the divergence/rotation ratio. ρ_{ll} and ρ_{tt} are observables, while $\rho_{\psi\psi}$ and $\rho_{\chi\chi}$ are the structure functions that make up the background error covariance matrix.

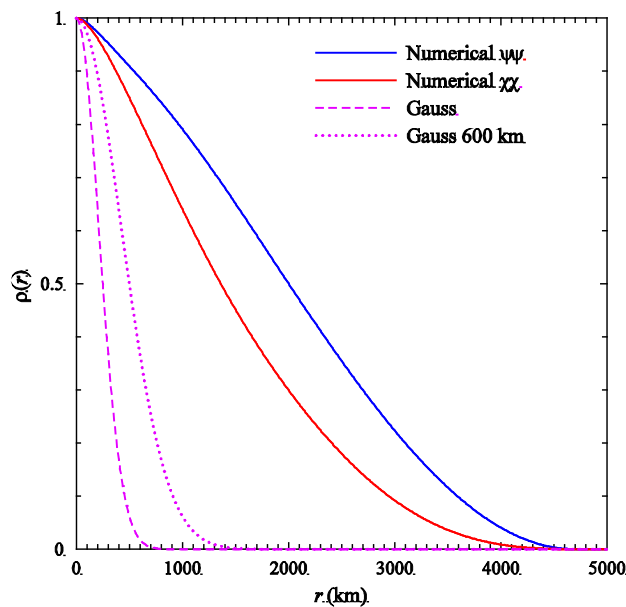


Figure 5 Numerical structure functions and Gaussian structure functions

Vogelzang and Stoffelen [2011] show how equations (3a-b) can be solved for $\rho_{\psi\psi}$ and $\rho_{\chi\chi}$. In the case of 2DVAR, this procedure leads to structure functions with a long range, see figure 5.

Figure 6 shows the impact of the numerical structure functions of figure 5 as the spectral ratio of the resulting analysis with the default analysis as a function of $s = 1/k$. Indeed application of numerical structure functions increases the information content of the analysis at small and intermediate scales considerably: up to a factor of 6 for v at scales around 150 km.

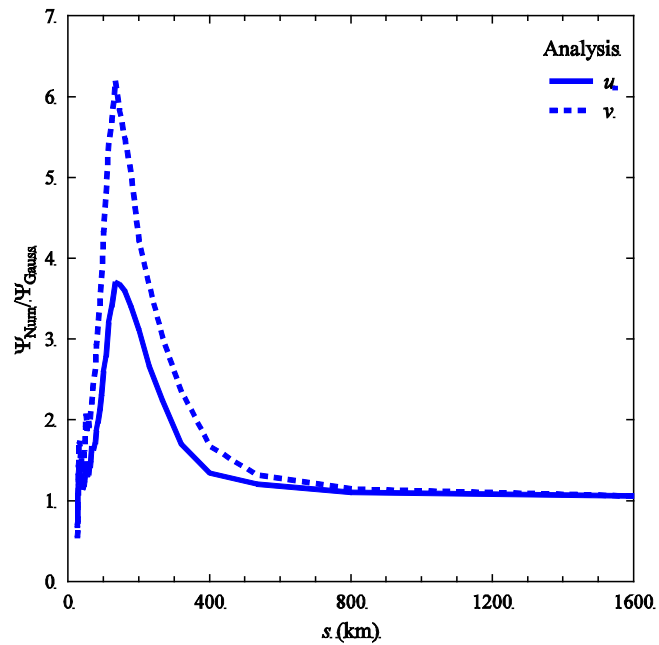


Figure 6. Spectral ratio

5 Challenges

Mesoscale data assimilation poses a number of challenges for the future.

- (1) The NWP model must be able to propagate mesoscale structures in a realistic way. This is a long-term measure, as it may involve reformulating the model physics and parameterisations. Simply decreasing the grid size and time step is not enough. Moreover, small-scale dynamic features grow non-linearly while their forecast range is limited. This may introduce unwanted errors over larger forecast times.
- (2) There must be sufficient three-dimensional data available to initialize ageostrophic flow. Though measurements are relatively abundant over land (radar, aircraft, in-situ), this is not the case over the oceans. Here more satellite observations will be needed.
- (3) Observations will have a larger weight when assimilation smaller scales. This is schematically depicted in figure 7 which shows the spectrum of observations (o) and that of the background of models with course resolution (b) and fine resolution (b')

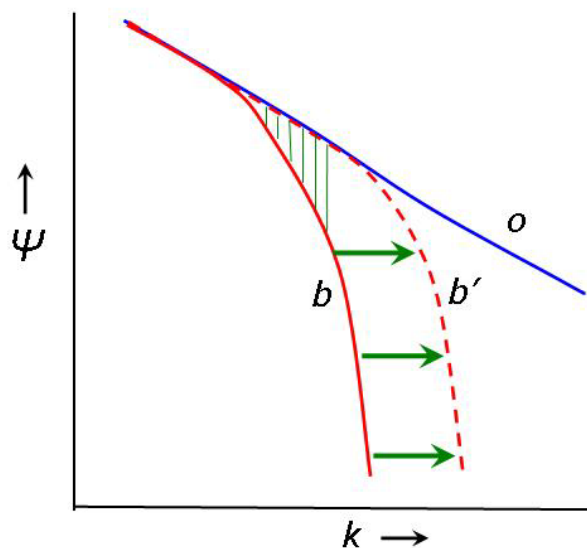





Figure 7 Mesoscale data assimilation

- If the model has course resolution, represented as the solid red curve labeled b , the area between the solid red and blue curves represents variance that is present in the observations, but not included in the model. This variance will therefore add to the representativeness error of the

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observations and hence to their total error. When the model resolution increases, as represented by the dashed red curve labeled b' , the area between the blue and dashed red curves decreases. As a consequence the representativeness error of the observations decreases and the observations get larger weight in the analysis.

- (4) The fact that in mesoscale data assimilation the observations get larger weight also bears the risk of overfitting. It is not clear yet how one should deal with spin-up effects and detrimental effects of uncertain weights in the background error correlation matrix. Adaptive background error covariances are notoriously difficult, though they are being implemented in Ensemble Kalman Filter (EKF) at ECMWF
- (5) One needs suitable verification metrics for mesoscales, involving wind and precipitation rather than pressure and temperature.

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