

How to sample the atmosphere with wind observations: What can we learn from a simple 1-D analysis?

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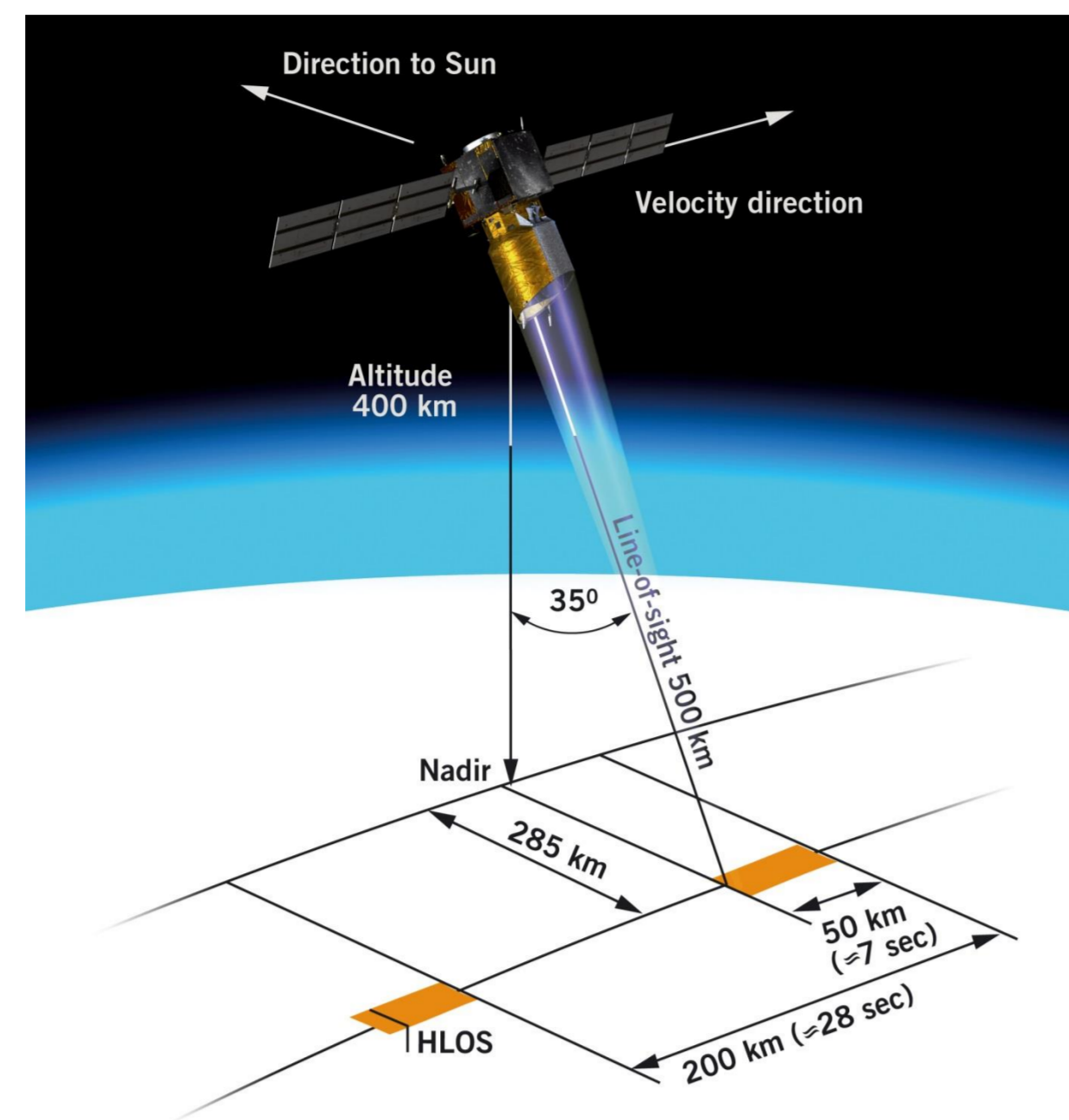
VAMP and VHAMP ESA projects – how to do Aeolus wind sampling

The goal of the project VAMP - "Vertical Aeolus Measurement Positioning" was to give recommendations for the operation of Aeolus with regard to spatial and temporal sampling, in particular for the positioning of the vertical measurement bins, to provide maximum mission benefit. A followon project, VHAMP - "Vertical and Horizontal Aeolus Measurement Positioning" included also the horizontal sampling strategy and various other scenarios.

The target is to assimilate Aeolus in Numerical Weather Prediction (NWP) model and define the best sampling strategy to maximize the impact of the observations in that context.

The VAMP and VHAMP projects were collaborative efforts a team consisting of KNMI, MET Norway and MISU. Complementary tools used in the project included a LIDAR observation simulation tool and Ensemble Data Assimilation experiment.

This poster presents a MET Norway contribution to this work with a statistical tool based on data assimilation theory for a one-dimensional control vector to analyze the average effect of various sampling scenarios on analysis quality in NWP.



The VAMP study was initiated in 2007, when the Aeolus LIDAR instrument was to be operated in so-called pulsed burst mode, which means that the instrument was to be switched on in cycles, measuring for 50 km alternated by being switched off for 150 km, as seen in the Figure above.

Later on it was decided to change the Aeolus laser operation from pulsed burst mode (BM) to continuous mode (CM) with a major impact on the Aeolus observation sizes and raised new scientific questions on the optimal use of Aeolus wind observations for NWP. In continuous mode a choice should be made on how to accumulate pulses horizontally to form observations to be assimilated in Numerical Weather Prediction (NWP).

Method and equations follows standard linear data assimilation theory

For analysis of horizontal line-of-sight (HLOS) winds in a single vertical column or horizontal line explicit representation of covariance matrices is possible and calculation of analysis error covariance matrix is tractable (full NWP covariance matrices not feasible)

Data assimilation schemes look for weight matrix W to give "best" analysis, if linear:

$$x_a = x_b + W(y - Hx_b)$$

Analysis quality is determined by analysis error covariance matrix:

$$A = (I - WH)B(I - WH)^T + W O W^T$$

The weight matrix given by:

$$W = B H^T (H B H^T + O)^{-1}$$

gives the optimal analysis in the sense of minimizing $\text{tr}(A)$, i.e. the analysis error variance

For this choice of W , the analysis error covariance matrix can be written

$$A = (I - WH)B$$

Here: We derive analysis quality for given observation distribution and quality scenarios (i.e. provide H and O , derive A)

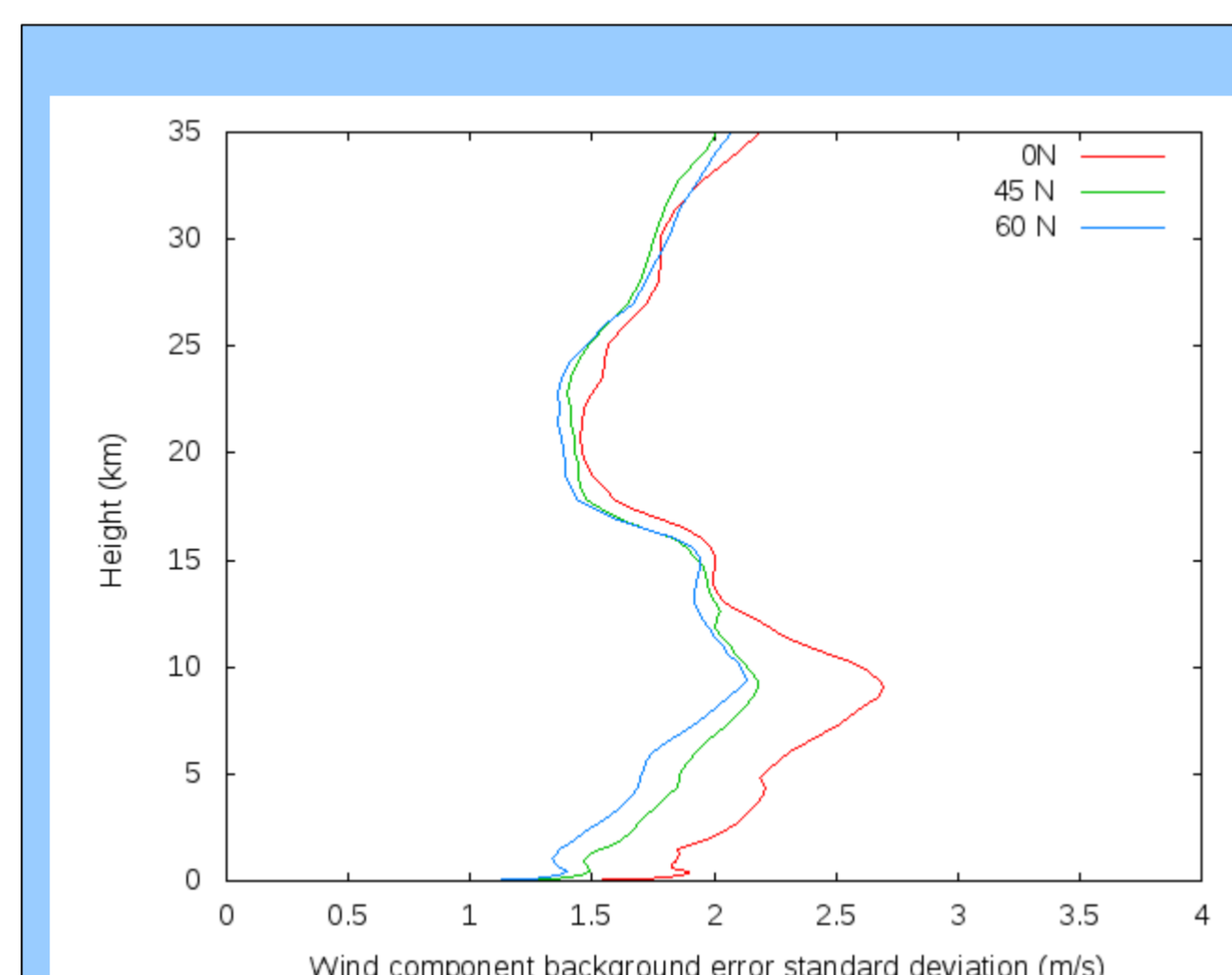
The outcome of this depends on the background errors (B) in such a way that the observations bring more improvements if they describe structures which are complementary (not redundant) to the information already available in the system (background info).

We can assume B and O are correctly specified or assess effect of misspecified B and O

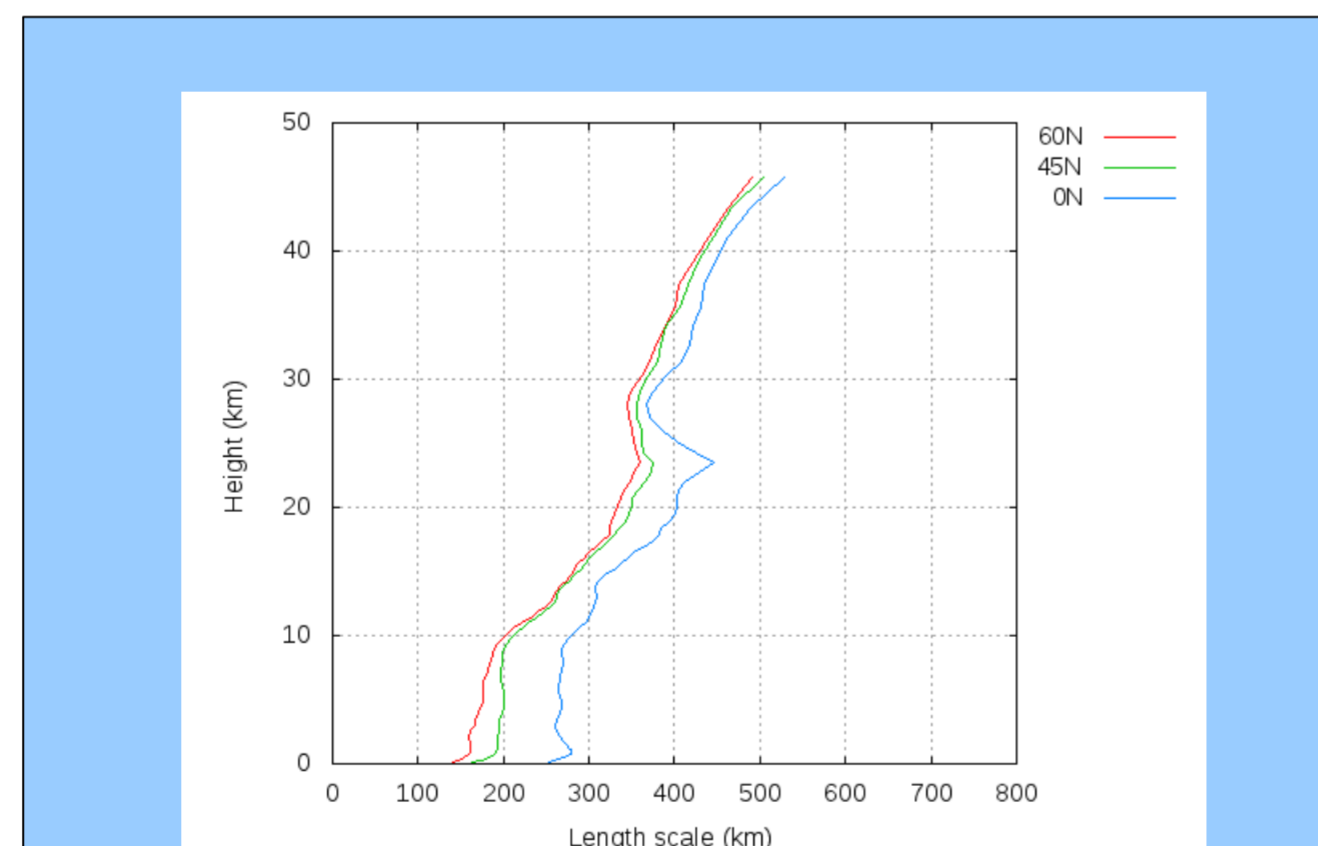
Analysis of horizontal sampling: Wind background error statistics from ECMWF

The results for how the observation sampling improves NWP analysis are strongly dependent on the error properties of the information already available in the NWP model as described by the background error statistics

In the examples presented in this poster we have extracted background error statistics from the ECMWF global model. These background error covariance data were extracted in 2010, when operational horizontal model resolution was T1279 (i.e. around 16 km.). This was done for points at three latitudes: (0N 30W), (45N 30W), (60N 0W). Some additional steps were necessary to transform this output to the necessary covariance matrix for the 1-D HLOS case studied here. The figures to the right illustrates the variation of this background error statistics.



Background error statistics: Wind component background error variance as a function of height



Background error statistics: Latitude dependence of horizontal length scale profile:

- Length scales generally increasing uniformly with height up to 20-25 km
- Length scales increasing while moving towards equator
- A stronger increase in horizontal scale when going from 45N to equator than when going from 60N to 45N.

Results from observation scenarios:

Average observation error statistics under the various scenarios were provided from KNMI based on their LIDAR simulation tool LIPAS.

The quality of the analysis obtained by assimilating the observations under the various scenarios are here measured with the analysis error variance relative to the background error covariance.

Mathematically in terms of matrices, that is $\text{tr}(A)/\text{tr}(B)$.

→ The smaller value of this quantity, the better analysis

	Burst 110 mJ	Cont 110 mJ	Cont 80 mJ
50 hPa	0.4004	0.3240	0.4067
250 hPa	0.3676	0.2472	0.3140
500 hPa	0.4557	0.3099	0.4269
700 hPa	0.4758	0.3927	0.4727

Burst vs continuous mode vs reduced laser energy

The table to the left indicates the analysis quality obtained for 3 sampling scenarios:

- "Burst mode", i.e. sampling over 50 km every 200 km
- "Continuous mode", sampling over 100 km every 100 km
- "Continuous" mode with less laser energy (80 mJ giving more measurement noise than 110 mJ)

The results are for background errors at 60N at various levels, and show that:

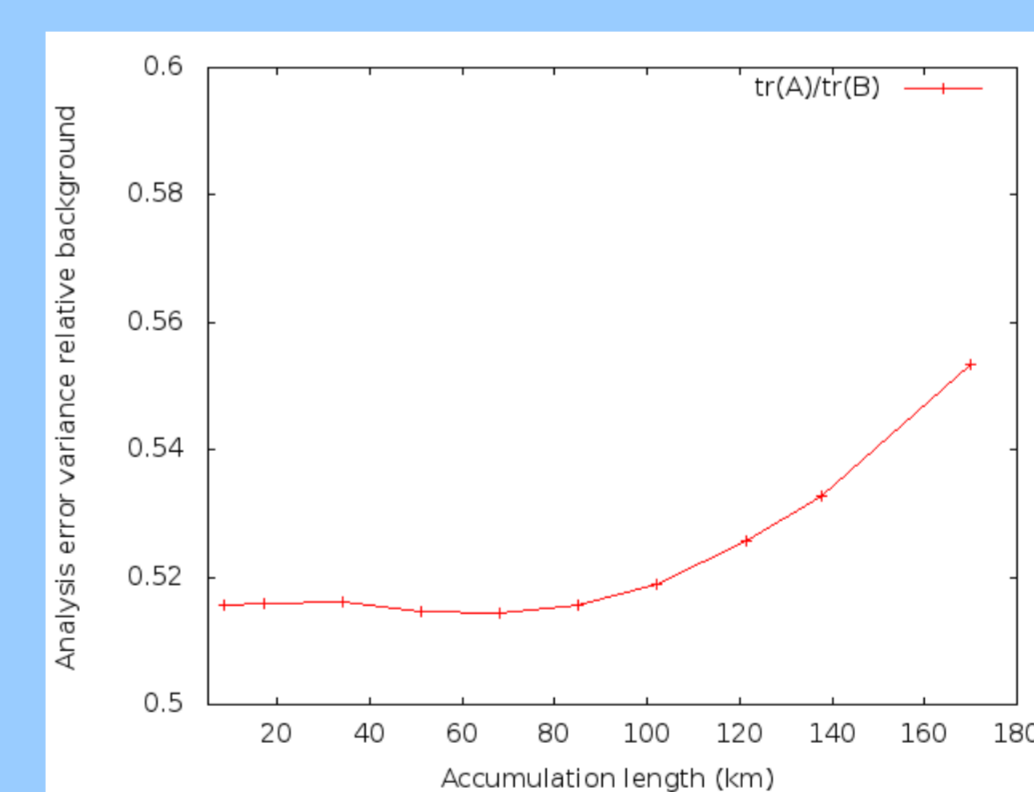
- for identical laser energy, continuous mode gives higher analysis quality than burst mode
- the effect of reducing the laser energy from 110 to 80 mJ in terms of reduction of expected analysis quality is quantified here, and is significant

Bias std (b)	0	0.5 m/s	1 m/s	2 m/s	4 m/s	8 m/s	16 m/s
Optimal O matrix: Tr(A)/tr(B)	0.4269	0.4556	0.4769	0.4884	0.4921	0.4931	0.4933
Non-optimal O matrix: Tr(A)/tr(B)	0.4269	0.4774	0.6290	1.2352	3.6600	13.36	52.16

Effect of unknown bias in observations

The above table shows a scenario when having a bias in the observations which is constant horizontally. In an ideal assimilation scheme this can be treated optimally in a statistical sense by including non-diagonal elements in the observation error covariance matrix. The results in that case is shown in the second row.

Usually it is not possible to handle biases in such a way, and the third line shows the results when the observations are biased, but it is not accounted for in the assimilation scheme: With increasing bias, this can become very detrimental.



Effect of continuous mode accumulation distance (with uncorrelated observations)

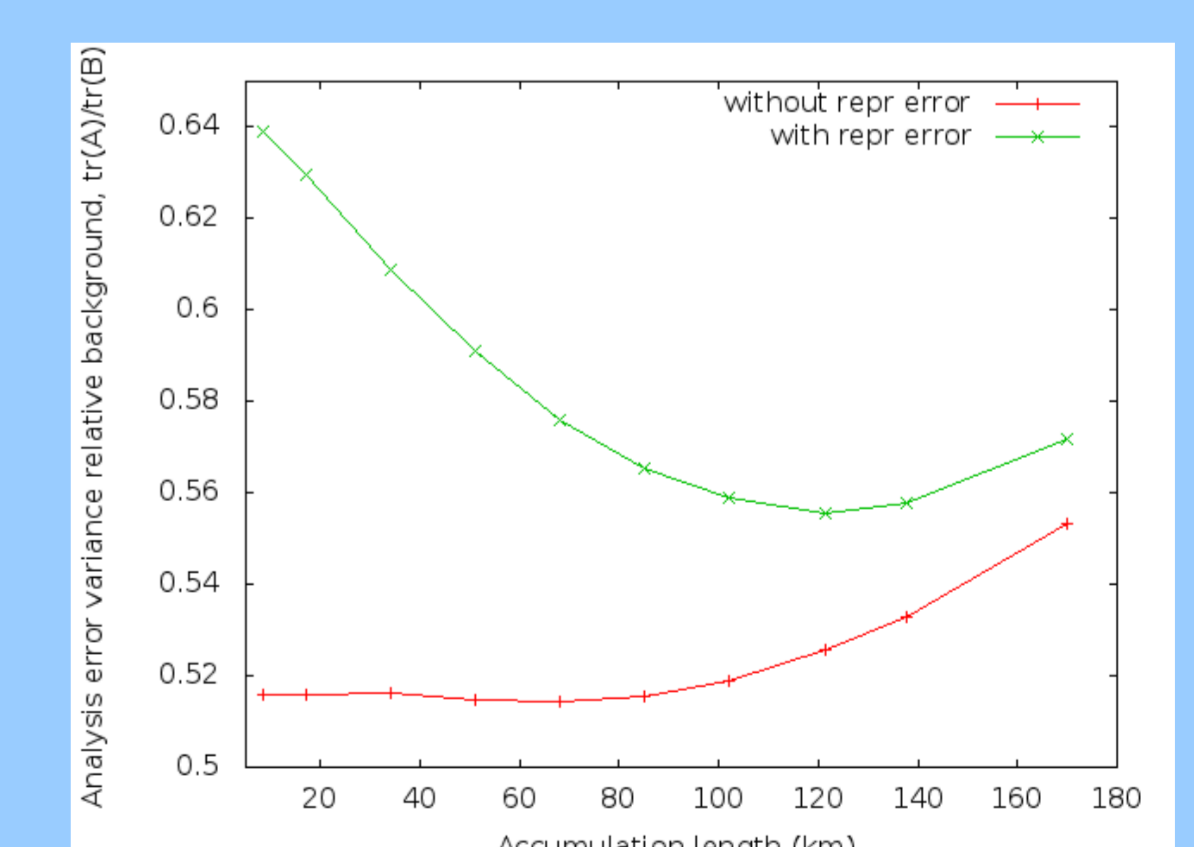
• Example: ECMWF 60N background error statistics with lengthscales reduced to 2/3 (to correspond to more recent models capturing smaller scales), continuous 80 mJ, 500hPa (Rayleigh channel average obs error data from LIPAS)

- 85 km or shorter accumulation seems good
- Decreasing analysis quality for longer accumulation distances
- Constant (or very slight decrease in) analysis quality for shorter accumulation distances

Effect of accumulation distance (correlated observations)

A formulation for correlated observation representativeness error was included here.

- As expected, less impact of Aeolus than with uncorrelated observations (even if the correlations are assumed perfectly handled with a non-diagonal obs error covariance matrix)
- Now short accumulation lengths no longer so favoured
- Optimal sampling length now at about 120 km



Discussion

The tool for assessing analysis quality here works in one dimension and gives the possibility of testing scenarios and parameter ranges cheaply without full observing system simulation experiments or EDA experiments. But some caution must be undertaken:

- Assesses analysis quality in an average sense
- Idealized univariate system only: Assesses optimality of horizontal line (VHAMP) or vertical column (VAMP) HLOS analysis
- Information on redundancy with other wind observations or observations of for instance geopotential only indirectly through B matrix
- Analysis quality not directly coupled to forecast quality
- No situation dependence
- Some forecast error structures more detrimental than others
- Some forecasts are more important than others (severe weather, ...)

Still, the limited number of scenarios assessed with EDAs experiments in VHAMP at MISU show qualitatively similar results to those found with this simple statistical tool.

Some main conclusions from the study

- For identical laser energy, continuous mode gives higher analysis quality than burst mode. The increase in accuracy in burst mode is outweighed by the increased information contained in the observations due to the increased number of observations in continuous mode
- There is a larger impact of Aeolus in the tropics than the extratropics
- There is an increase in impact in the troposphere up to tropopause level, then decreasing impact above that
- With uncorrelated observations, the sampling length should be chosen 65 km or shorter
- Correlated observation errors will change that conclusion. A relatively realistic scenario (although with some discussable assumptions) for observation error correlations coming from representativeness errors showed a best accumulation length of around 120 km

More details in reports available on request:

Schyberg, H. (2013), Information content in horizontal Aeolus sampling scenarios. VHAMP Technical Note no 8. (Document AE-TN-metno-VHAMP-008-v41).

Schyberg, H. (2010), Impact of the vertical sampling scenarios on NWP and modeling of stratospheric circulation part 1. VAMP Technical Note no 5. (Document AE-TN-metno-VAMP-005-p1_v7).

Marseille et al (2012), Horizontal and vertical background error correlations. VHAMP Technical Note no 6.