

# Accounting for correlated observation error in variational ocean data assimilation

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1: CERFACS, Toulouse

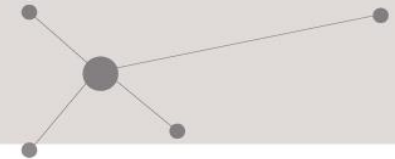
2: Météo-France, Toulouse

3: École Polytechnique, Montréal

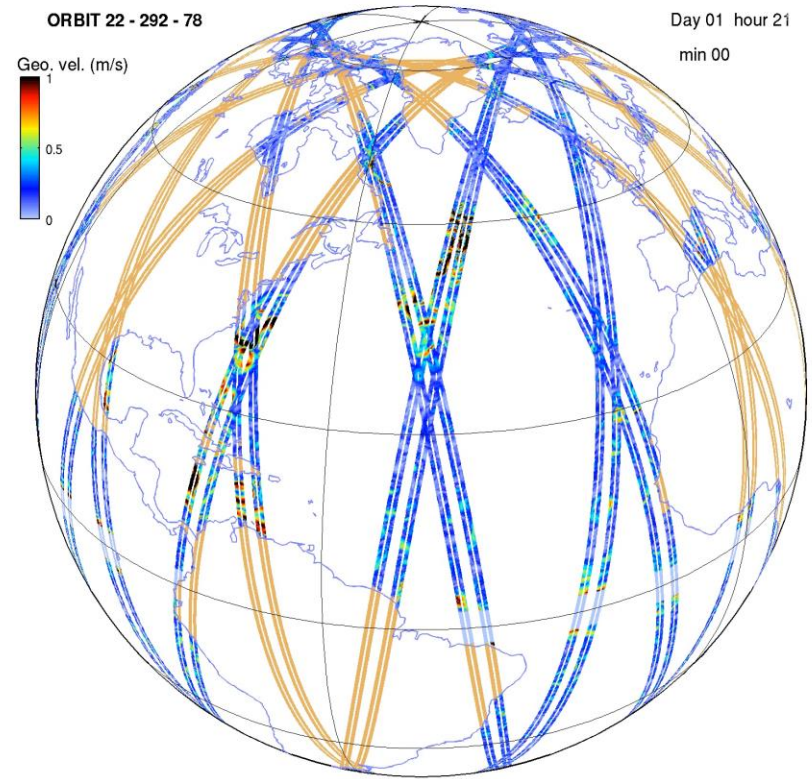
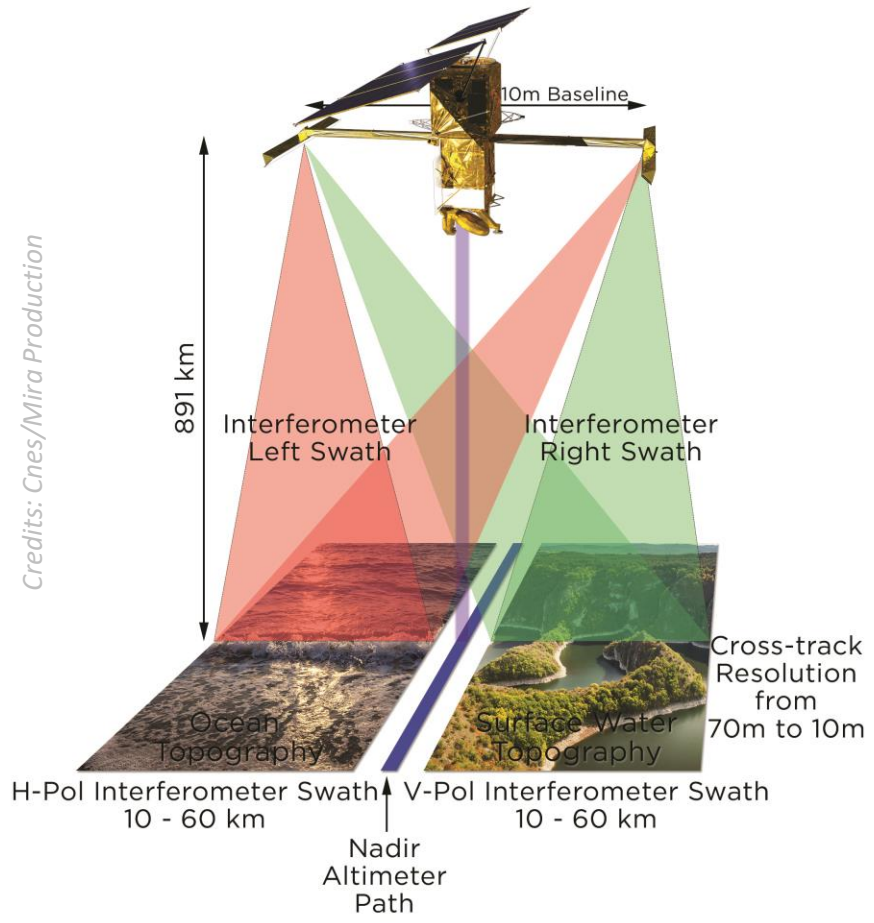
DA-TT Meeting, 9-11 May 2023, CNR Rome

\* Work supported by the Copernicus Climate Change Service

# Example: the SWOT mission



Credits: Cnes/Mira Production



Credits: JPL/C.Ubelmann

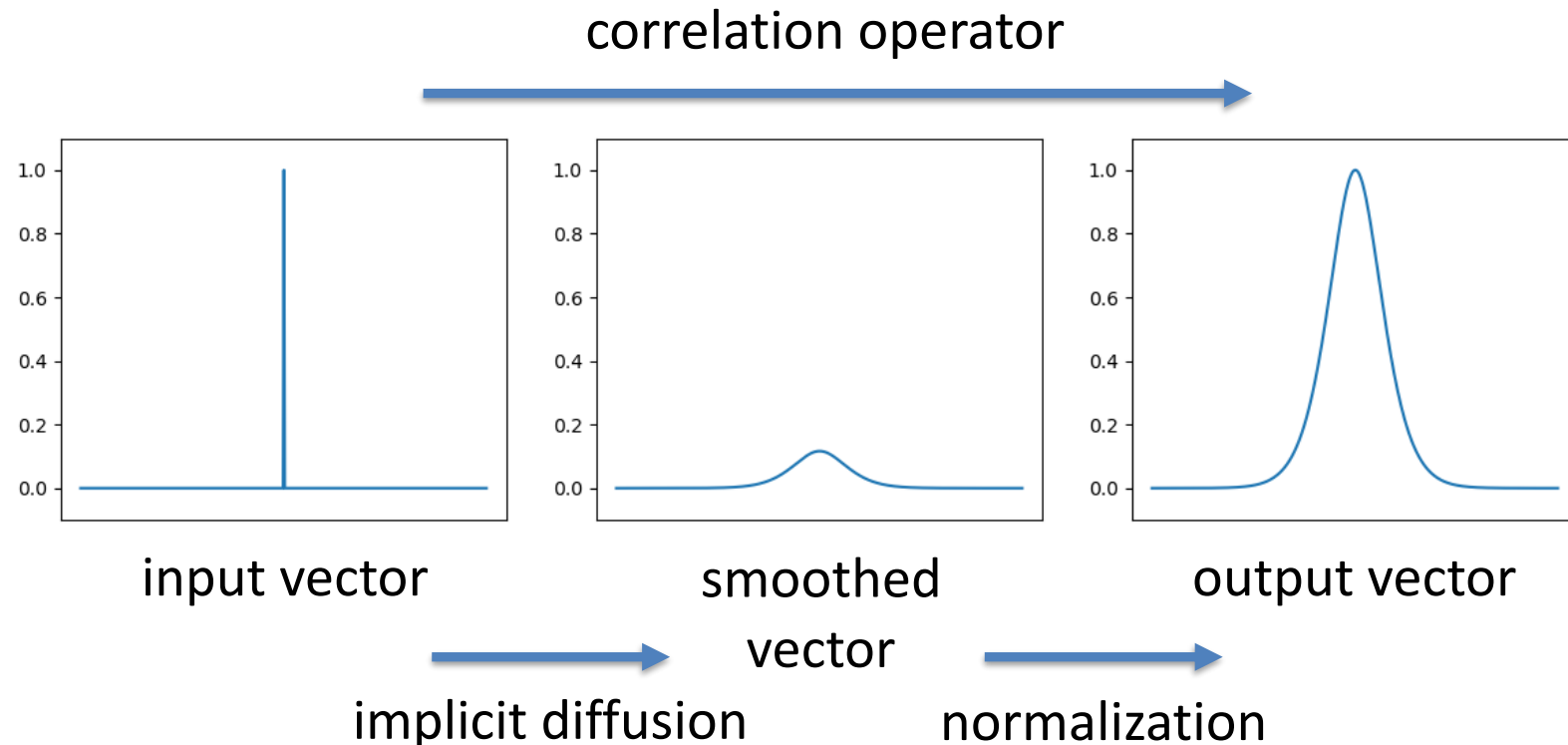
## Example: the SWOT mission

**King, R. R. and Martin, M. J. (2021):** Assimilating realistically simulated wide-swath altimeter observations in a high-resolution shelf-seas forecasting system, *Ocean Sci.*, 17, 1791–1813, <https://doi.org/10.5194/os-17-1791-2021>, 2021.

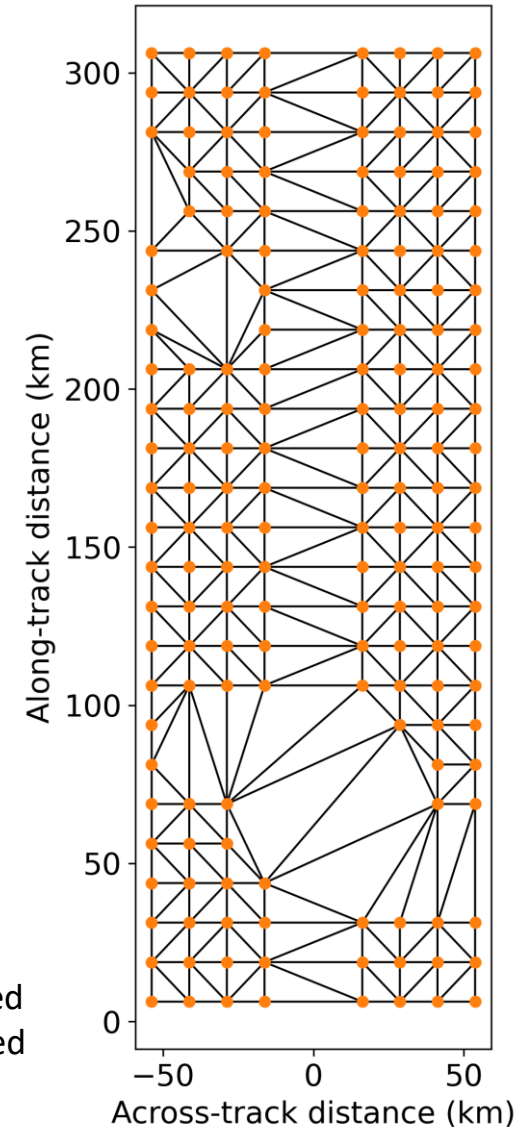
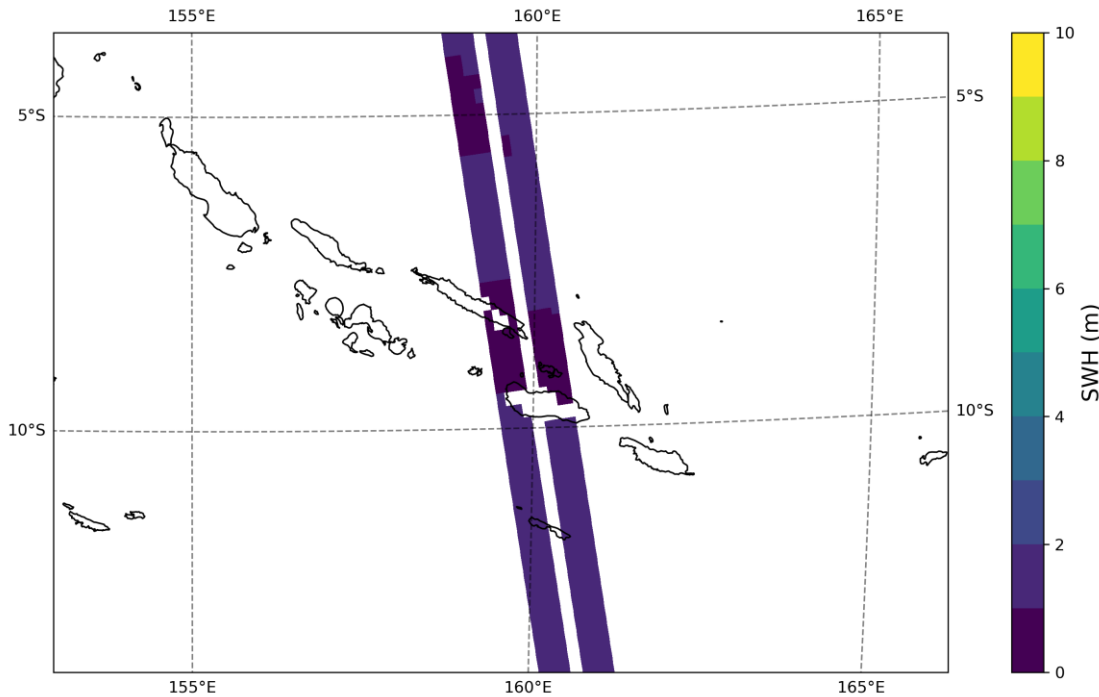
	SSH (m)		Temperature (K)		Salinity (PSU)		Surface Current Speed	
No SWOT (Control)	0.034		0.324		0.053		0.104	
white noise only	0.027	(-21%)	0.340	(+5%)	0.051	(-4%)	0.091	(-13%)
Full error	0.041	(+21%)	0.391	(+21%)	0.054	(+2%)	0.114	(+13%)
Full error, Half swath, Superobbed	0.032	(-6%)	0.324	(0%)	0.052	(-2%)	0.104	(0%)

« when correlated errors are included in the full swath SWOT observations, there is a degradation in the sub-surface temperature and salinity, and the SSH and surface currents are degraded with a clear increase in the mean surface currents. While restricting the SWOT data to the inner half of the swath and applying observation averaging with a 5 km radius negated most of the negative impacts, it also severely limited the positive impacts. »

- Diffusion operators are already in use in DA to model **correlation operators for background error**
- With an implicit scheme, their inverse is easily accessible which makes them suitable to model **inverse correlation operators for observation error**
- The cost of a **product with  $R^{-1}$**  would be **much lower** than the cost of a **product with  $B$**



Diffusion operators can be discretized on a **mesh with a finite element method**, which makes them suitable with **unstructured observations**

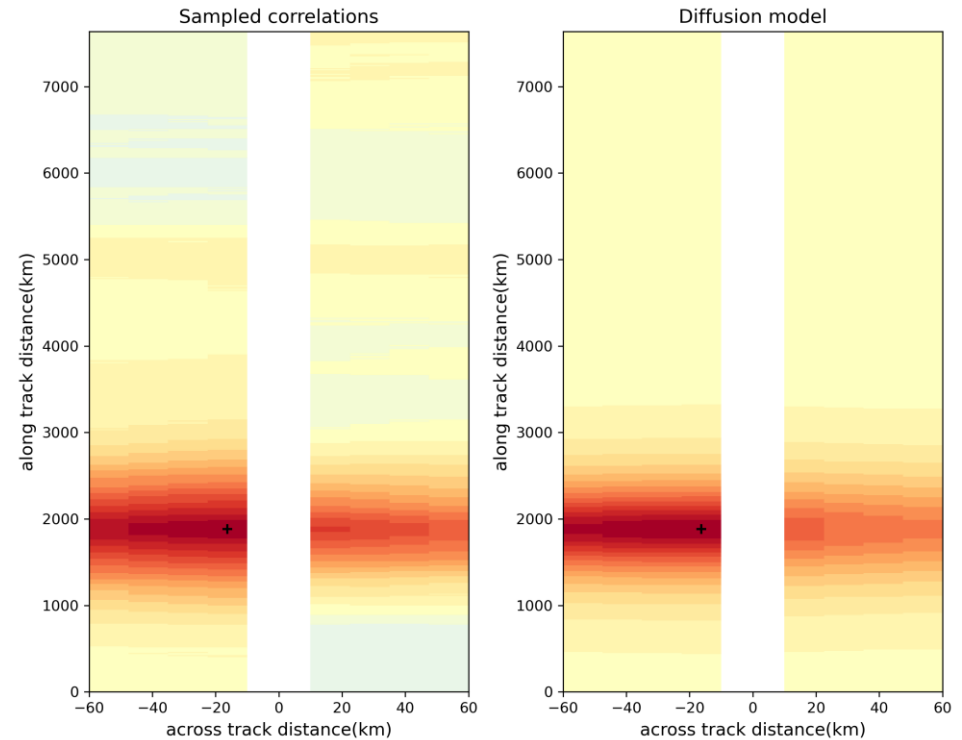
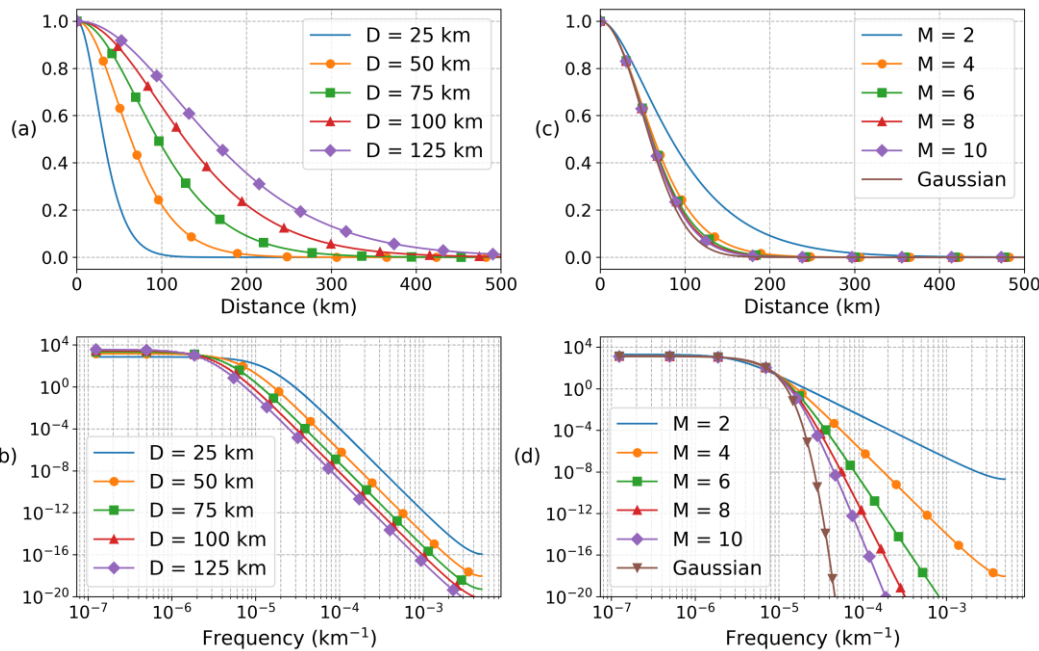


**Guillet, O, Weaver, AT, Vasseur, X, Michel, Y, Gratton, S, Gurol, S.** Modelling spatially correlated observation errors in variational data assimilation using a diffusion operator on an unstructured mesh. *Q J R Meteorol Soc* 2019; 145: 1947– 1967. <https://doi.org/10.1002/qj.3537>



Both the **cut-off** and **roll-off** of the error spectrum modelled by diffusion operators can be adjusted using a **Daley length scale  $D$** , and a **smoothness parameter  $M$** .

The **spatially variable and anisotropic diffusion tensor** makes the operator flexible enough to **fit estimated observation error correlations**



# Understanding DA with a non-diagonal $R$

In variational DA, we need to converge **fast** and towards an **accurate analysis**. The **choice of parameters for  $R$**  has a role to play for both properties. To gain insight on the behaviour of the DA algorithm when **both  $B$  and  $R$  are non-diagonal**, we study a very simple system

- 1D **periodic** domain
  - **Regular** model and observation grids
  - **Spatially constant** covariance parameters
- 
- $B$  and  $R$ , and  $HBH^T$  are **circulant matrices**
  - All three are diagonal in a **Fourier basis**
  - Their eigenvalues represent **error power spectrums**

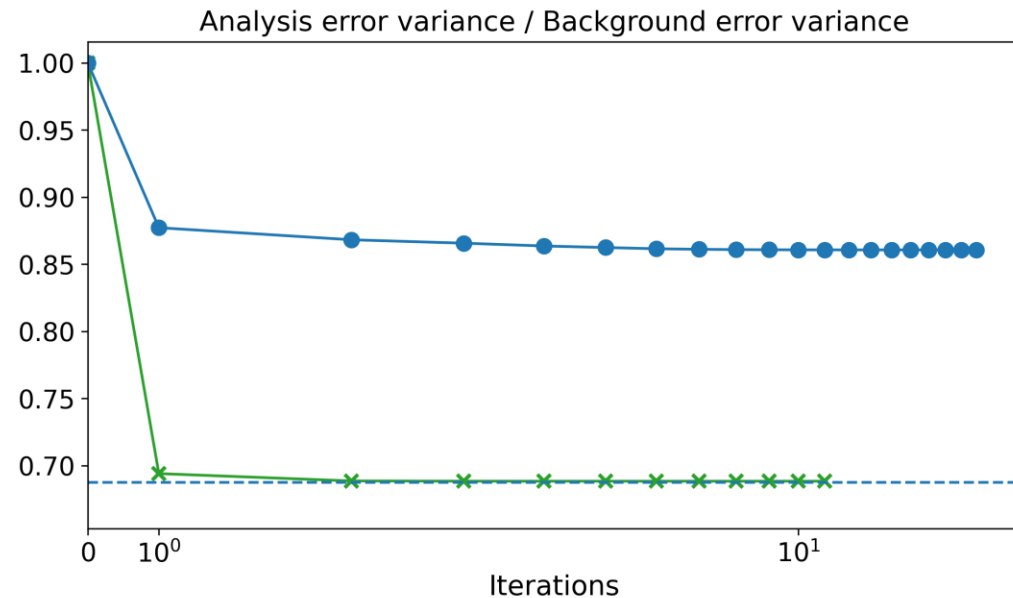
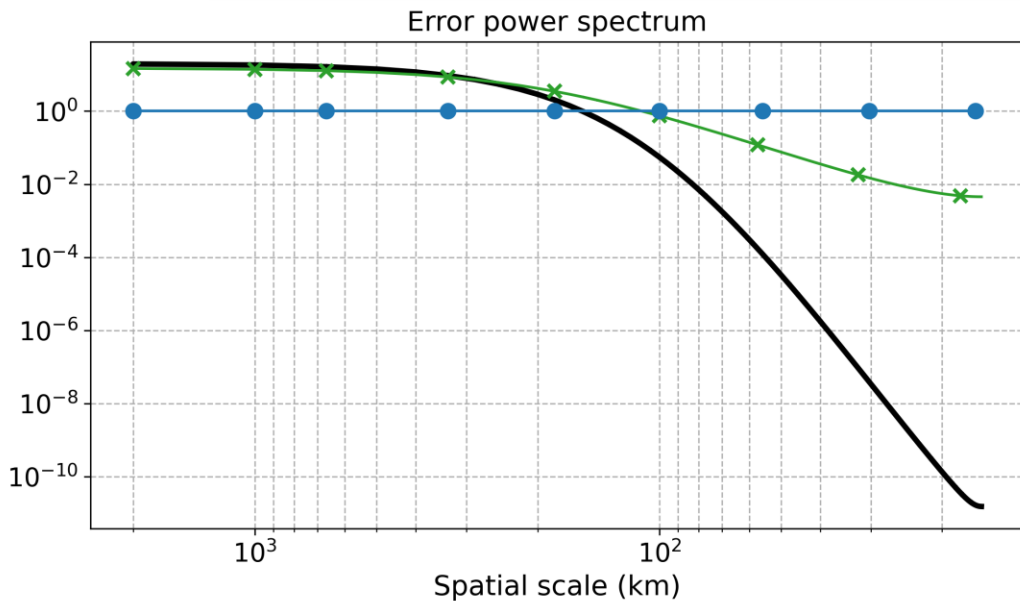
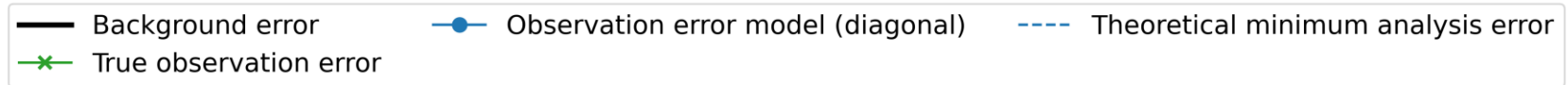
Indicator of the **convergence rate**:      Condition number =  $\max_i 1 + \frac{\lambda_i(\mathbf{HBH}^T)}{\lambda_i(\mathbf{R})}$

**Goux O., Gürol S., Weaver A. T., Guillet O., Diouane Y. (2022)**. Impact of correlated observation errors on the convergence of the conjugate gradient algorithm in variational data assimilation 2212.02305, arXiv

# Convergence experiment

- Ensembles of background and observations are simulated with known error statistics ( $B$  and  $R$ )
- They are assimilated using  $B$  and  $\tilde{R}$
- The **analysis error variance** is estimated at each iteration of the B-PCG from the ensemble of solutions

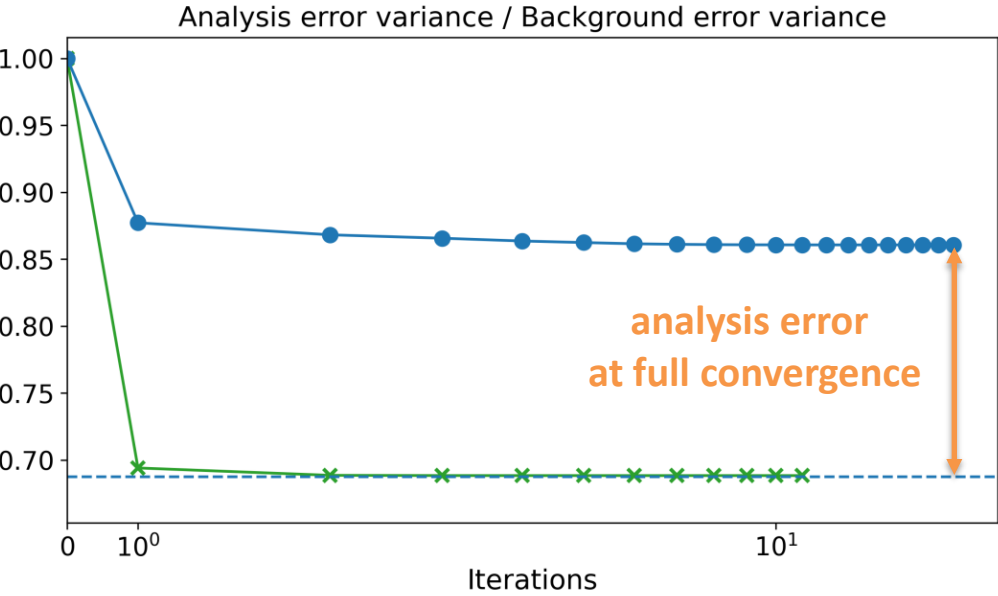
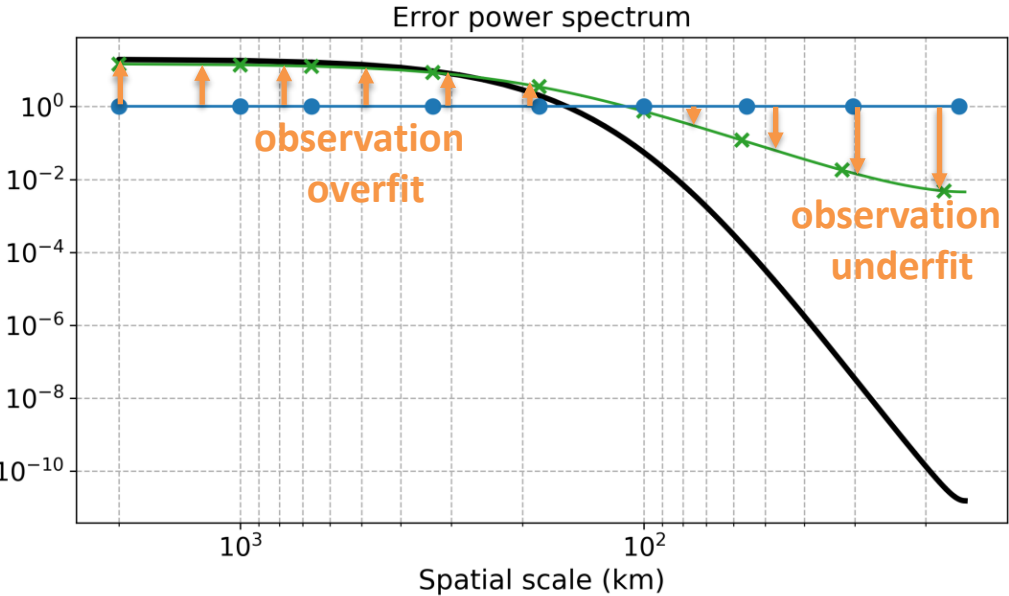
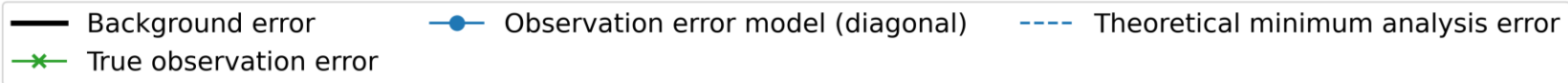
True parameters:  $D_b = 60$  km ;  $M_b = 8$  ;  $D_o = 30$  km ;  $M_o = 2$





# Convergence experiment

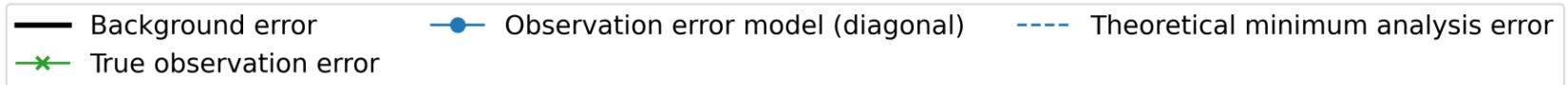
All differences between the true observation error and the observation error model contribute to a sub-optimal analysis error at full convergence.



Using a non-diagonal  $R$  induces an **overfit** of the observations at **large spatial scales** and an **underfit** at **small spatial scales**

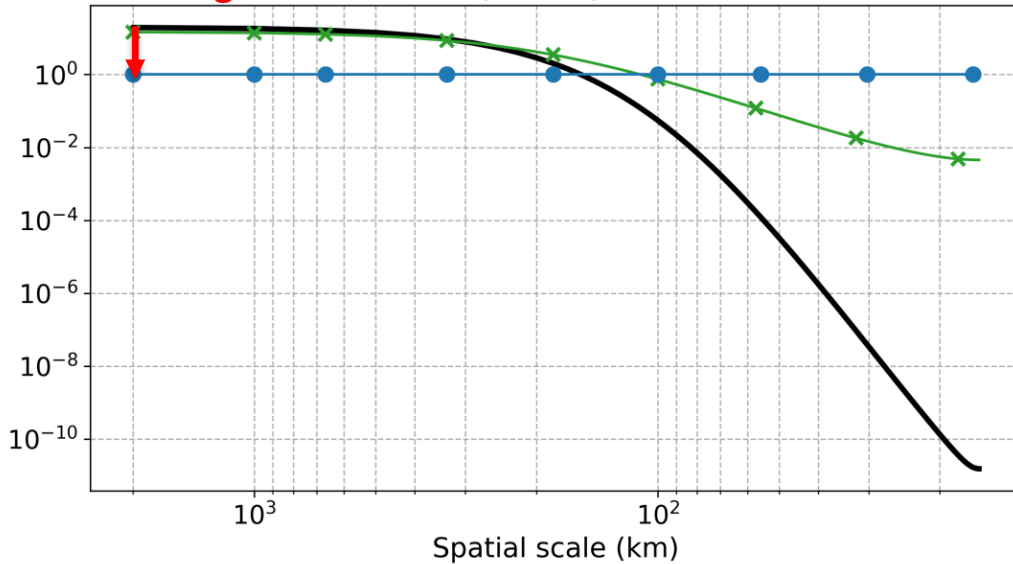
# Convergence experiment

The largest ratio of the eigenvalues of  $B$  and  $R$  determines the condition number and strongly influences the convergence rate of CG

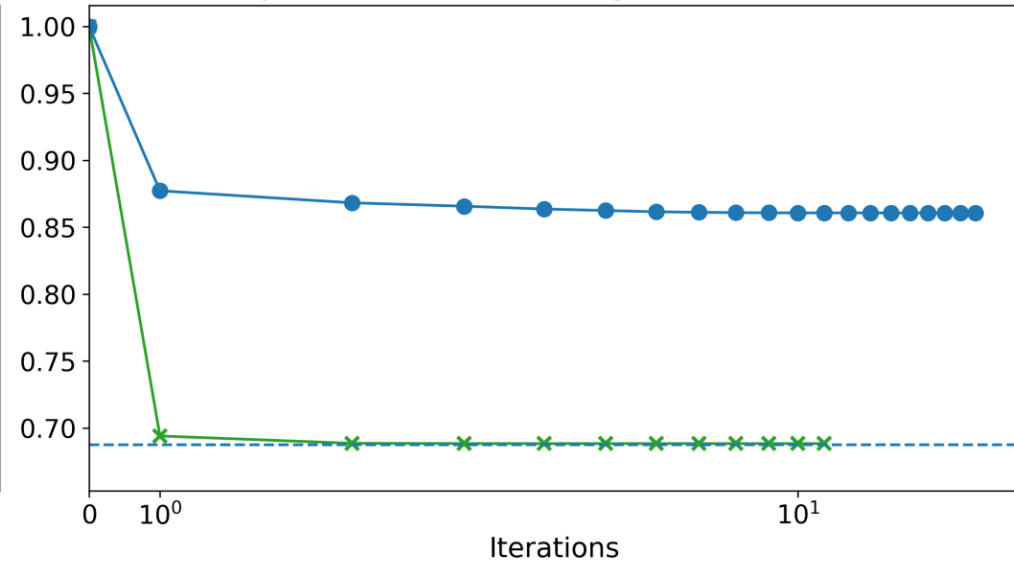


conditioning

Error power spectrum



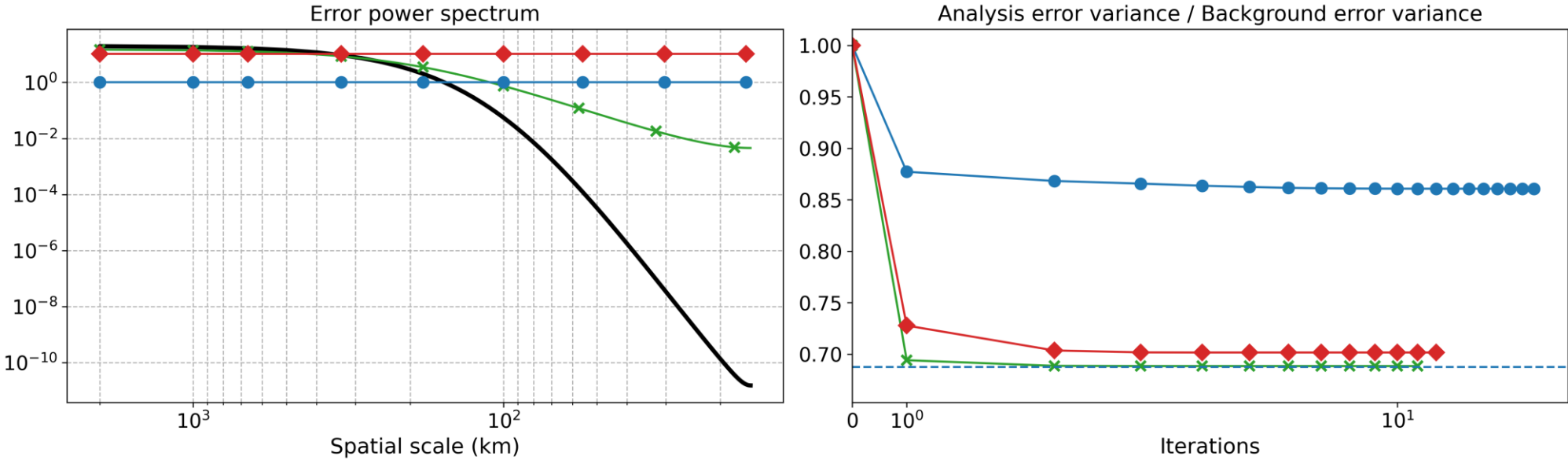
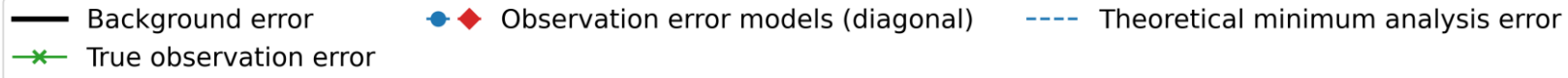
Analysis error variance / Background error variance



Using a non-diagonal  $R$  compared to a diagonal  $R$  does not necessarily degrade the conditioning or slow down the convergence

# Convergence experiment

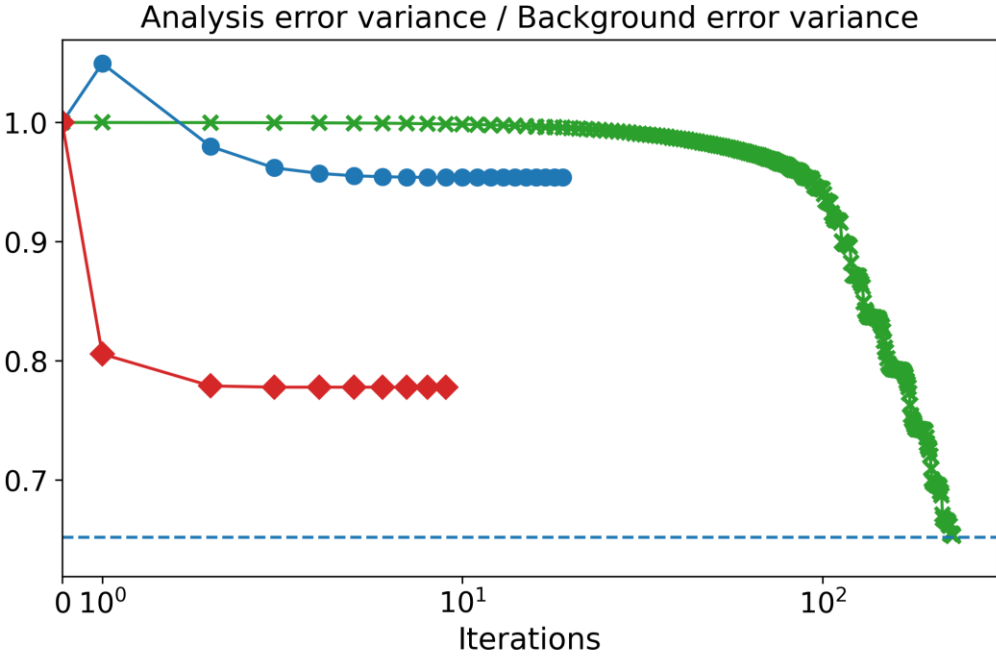
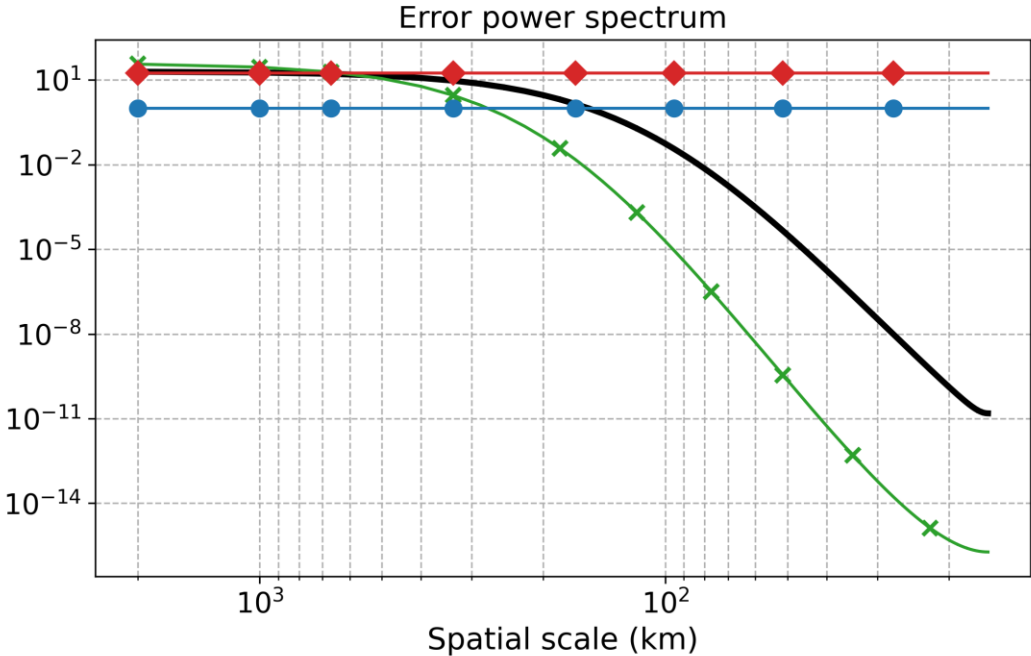
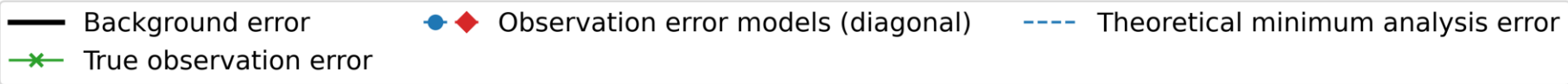
We use **variance inflation** with the inflation factor that minimizes the analysis error at full convergence to find the **best possible diagonal observation error model**.



Variance inflation prioritizes **reducing the overfit at large spatial scales** where errors are large at the expense of small spatial scales.

# Convergence experiment

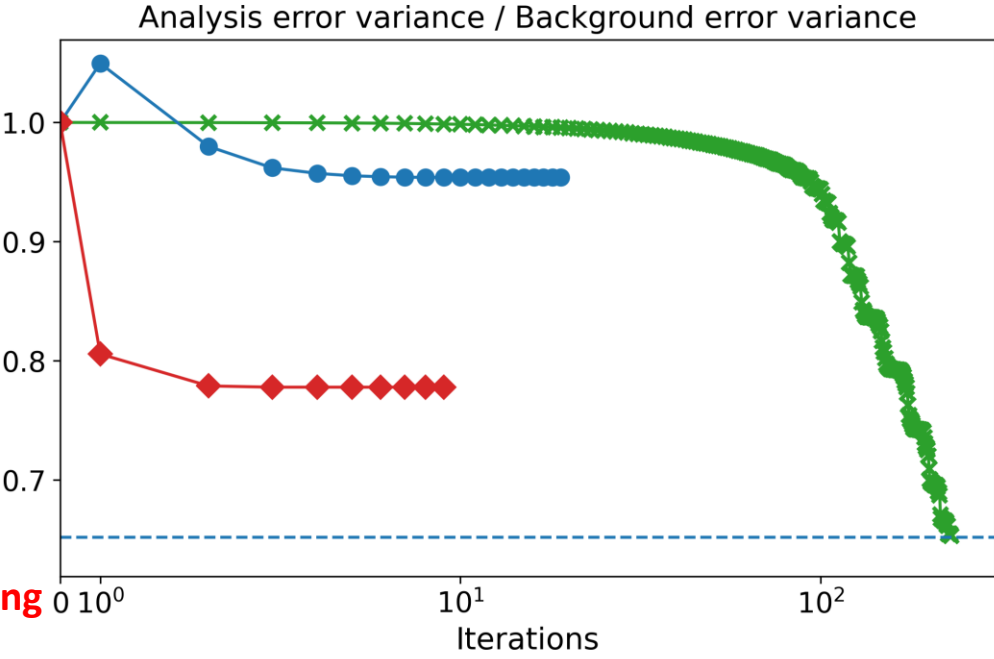
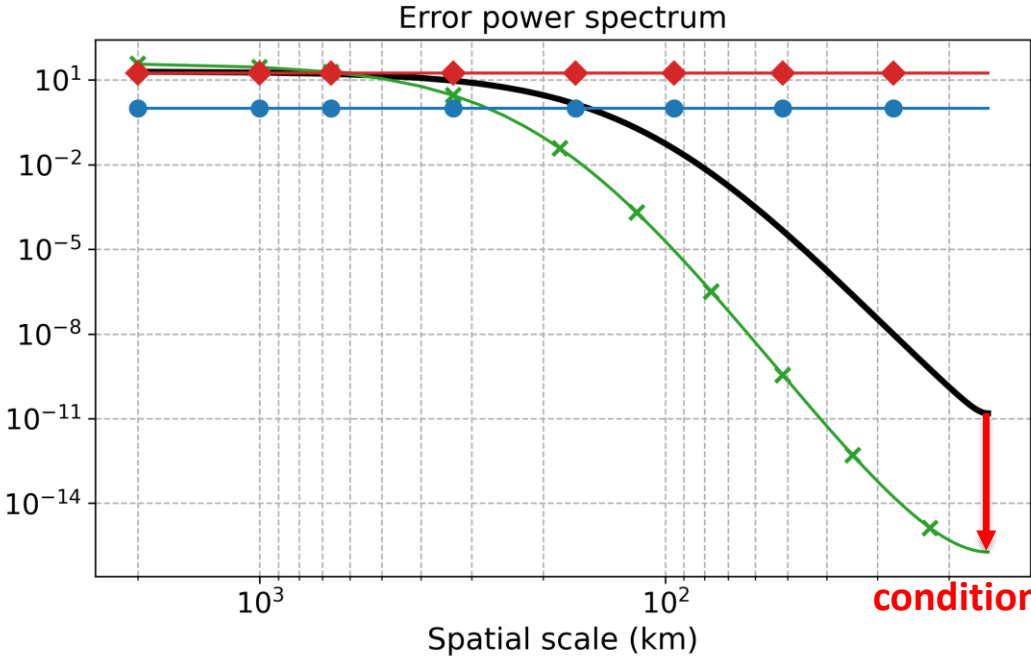
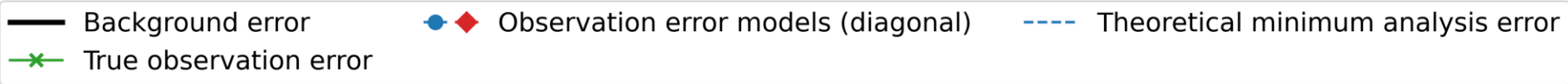
True parameters:  $D_b = 60 \text{ km}$  ;  $M_b = 8$  ;  $D_o = 120 \text{ km}$  ;  $M_o = 10$



Using the most accurate parameters for the observation error leads to a very low analysis error but sometimes only after a **prohibitive number of iterations** (especially if  $M_o > M_b$ )

# Convergence experiment

True parameters:  $D_b = 60 \text{ km}$  ;  $M_b = 8$  ;  $D_o = 120 \text{ km}$  ;  $M_o = 10$

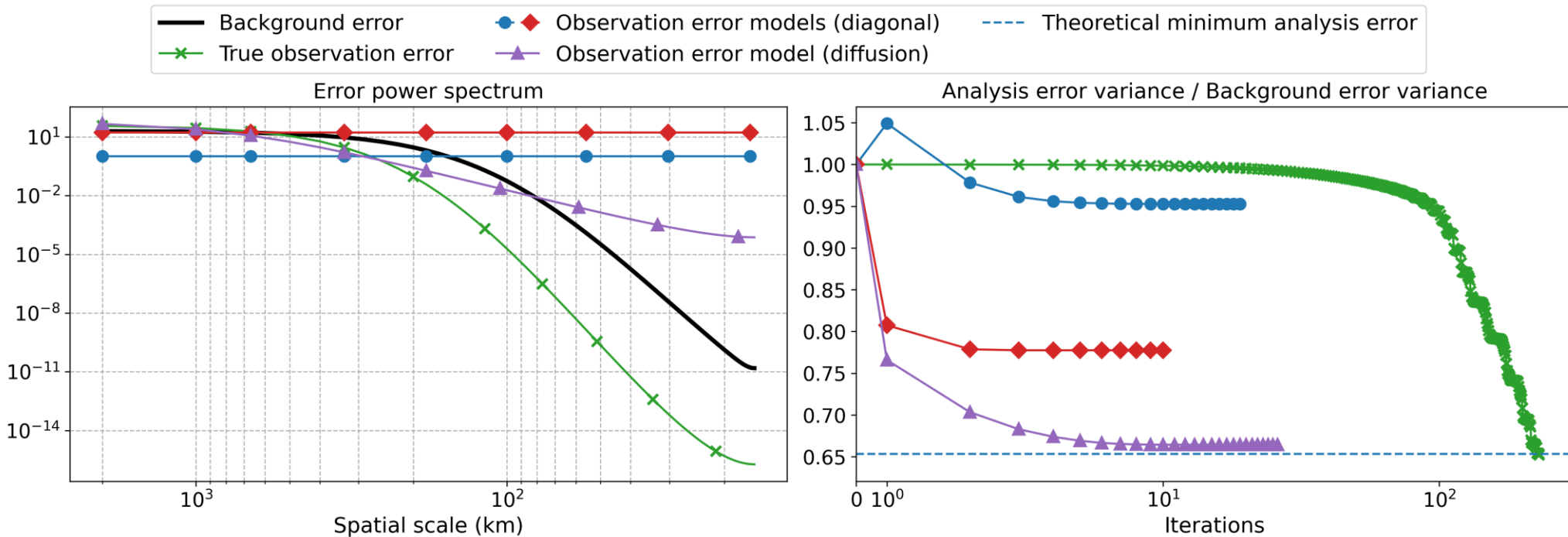


Using the most accurate parameters for the observation error lead to a very low analysis error but sometimes only after a **prohibitive number of iterations** (especially if  $M_o > M_b$ )

# Convergence experiment

True parameters:  $D_b = 60$  km ;  $M_b = 8$  ;  $D_o = 120$  km ;  $M_o = 10$

'Reconditioned' observation error model :  $D_o = 120$  km ;  $M_o = 2$



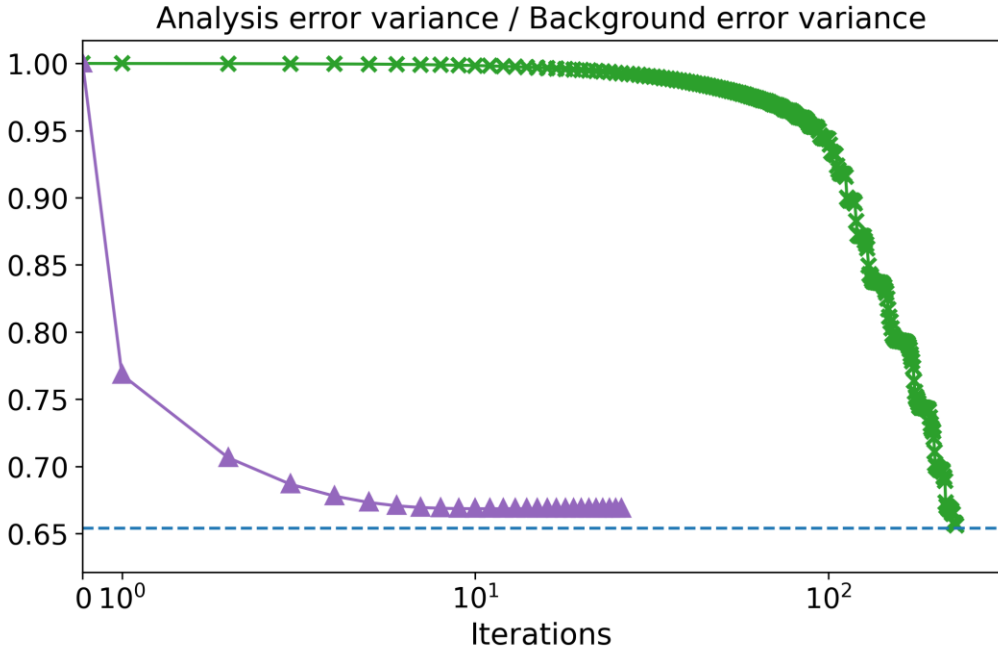
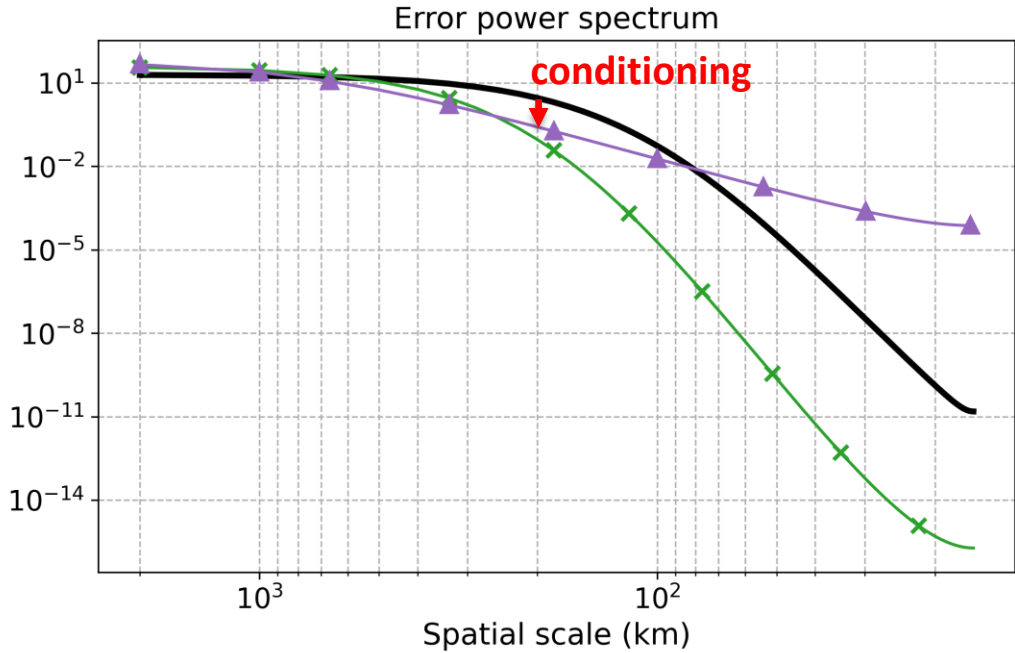
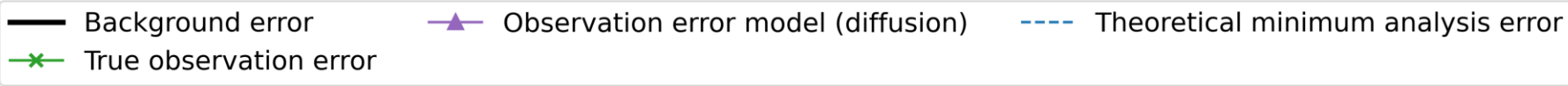
Reducing  $M_o$  is a viable strategy to reach a reasonable convergence rate without degrading too much the analysis error at full convergence.



# Convergence experiment

True parameters:  $D_b = 60 \text{ km}$  ;  $M_b = 8$  ;  $D_o = 120 \text{ km}$  ;  $M_o = 10$

'Reconditioned' observation error model :  $D_o = 120 \text{ km}$  ;  $M_o = 2$



Reducing  $M_o$  increases the observation error power specifically at the smallest spatial scales where both the background and observation error are insignificant, which limits the impact on the analysis error.

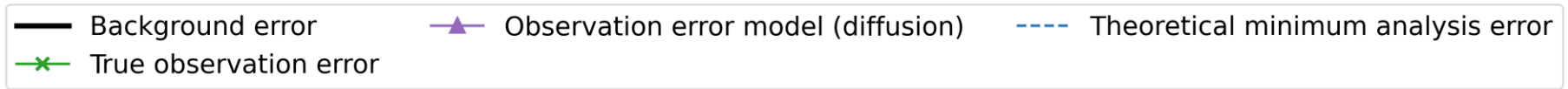
- Diffusion operators could be used in an operational context to model the inverse of the observation error correlation operator.
- The choice of parameters of the diffusion operator, or any observation error correlation model, should account for their impact on the convergence rate of the B-PCG, as a non-diagonal  $\mathbf{R}$  can drastically improve or degrade the convergence rate.
- The conditioning tends to be improved by using a non-diagonal  $\mathbf{R}$  over a diagonal  $\mathbf{R}$  if  $M_o \leq M_b$ , and enforcing this relation even if it is not representative of the estimated error statistics is a viable 'reconditioning' strategy.

The next step is to implement diffusion operators for observation error correlations in NEMOVAR to evaluate the impact of a non-diagonal  $\mathbf{R}$  in an operational system.

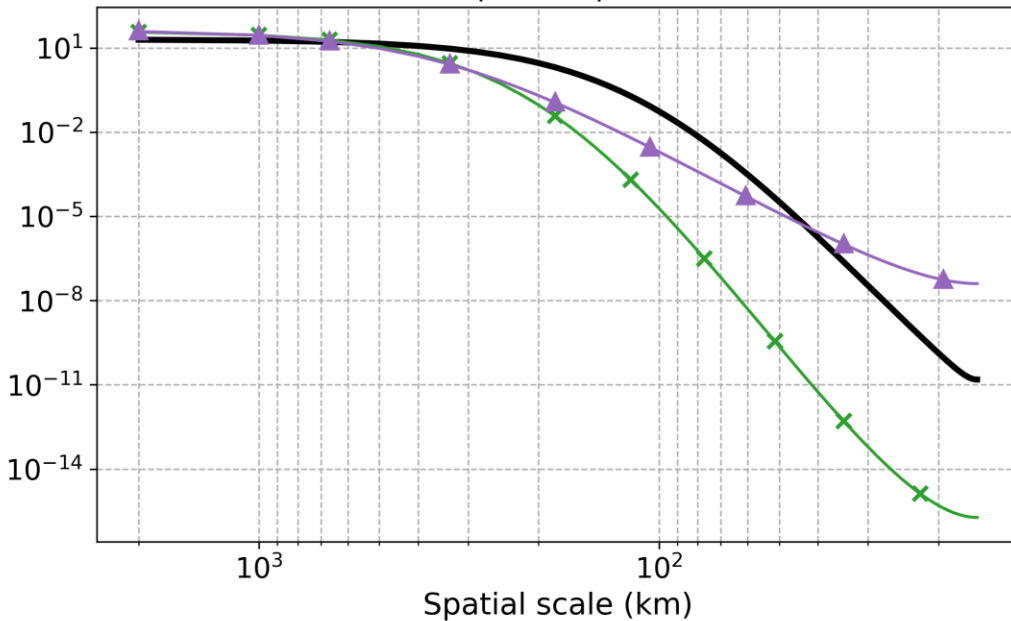
# Annex: reconditioning

True parameters:  $D_b = 60 \text{ km}$  ;  $M_b = 8$  ;  $D_o = 120 \text{ km}$  ;  $M_o = 10$

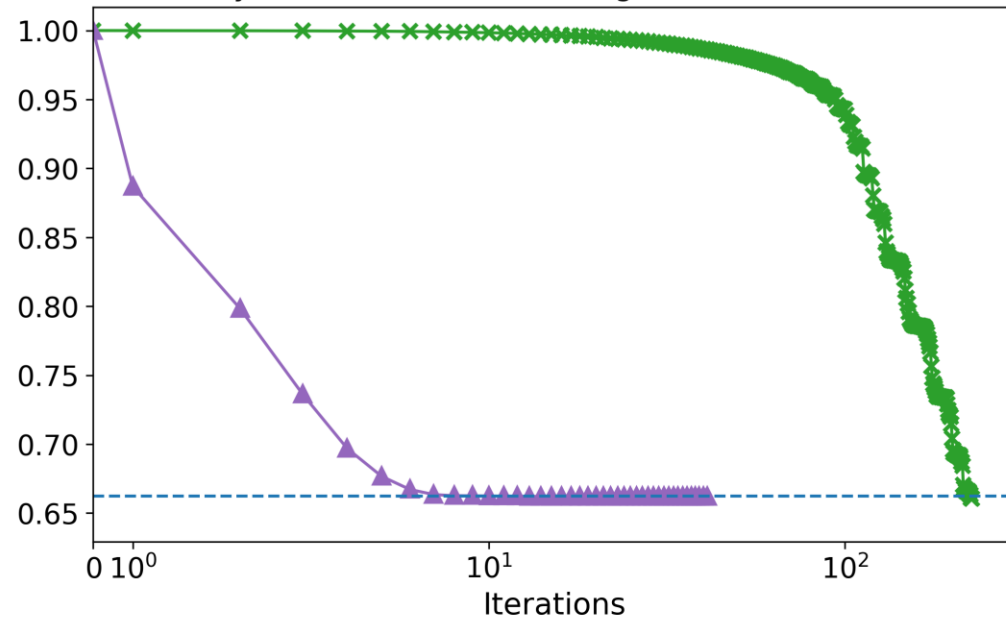
'Reconditioned' observation error model :  $D_o = 120 \text{ km}$  ;  $M_o = 4$



Error power spectrum



Analysis error variance / Background error variance

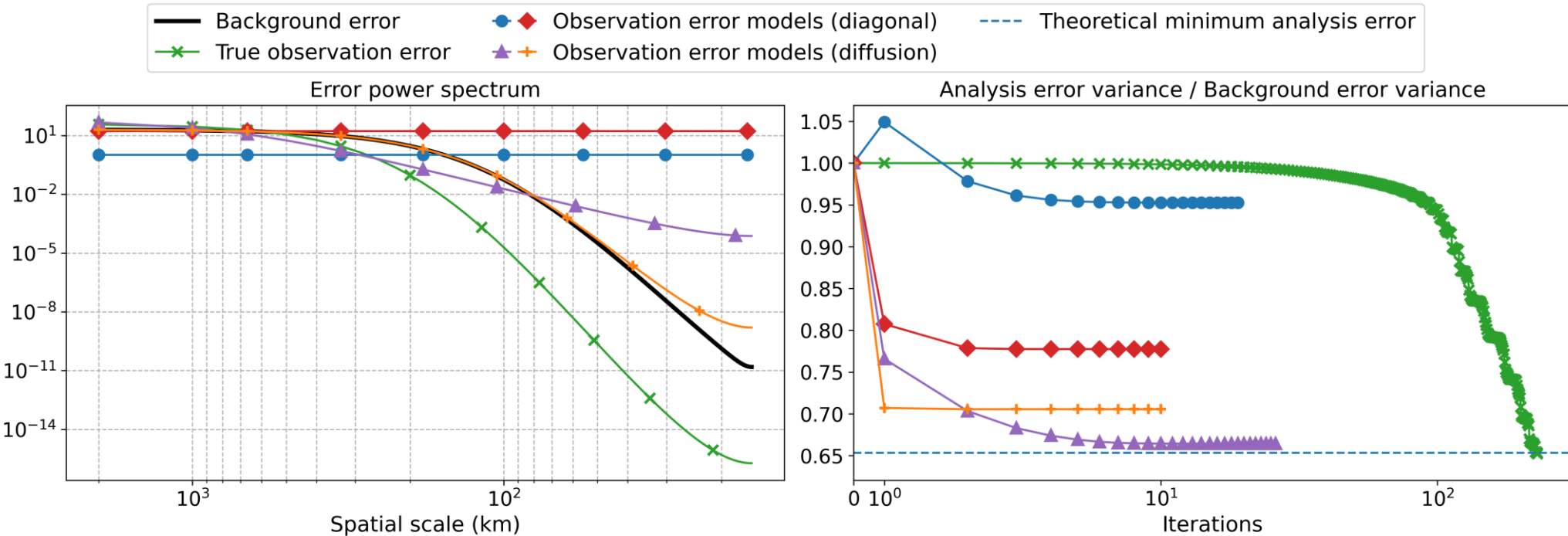


# Annex: minimal condition number

True parameters:  $D_b = 60$  km ;  $M_b = 8$  ;  $D_o = 120$  km ;  $M_o = 10$

'Reconditioned' observation error model :  $D_o = 120$  km ;  $M_o = 2$

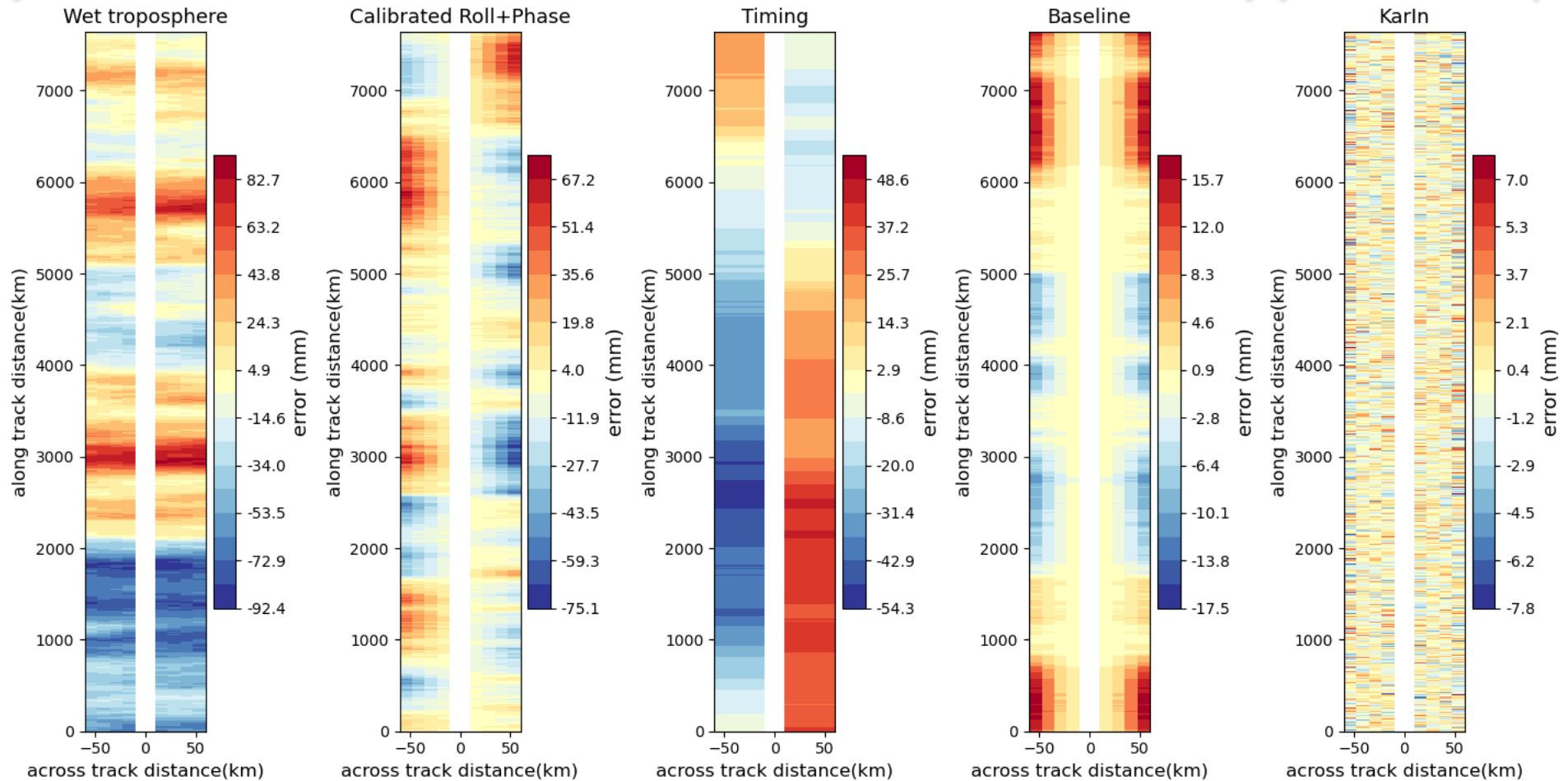
'Fastest' observation error model :  $D_o = 60$  km ;  $M_o = 8$



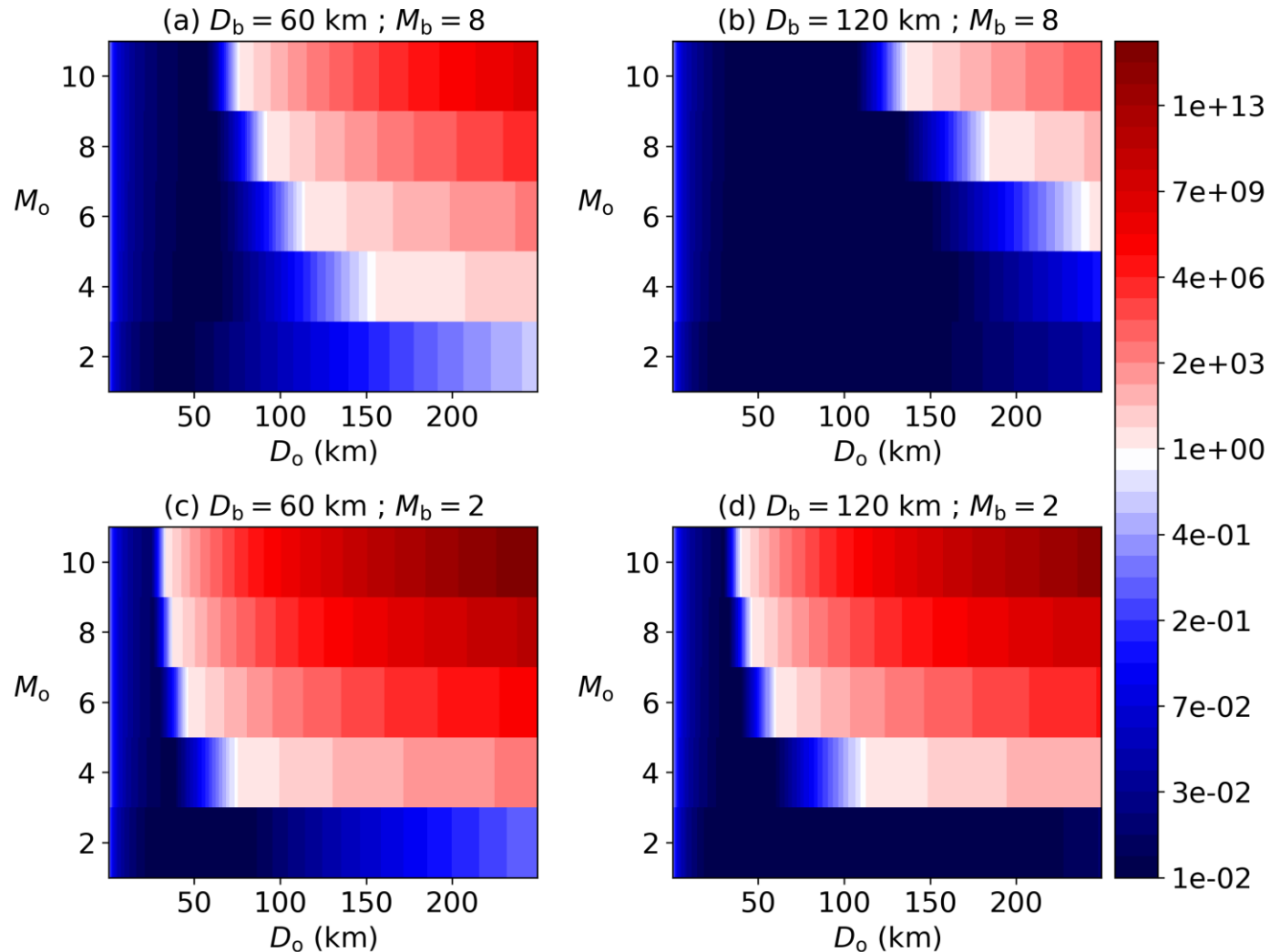
Even if we **completely prioritize the convergence speed** by specifying an observation error power as close as possible to the background error power, the analysis error at full convergence is **still lower than with the best diagonal model**.

## Spatially correlated errors

## Uncorrelated error



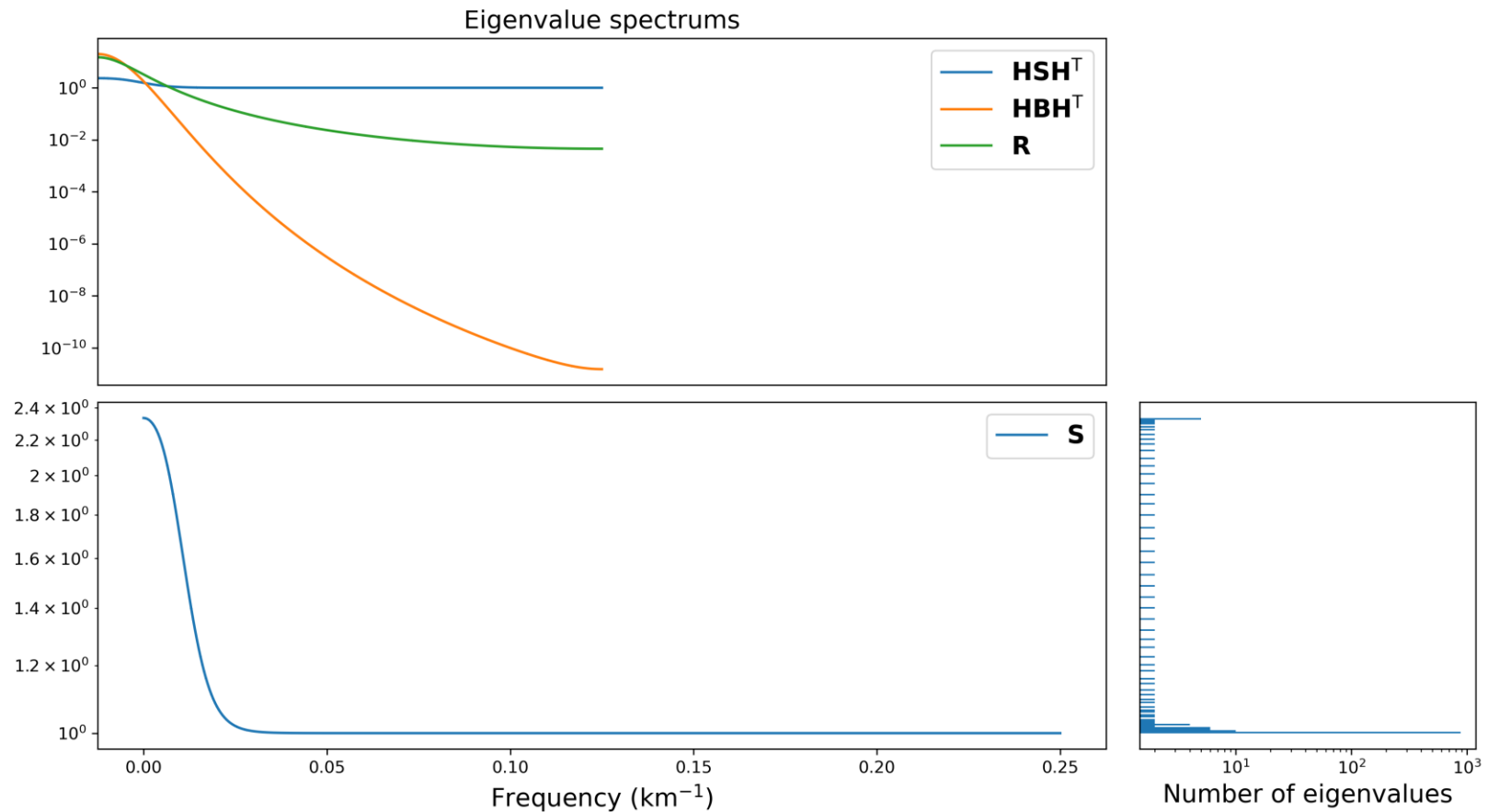
Condition number with a non-diagonal  $\mathbf{R}$  / Condition number with a diagonal  $\mathbf{R}$





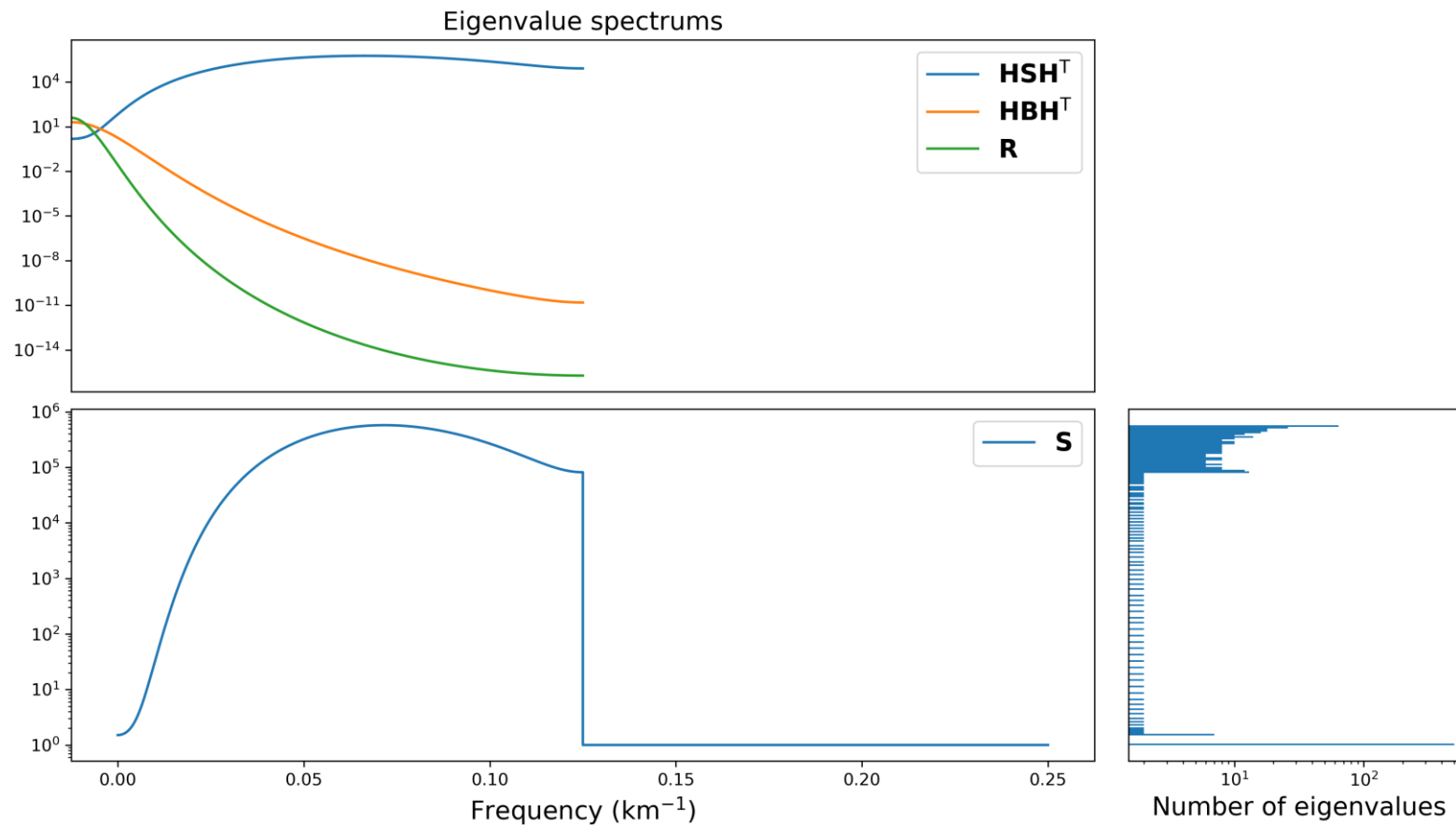
# Annex: clustering with small OECs

Parameters:  $D_b = 60$  km ;  $M_b = 8$  ;  $D_o = 30$  km ;  $M_o = 2$



# Annex: clustering with large OECs

Parameters:  $D_b = 60$  km ;  $M_b = 8$  ;  $D_o = 120$  km ;  $M_o = 10$



Nadir altimeter error correlations estimated via the JPL/CNES SWOT simulator

