

# Simulation of error cycling

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ISDA, Reading, 21 July 2016

with inputs from

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## Motivations and questions

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EDA and innovations for diagnosing contributions  
(background errors, observation errors, model errors)  
in error cycling over one week.

Revisit formalism & some previous EDA experiments  
in the litterature :

- ⇒ Respective global amplitudes of these 3 error sources ?
- ⇒ Evolution of error contributions during the cycling ?

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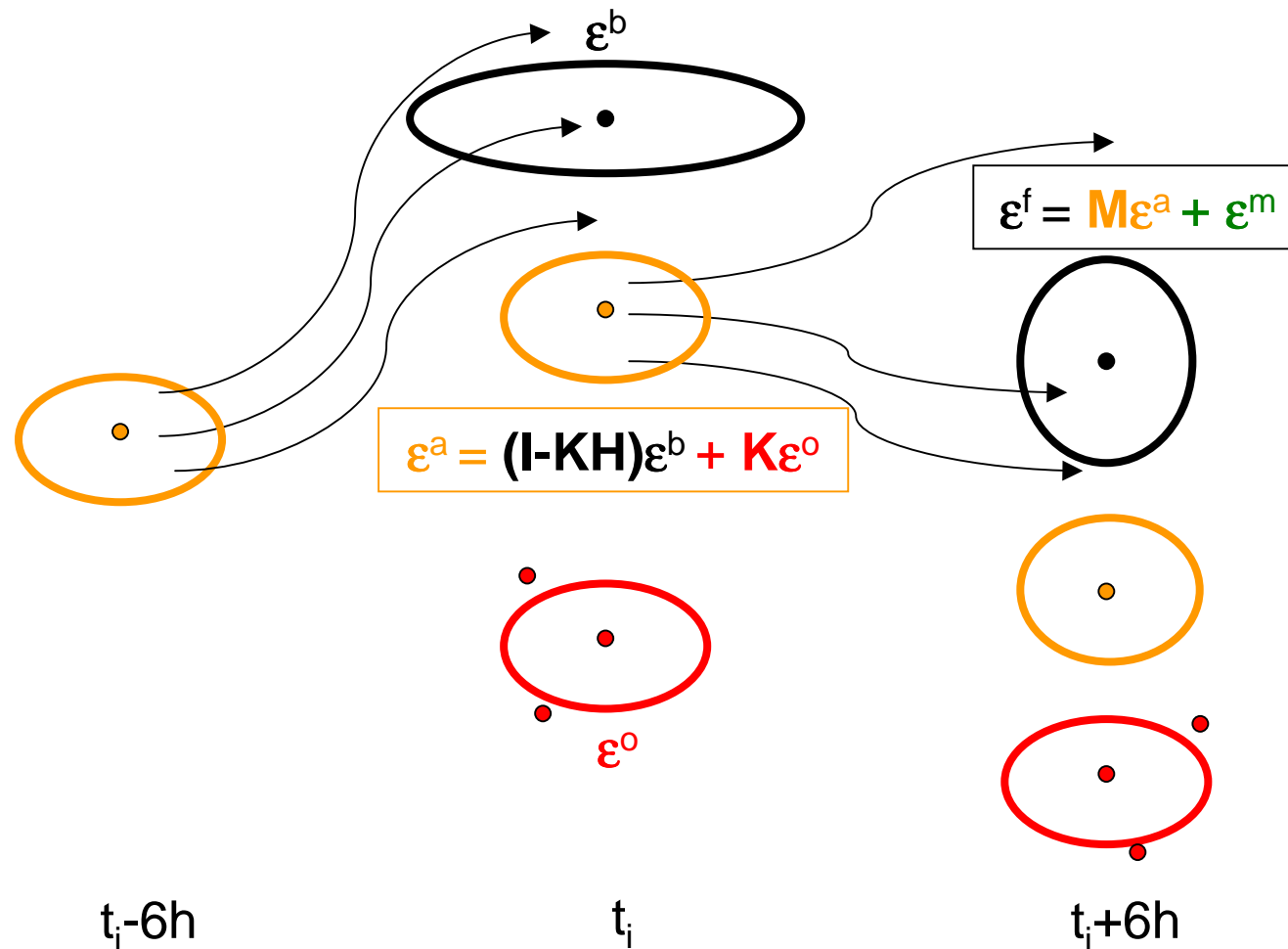
- EDA context at Météo-France
- Quasi-linear expansion of forecast errors
- Old background errors / Recent observation errors
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# Ensemble of perturbed Data Assimilations (EDA) : simulation of error cycling



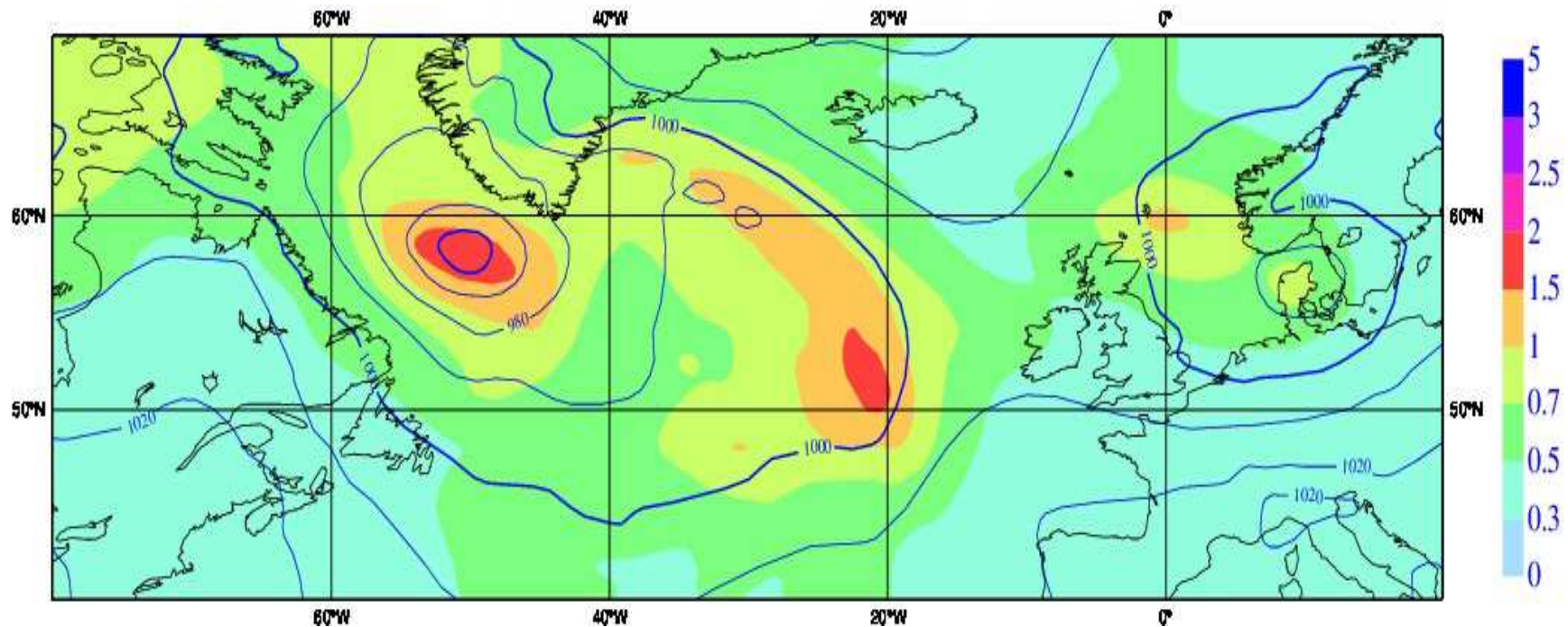
# Global operational EDA at Météo-France

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- 25 members, T479 (40 km) L105, Arpege 4D-Var (minim T149), 6h cycle.
- 4D-Var analysis perturbations :  
observation perturbations (drawn from **R**, incl. spatial corr. for AMVs),  
background perturbations (evolved analysis pertbs and model pertbs).
- Multiplicative inflation of forecast perturbations,  
using innovation-based diagnostics.
- Spatially filtered variances for observation QC and minimisation,  
wavelet-filtered 3D correlations.

An EDA is also being developed at mesoscale (AROME, oper 2018).

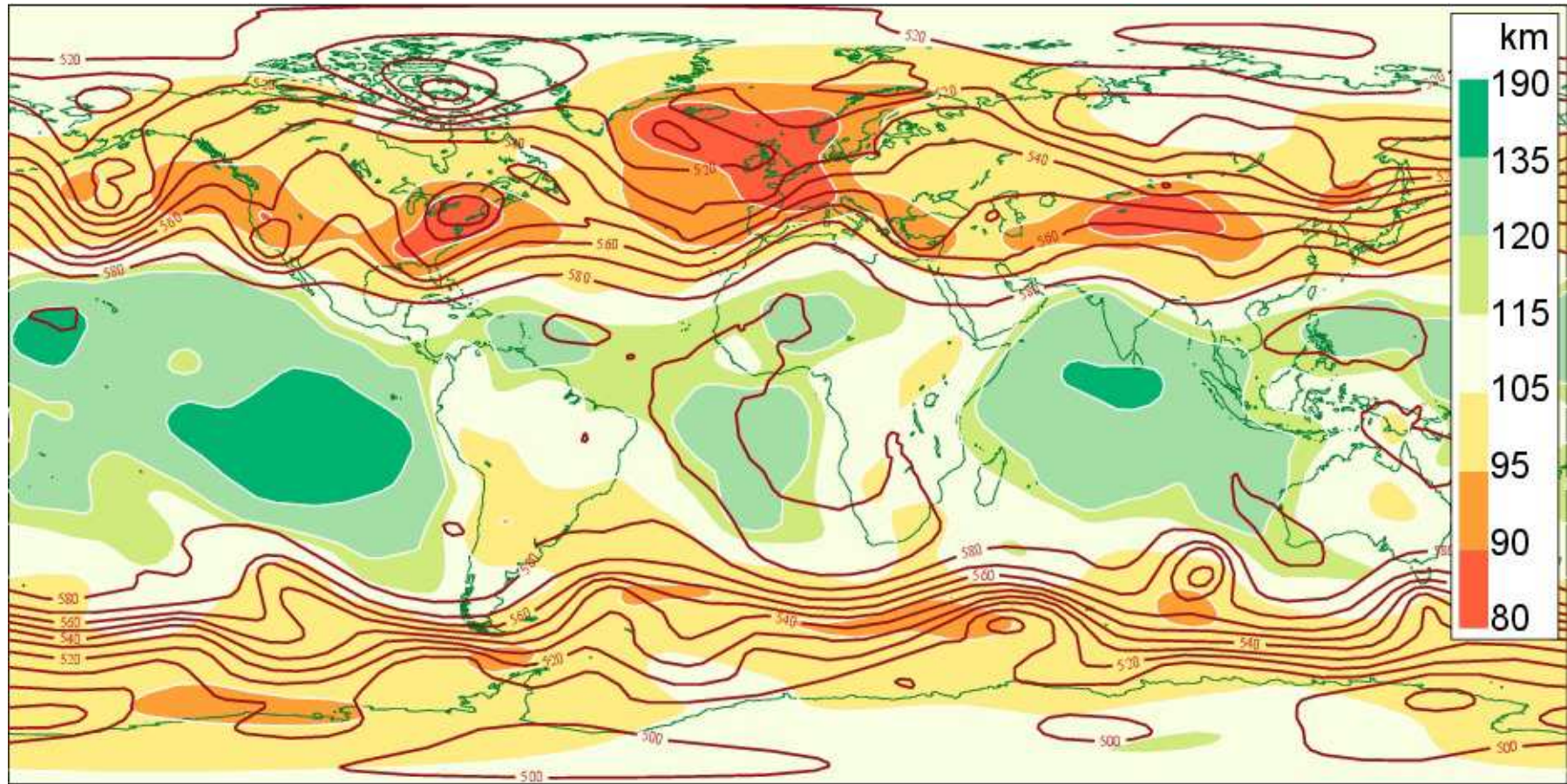
# Dynamics of background error variances with EDA



Standard deviations of surface pressure (hPa) (2/2/2010)  
(superimposed with MSLP analysis, in hPa).



# Dynamics of horizontal correlations from ensemble and wavelet filtering

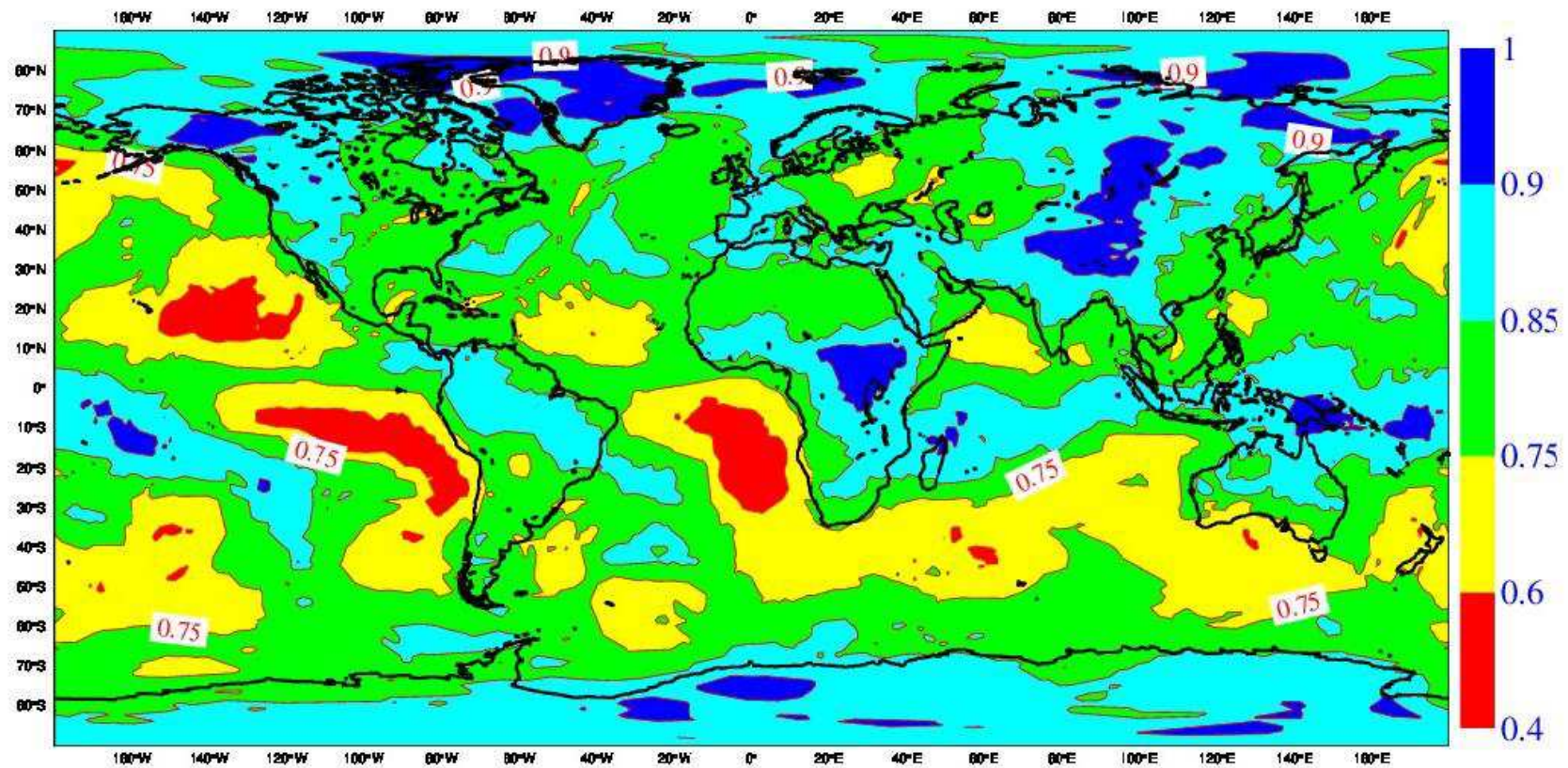


Length scales (km) for wind near 500 hPa (28/2/2010),  
superimposed with geopotential

(Berre, Varella et Desroziers 2015)



# Dynamics of vertical correlations from ensemble and wavelet filtering



Vertical correlations of temperature between 850 & 870 hPa (28/2/2010)

(Berre, Varella and Desroziers 2015)

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# Expansion of forecast error contributions (quasi-linear framework)

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At a given step  $t_0$  of the cycling :

$$\boldsymbol{\varepsilon}_0^a = (\mathbf{I} - \mathbf{K}_0 \mathbf{H}_0) \boldsymbol{\varepsilon}_0^b + \mathbf{K}_0 \boldsymbol{\varepsilon}_0^o$$

$$\begin{aligned} \boldsymbol{\varepsilon}_0^f &= \mathbf{M}_0 \boldsymbol{\varepsilon}_0^a + \boldsymbol{\varepsilon}_0^m \\ &= \mathbf{M}_0 (\mathbf{I} - \mathbf{K}_0 \mathbf{H}_0) \boldsymbol{\varepsilon}_0^b + \mathbf{M}_0 \mathbf{K}_0 \boldsymbol{\varepsilon}_0^o + \boldsymbol{\varepsilon}_0^m \end{aligned}$$

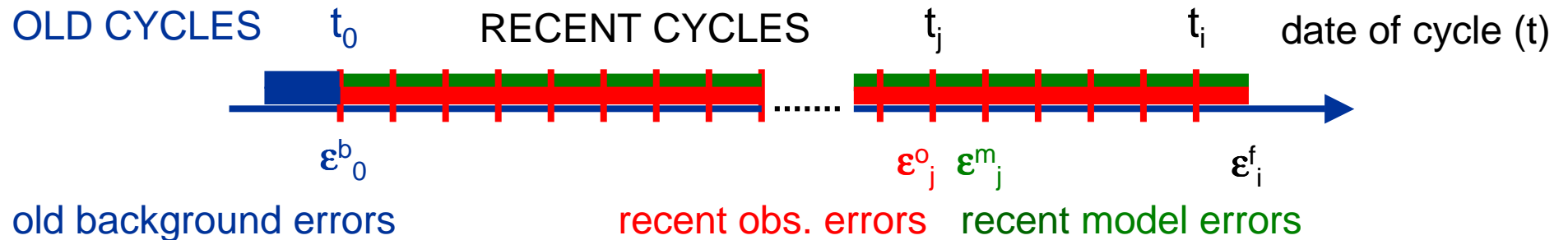
At a later step  $t_i$  (e.g. one week later) :

$$\boldsymbol{\varepsilon}_i^f = \mathbf{T}_{i+1} \boldsymbol{\varepsilon}_0^b + \sum_{j \geq 0} \mathbf{T}_{i-j} \mathbf{M}_j \mathbf{K}_j \boldsymbol{\varepsilon}_j^o + \sum_{j \geq 0} \mathbf{T}_{i-j} \boldsymbol{\varepsilon}_j^m$$

where  $\mathbf{T}_{i-j} = \prod_k \mathbf{M}_k (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k)$  = cycling operator  
(over  $k$  successive analysis/forecast steps from  $t_j$  to  $t_i$ ).

# Age of error contributions

Error contributions over one week, from  $t_0$  to  $t_i$  :



Full expansion of forecast errors at  $t_i$  :

$$\epsilon^f_i = \mathbf{T}_{i+1} \epsilon^b_0 + \sum_{j \geq 0} \mathbf{T}_{i-j} \mathbf{M}_j \mathbf{K}_j \epsilon^o_j + \sum_{j \geq 0} \mathbf{T}_{i-j} \epsilon^m_j$$

where  $\mathbf{T}_{i-j} = \prod_k \mathbf{M}_k (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k)$  = cycling operator  
(over k successive analysis/forecast steps from  $t_j$  to  $t_i$ ).

# Several processes in error cycling

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Expansion of forecast errors :

$$\boldsymbol{\varepsilon}_i^f = \mathbf{T}_{i+1} \boldsymbol{\varepsilon}_0^b + \sum_{j \geq 0} \mathbf{T}_{i-j} \mathbf{M}_j \mathbf{K}_j \boldsymbol{\varepsilon}_j^o + \sum_{j \geq 0} \mathbf{T}_{i-j} \boldsymbol{\varepsilon}_j^m$$

where  $\mathbf{T}_{i-j} = \prod_k \mathbf{M}_k (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k) = \text{cycling operator}$ .

- **Old background errors  $\boldsymbol{\varepsilon}_0^b$  :**  
repeted analysis damping & model propagation.
- **Recent observation errors  $\boldsymbol{\varepsilon}_j^o$  :**  
filtering (**K**) & propagation (**M**) ; damping & propagation (**T**) ; accumulation ( $\Sigma$ ).
- **Recent model errors  $\boldsymbol{\varepsilon}_j^m$  :**  
damping & propagation ; accumulation.

# Links with EDA and innovations

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Same equation for errors and perturbations :

$$\boldsymbol{\varepsilon}_i^f = \mathbf{T}_{i+1} \boldsymbol{\varepsilon}_0^b + \sum_{j \geq 0} \mathbf{T}_{i-j} \mathbf{M}_j \mathbf{K}_j \boldsymbol{\varepsilon}_j^o + \sum_{j \geq 0} \mathbf{T}_{i-j} \boldsymbol{\varepsilon}_j^m$$

Simulation of error cycling : **cycle observation and model perturbations** added to deterministic system (e.g. with 4D-Var and non linear forecasts included).

Observation and model perturbations are often (+/- indirectly) derived from **innovation-based estimates of covariances**.

**Amplitudes of some estimated (accumulated) error contributions** can be diagnosed and compared using EDA and innovations.

# Experimental framework

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- Revisit some sensitivity experiments with a previous EDA configuration :  
no model perturbations (offline tuning of horizontally averaged variances) ;  
same  $\mathbf{K}$  in all compared configurations (static spectral correlations,  
flow-dependent variances).
- Comparison « cold start » / « warm start » ensembles :  
diagnosis / evolution of old background perturbations.
- EDA configurations without (recent) model perturbations :
  - ° to diagnose the 2 other contributions  
(old background errors, recent observation errors).
  - ° to estimate model error variance  
by comparison with innovation-based estimates of forecast errors.
- Offline diagnosis of global amplitudes (variances) of perturbations.



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# Contribution of recent observation errors

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$$\epsilon_i^f = T_{i+1} \epsilon_0^b + \sum_{j \geq 0} T_{i-j} M_j K_j \epsilon_j^o + \sum_{j \geq 0} T_{i-j} \epsilon_j^m$$

**Contribution of recent observation errors to forecast errors :**

$$\epsilon_i^{fo} = \sum_{j \geq 0} T_{i-j} M_j K_j \epsilon_j^o$$

**Simulation and evolution using EDA :**

\* use  $\epsilon_0^b=0$  (cold start = start from unperturbed background),

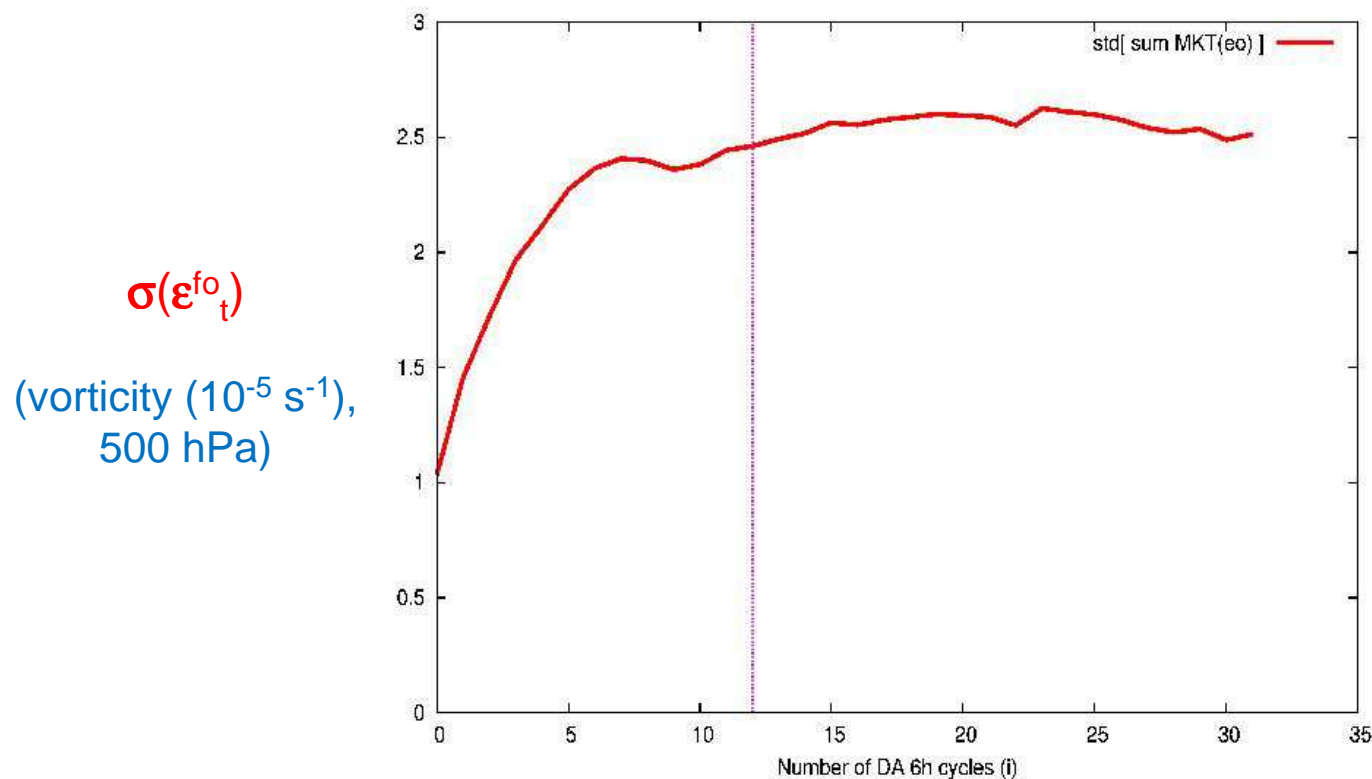
then cycle with  $\epsilon_j^o$  (  $j \geq 0$  ) (and with  $\epsilon_j^m = 0$ ).

\* compute evolution of EDA spread :  $\sigma( \epsilon_t^{fo} = \sum T_{t-j} M_j K_j \epsilon_j^o )$ .

# Accumulation of recent observation errors

Evolution of  $\sigma(\epsilon_t^{fo} = \sum_{j \geq 0} \mathbf{T}_{t-j} \mathbf{M}_j \mathbf{K}_j \epsilon_j^o)$

at successive analysis steps ( $t_0, t_1, \dots, t_i$ )



Observation error contribution increases (accumulation),  
then it stabilizes after 3-5 days of cycling,

(El Ouaraini and Berre 2011,  
see also Fisher et al 2005)

due to analysis damping :  $\mathbf{T}_{t-j} = \prod_k \mathbf{M}_k (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k)$ .

# Accumulation of recent observation errors

Evolution of  $\boldsymbol{\varepsilon}_t^{fo} = \sum_{j \geq 0} \mathbf{T}_{t-j} \mathbf{M}_j \mathbf{K}_j \boldsymbol{\varepsilon}_j^o$

at successive analysis steps  $(t_0, t_1, t_2, \dots, t_i)$  :

$$\boldsymbol{\varepsilon}_0^{fo} = \mathbf{M}_0 \mathbf{K}_0 \boldsymbol{\varepsilon}_0^o$$

$$\boldsymbol{\varepsilon}_1^{fo} = \mathbf{M}_1 \mathbf{K}_1 \boldsymbol{\varepsilon}_1^o + \mathbf{T}_1 \boldsymbol{\varepsilon}_0^{fo}$$

$$\boldsymbol{\varepsilon}_2^{fo} = \mathbf{M}_2 \mathbf{K}_2 \boldsymbol{\varepsilon}_2^o + \mathbf{T}_1 \boldsymbol{\varepsilon}_1^{fo} + \mathbf{T}_2 \boldsymbol{\varepsilon}_0^{fo}$$

....

$$\boldsymbol{\varepsilon}_t^{fo} = \mathbf{M}_t \mathbf{K}_t \boldsymbol{\varepsilon}_t^o + \mathbf{T}_1 \boldsymbol{\varepsilon}_{t-1}^{fo} + \mathbf{T}_2 \boldsymbol{\varepsilon}_{t-2}^{fo} + \dots + \mathbf{T}_{12} \boldsymbol{\varepsilon}_{t-12}^{fo} + \left( \sum_{k > 12} \mathbf{T}_k \boldsymbol{\varepsilon}_{t-k}^{fo} \right)$$

...

$\mathbf{T}$  is mainly damping, so old obs. error contrib. (with time-lag  $k > 12$ ) become negligible, and  $\sigma(\boldsymbol{\varepsilon}_t^{fo})$  stabilizes ~ at step  $t = 12$  (3 days).

# Contribution of old background errors

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$$\boldsymbol{\varepsilon}_i^f = \underbrace{\mathbf{T}_{i+1} \boldsymbol{\varepsilon}_0^b}_{\text{old background errors}} + \sum_{j \geq 0} \mathbf{T}_{i-j} \mathbf{M}_j \mathbf{K}_j \boldsymbol{\varepsilon}_j^o + \sum_{j \geq 0} \mathbf{T}_{i-j} \boldsymbol{\varepsilon}_j^m$$

Contribution of « old » background errors :

$$\boldsymbol{\varepsilon}_i^{fb} = \mathbf{T}_{i+1} \boldsymbol{\varepsilon}_0^b \quad \text{with } \mathbf{T}_{i+1} = \prod_{k=0}^i \mathbf{M}_k (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k)$$

**Simulation and evolution using EDA :**

use warm start = ensemble started 6 days before  $t_0$  :

\* use  $\boldsymbol{\varepsilon}_0^b = \sum_{j < 0} \mathbf{T}_{0-j} \mathbf{M}_j \mathbf{K}_j \boldsymbol{\varepsilon}_j^o$  (= contribution of old observation errors),

then cycle with  $\boldsymbol{\varepsilon}_j^o$  ( $j \geq 0$ ) (and with  $\boldsymbol{\varepsilon}_j^m = 0$ ).

\* compute evolution of sqrt of  $\sigma^2(\boldsymbol{\varepsilon}_t^{fb}) = \sigma^2(\boldsymbol{\varepsilon}_t^{fb} + \boldsymbol{\varepsilon}_t^{fo}) - \sigma^2(\boldsymbol{\varepsilon}_t^{fo})$

(~sqrt of EDA variance difference between warm start and cold start)

# Evolution of old background error contribution

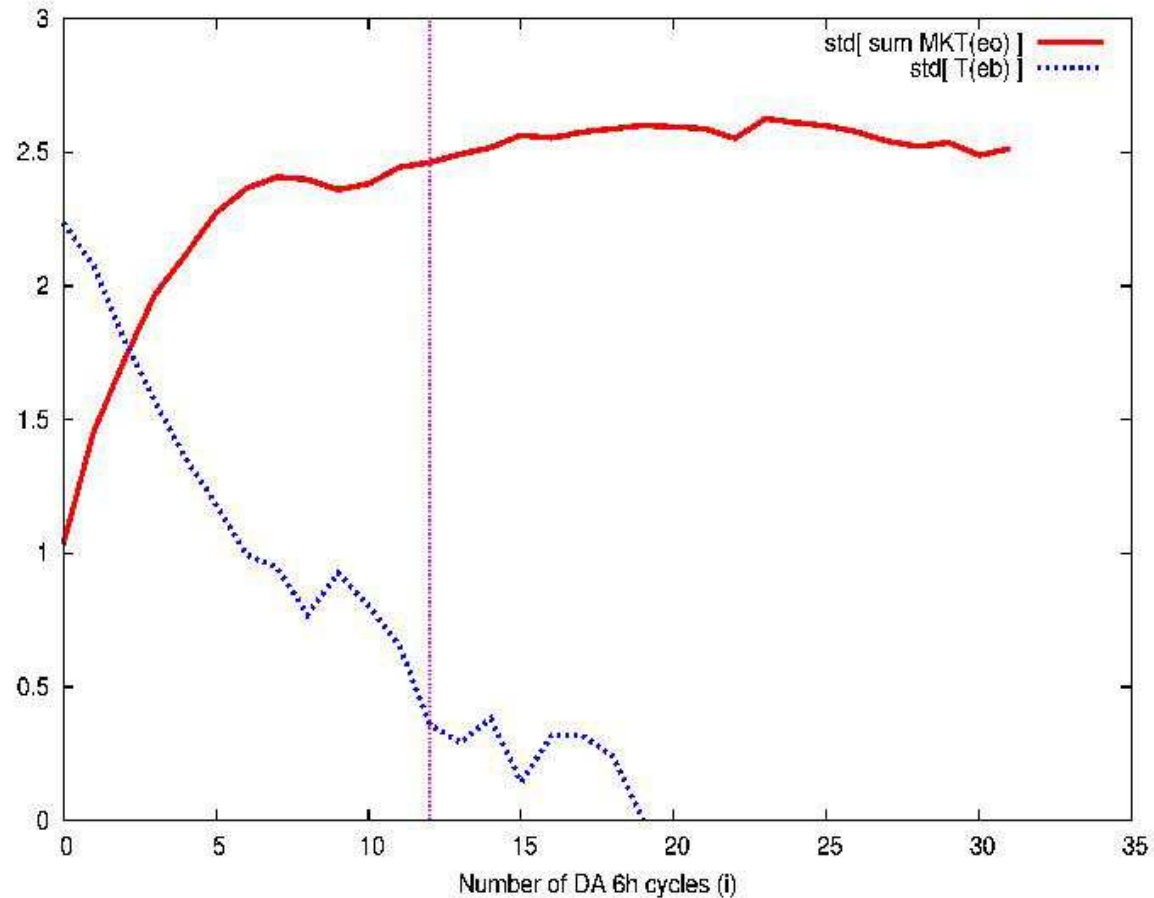
$$\sigma(\epsilon_t^{fb} = \mathbf{T}_{t+1} \epsilon_0^b)$$

with

$$\mathbf{T}_{t+1} = \prod_{k=0}^t \mathbf{M}_k (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k)$$

$$\sigma(\epsilon_t^{fo})$$

(vorticity ( $10^{-5} \text{ s}^{-1}$ ),  
500 hPa)

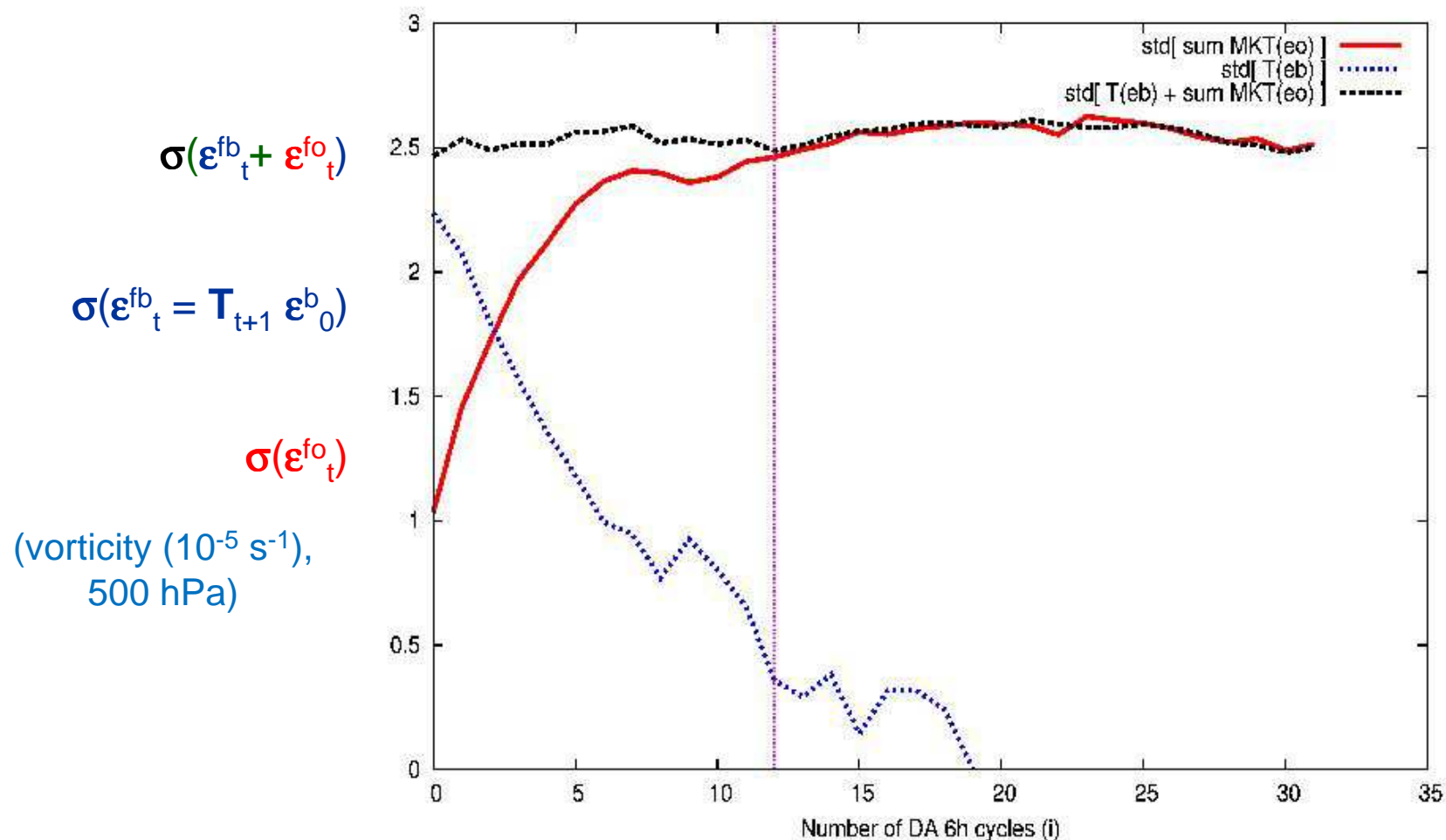


$$\epsilon_0^b = \sum_{j < 0} \mathbf{T}_{0-j} \mathbf{M}_j \mathbf{K}_j \epsilon_j^o \quad (\text{contribution of old observation errors})$$

$$\sigma(\epsilon_0^{fb}) > \sigma(\epsilon_0^{fo}) \quad (\text{for vorticity}).$$

$$\sigma(\epsilon_i^{fb} = \mathbf{T}_{i+1} \epsilon_0^b) \text{ decreases } \sim \text{linearly / analysis damping.}$$

# Contribution of old+recent observation errors



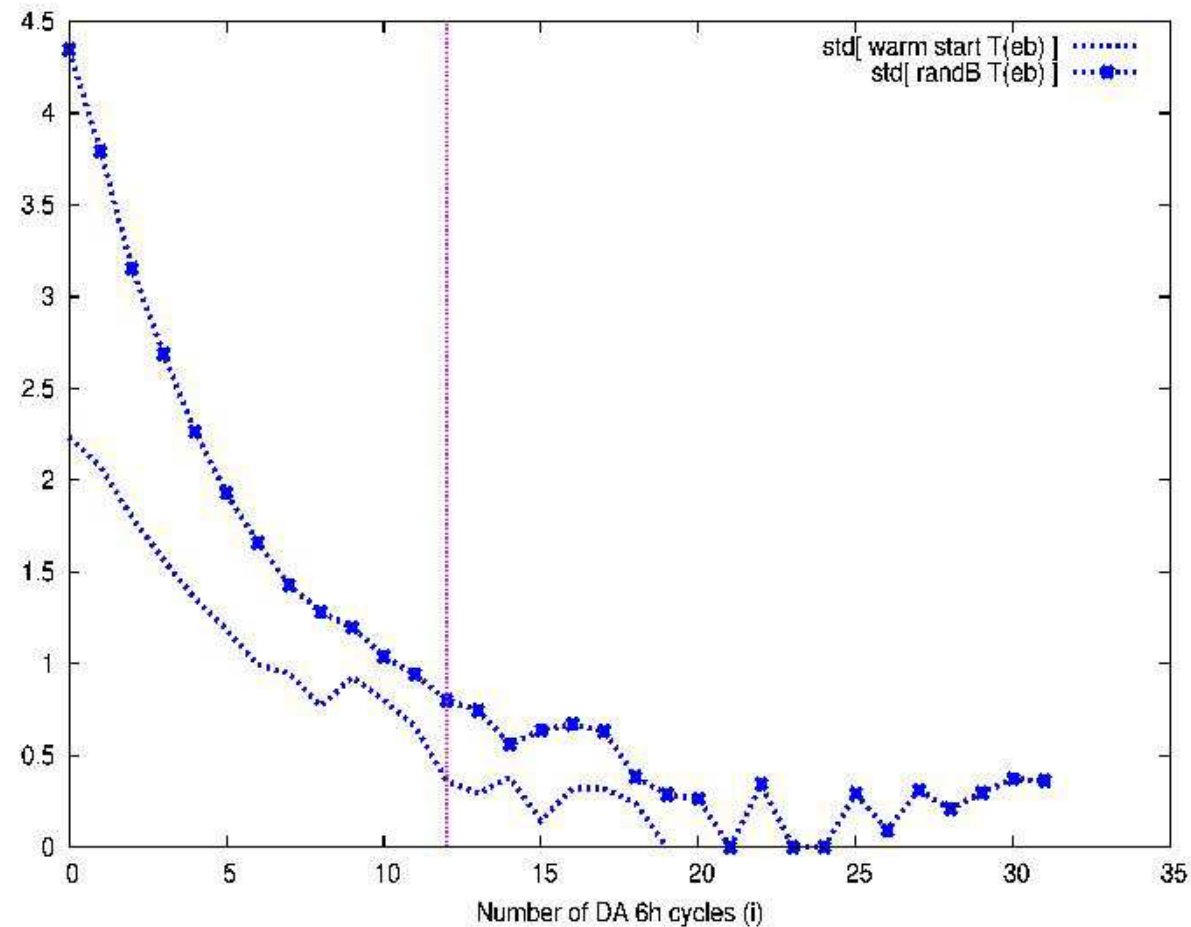
**Total contribution of (old+recent) obs errors is stable :**  
damping of old observation errors is compensated by  
accumulation of recent obs errors.



# Dependence on amplitude of old background errors

$$\sigma(\epsilon_t^{fb} = T_{t+1} \epsilon_0^b)$$

(vorticity ( $10^{-5} \text{ s}^{-1}$ ),  
500 hPa)



.....  $\epsilon_0^b = \sum_{j < 0} T_{0-j} \mathbf{M}_j \mathbf{K}_j \epsilon_j^o$  (old observation errors)

■.....■  $\epsilon_0^b = \mathbf{B}^{1/2} \boldsymbol{\eta}$  (old model errors + old observation errors)

$\sigma(\epsilon_t^{fb} = T_{t+1} \epsilon_0^b)$  decreases ~ linearly / analysis damping.

# First conclusions / formalism + experiments

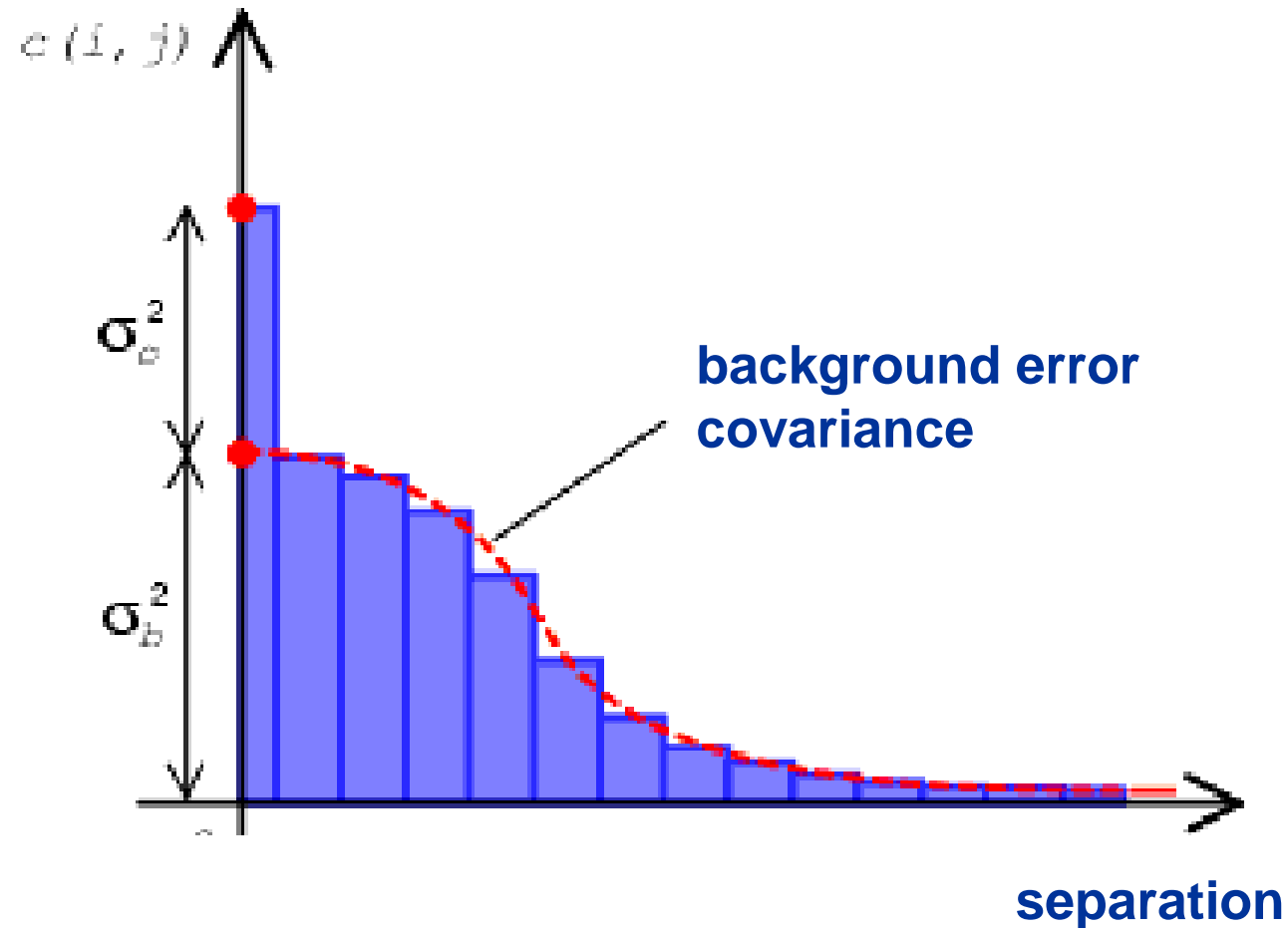
- Quasi-linear expansion of forecast errors / contributions of old background errors, recent observation errors, recent model errors.
- Compare cold/warm start EDA (without recent model perturbations) to diagnose error contrib. of old background and recent observations.
- Old background errors vanish ( $\sim$ linearly) after 3-5 days of cycling.
- Compensated by accumulation of recent observation errors.
- This may help for interpretation/diagnosis of total forecast errors ( $\sim$  recent observation & model errors).

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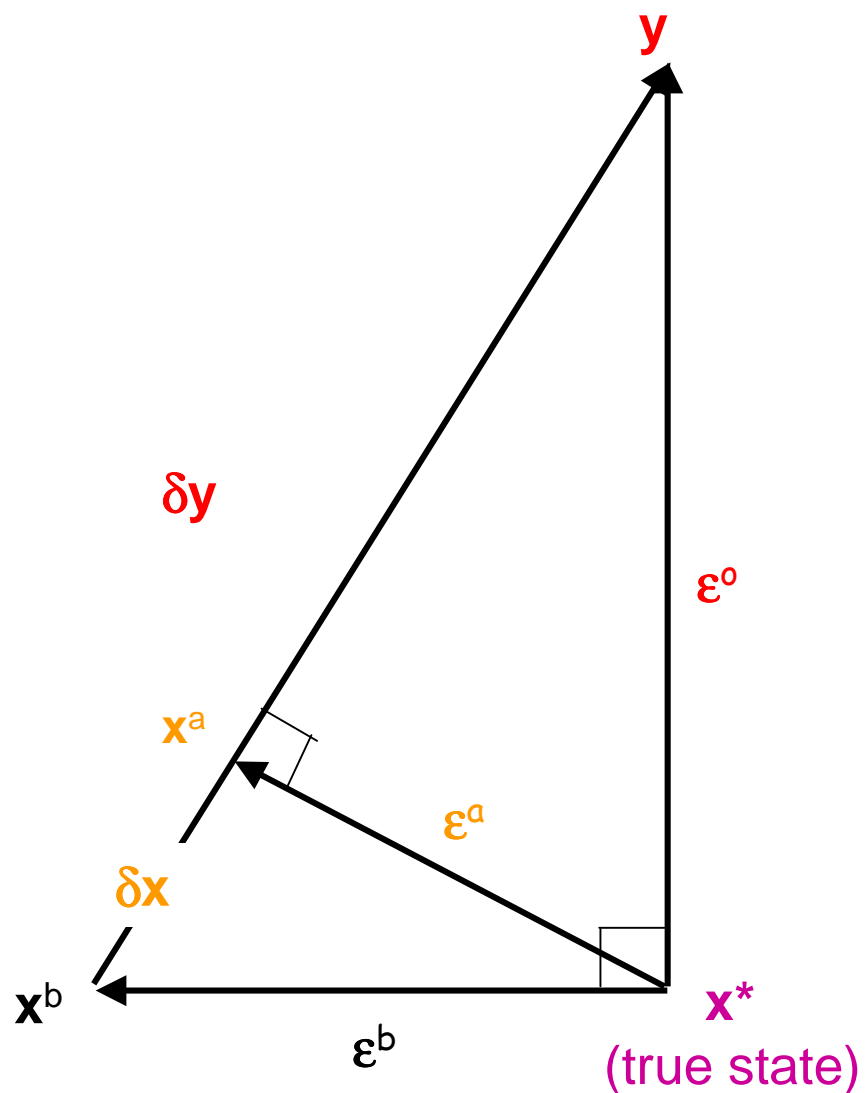
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# Innovation covariances



$$E[ (\mathbf{y}-\mathbf{H}\mathbf{x}^b)(\mathbf{y}-\mathbf{H}\mathbf{x}^b)^T ] = \mathbf{R} + \mathbf{H}\mathbf{B}\mathbf{H}^T$$

# Covariances of analysis residuals



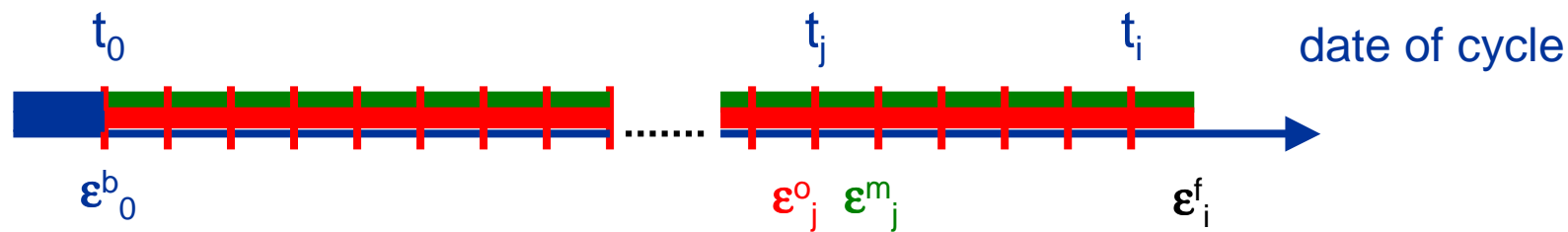
$$\delta y = y - H(x^b) \quad (\text{innovation})$$

$$H \delta x = H(x^b) - H(x^a) \quad (\text{increment})$$

$$E[H \delta x \delta y^T] = HB^*H^T$$

$$E[(y - H(x^a)) \delta y^T] = R^*$$

# Estimation of model error contributions (to forecast errors)

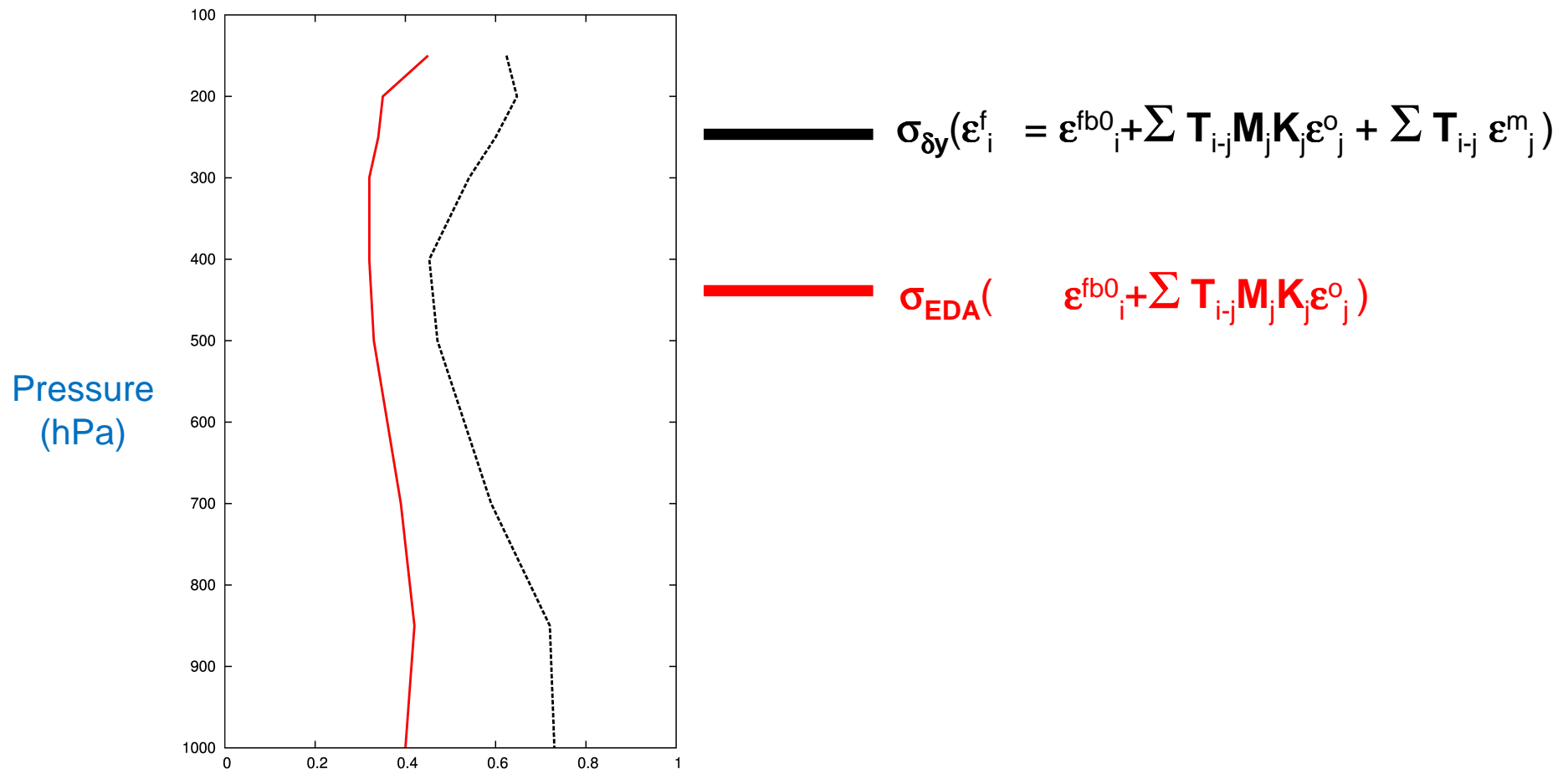


Error  $\epsilon^f_i$  of forecast issued from cycle  $t_i$  :

$$\epsilon^f_i = \mathbf{T}_{i+1} \epsilon^b_0 + \underbrace{\sum_{j \geq 0} \mathbf{T}_{i-j} \mathbf{M}_j \mathbf{K}_j \epsilon^o_j}_{\text{obs. errors accumulated from } t_0 \text{ to } t_i} + \underbrace{\sum_{j \geq 0} \mathbf{T}_{i-j} \epsilon^m_j}_{\text{model errors}} \quad [ \mathbf{T}_{i-j} = \prod_k \mathbf{M}_k (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k) ]$$

⇒ Compare  $\sigma_{\delta y}(\epsilon^f_i = \epsilon^{fb0}_i + \sum \mathbf{T}_{i-j} \mathbf{M}_j \mathbf{K}_j \epsilon^o_j + \sum \mathbf{T}_{i-j} \epsilon^m_j)$  (innovation-based)  
with  $\sigma_{\text{EDA}}(\epsilon^{fb0}_i + \sum \mathbf{T}_{i-j} \mathbf{M}_j \mathbf{K}_j \epsilon^o_j)$  (using unperturbed model from  $t_0$  to  $t_i$ ).

# Total forecast error **versus** observation error contribution



Standard deviation of forecast errors  
(aircraft observations of temperature (K))

(Raynaud et al 2012)



# Total forecast error **versus** **observation error contribution**

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$$\sigma^2_{\delta y}(\epsilon^{fb0}_i + \sum \mathbf{T}_{i-j} \mathbf{M}_j \mathbf{K}_j \epsilon^o_j + \sum \mathbf{T}_{i-j} \epsilon^m_j) \sim \sigma^2(\sum \mathbf{T}_{i-j} \mathbf{M}_j \mathbf{K}_j \epsilon^o_j) + \sigma^2(\sum \mathbf{T}_{i-j} \epsilon^m_j)$$

If  $\text{cov}(\epsilon^{fb0}_i, \epsilon^m_j) \sim 0$ , i.e.

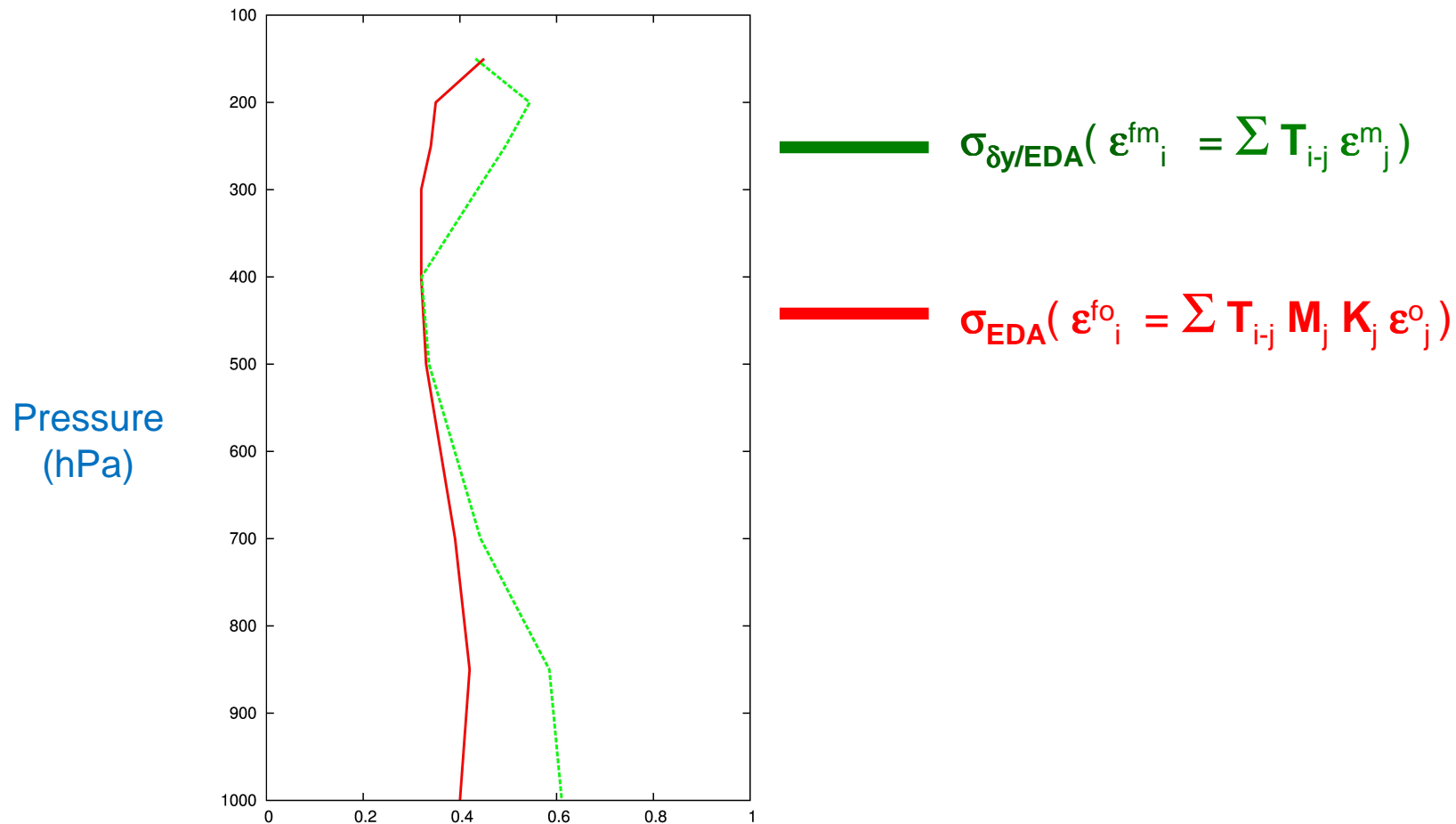
if the one-week period is large enough to neglect time correlations

between old background errors & recently accumulated model errors,

in addition to :

$$\sigma^2_{EDA}(\epsilon^{fb0}_i + \sum \mathbf{T}_{i-j} \mathbf{M}_j \mathbf{K}_j \epsilon^o_j) = \sigma^2_{EDA}(\sum \mathbf{T}_{i-j} \mathbf{M}_j \mathbf{K}_j \epsilon^o_j) \quad \text{if } \sigma^2(\epsilon^{fb0}_i) \sim 0$$

# Quantification of model error accumulated during cycling



# Possible guidance for model error representation ?

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- Variance of model error accumulated over 3-5 days can be diagnosed :  
model error contrib. ~ one half of 6h forecast error variance ;  
obs. error contrib. ~ other half.
- Variance of model error accumulated over 6h: similar formalism,  
but assumptions/diagnostics on temporal correlations required.
- Importance of innovation-based estimates (**R** and **B**).
- Possible model error representations ( $\mathbf{Q}^{1/2}\boldsymbol{\eta}$ , SPPT, SKEB, etc)  
may be compared/adjusted with such diagnostics.

# Conclusions

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- EDA for estimation of flow-dependent covariances, combined with spatial filtering methods.
- EDA (and innovations) for diagnosing **contributions to error cycling** :
  - **obs. errors** contribute ~ within the last 3-5 days of DA cycling.
  - **old background errors** vanish ~ after 3-5 days of DA cycling.
  - **model error** contrib. are similar in amplitude to obs. error contrib.
- LAM : contribution of **LBC errors** over 1/3 of ALADIN-France domain due to advection in the cycling (El Ouaraini et al 2015).
- Extension to diagnostics of spatial structures, pursue comparison EDA vs innovations, etc.

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**Thank you for your attention**