

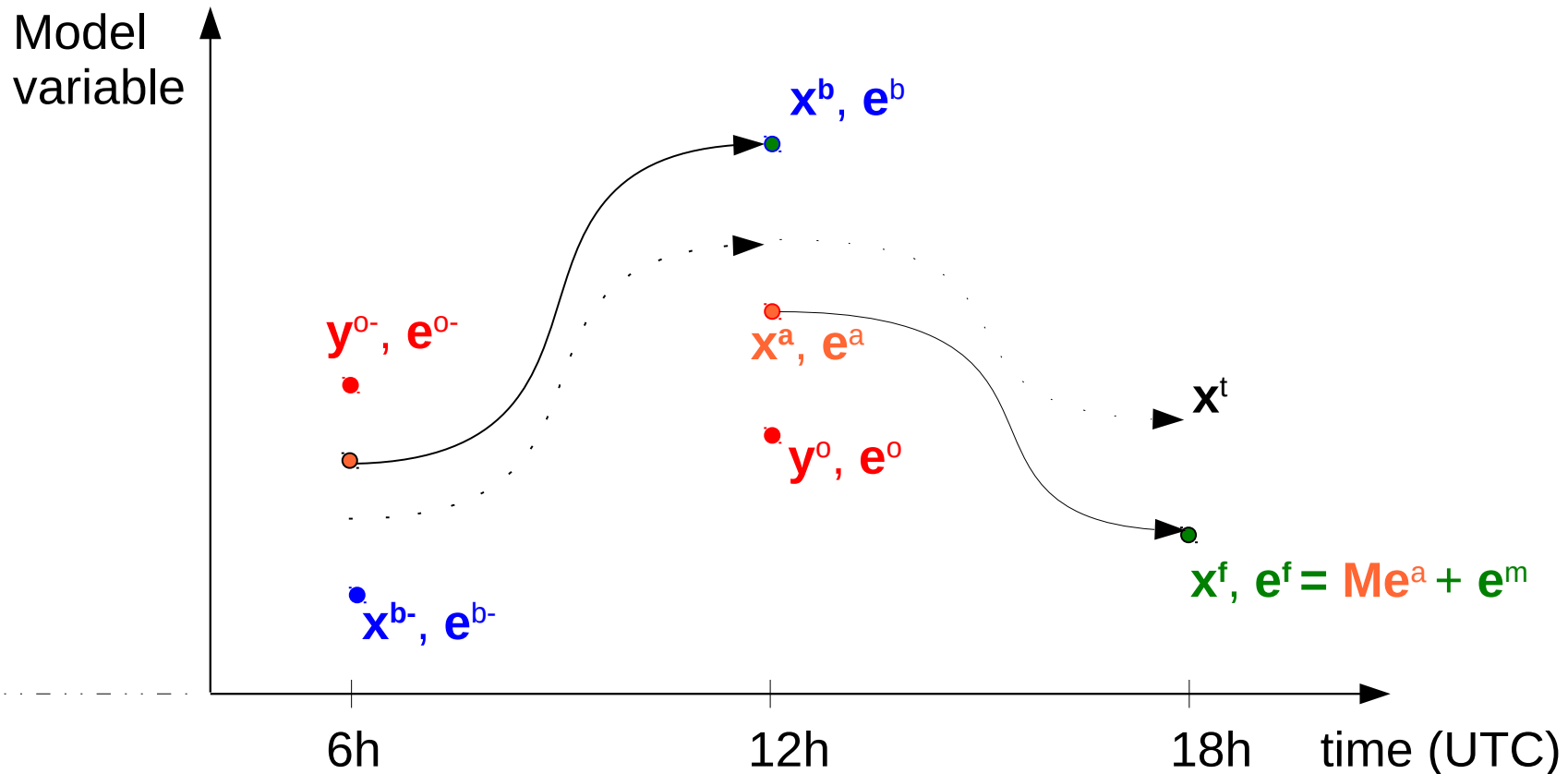


# Simulation and diagnosis of error contributions in DA cycling

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Workshop on Sensitivity Analysis and Data Assimilation  
Aveiro, 4 July 2018

# Error contributions and their propagation

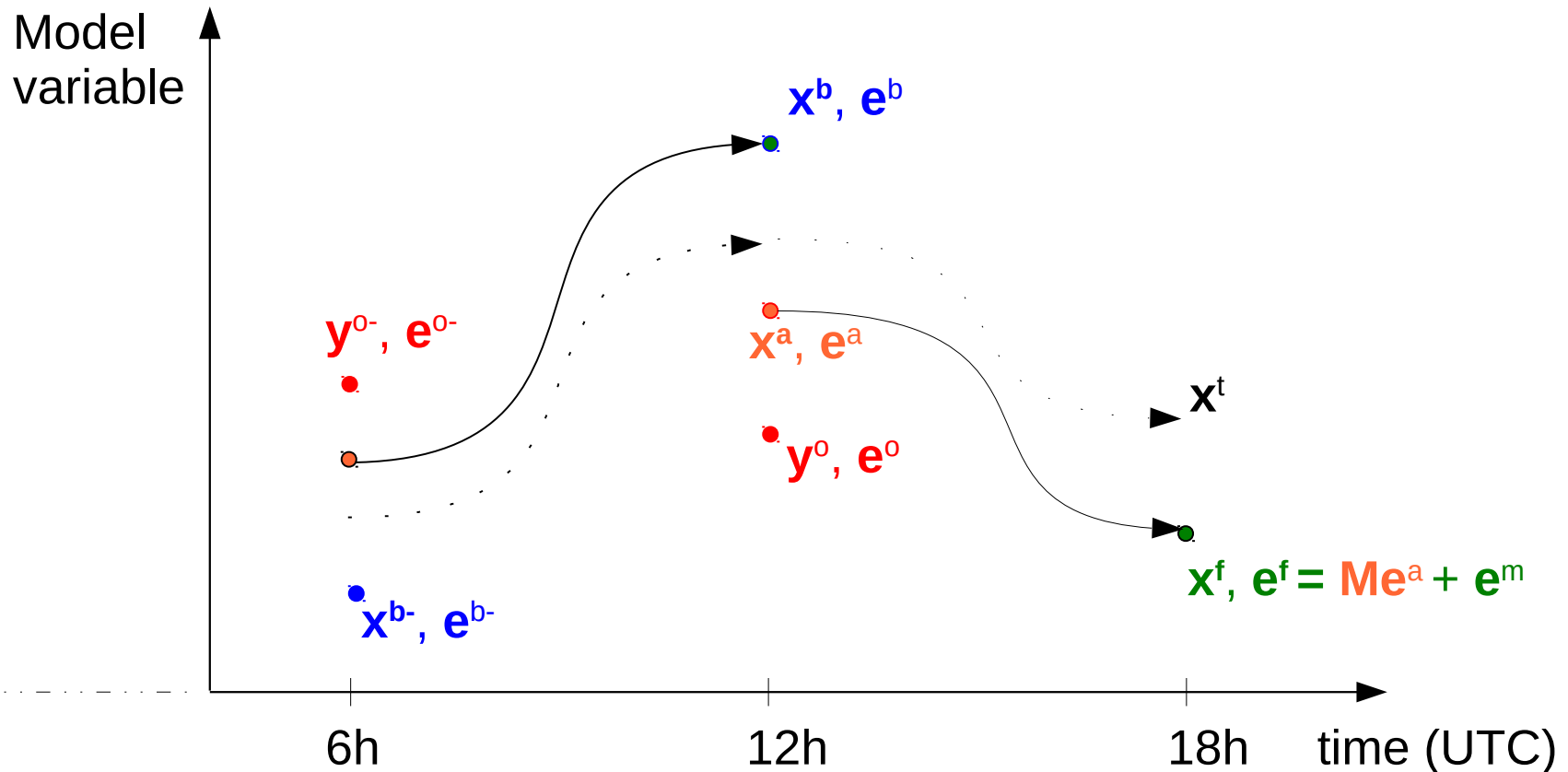


Each error contribution is partly **propagated** by the successive analysis/forecast steps.

**Forecast errors** = propagation of errors with **different ages** :

- \* recent analysis & model errors ;
- \* recent background & observation errors ;
- \*  $\pm$  old background, observation & model errors.

# Error contributions and their propagation



- Goal : simulate error contributions, diagnose their amplitude and propagation.
- Motivations : knowledge about error dynamics in DA cycling, develop error simulation and estimation methods.

# Outline

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- Expansion of forecast error contributions
- Propagation of *old* versus *recent* error contributions
- *Observation* versus *model* error contributions
- Conclusions

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# What does contribute to forecast errors ? ( linear expansion at cycling step $t_i$ )

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$$\epsilon_i^f = M_i \epsilon_i^a + \epsilon_i^m$$

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

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$$\begin{aligned}\epsilon_i^f &= \mathbf{M}_i \epsilon_i^a + \epsilon_i^m \\ &= \mathbf{M}_i (\mathbf{I} - \mathbf{K}_i \mathbf{H}_i) \epsilon_i^b + \mathbf{M}_i \mathbf{K}_i \epsilon_i^o + \epsilon_i^m \\ &= \mathbf{M}_i (\mathbf{I} - \mathbf{K}_i \mathbf{H}_i) [\mathbf{M}_{i-1} (\mathbf{I} - \mathbf{K}_{i-1} \mathbf{H}_{i-1}) \epsilon_{i-1}^b + \mathbf{M}_{i-1} \mathbf{K}_{i-1} \epsilon_{i-1}^o + \epsilon_{i-1}^m] + \mathbf{M}_i \mathbf{K}_i \epsilon_i^o + \epsilon_i^m\end{aligned}$$



# What does contribute to forecast errors ? ( linear expansion at cycling step $t_j$ )

$$\begin{aligned}
 \epsilon_i^f &= \mathbf{M}_i \epsilon_i^a + \epsilon_i^m \\
 &= \mathbf{M}_i (\mathbf{I} - \mathbf{K}_i \mathbf{H}_i) \epsilon_i^b + \mathbf{M}_i \mathbf{K}_i \epsilon_i^o + \epsilon_i^m \\
 &= \mathbf{M}_i (\mathbf{I} - \mathbf{K}_i \mathbf{H}_i) [\mathbf{M}_{i-1} (\mathbf{I} - \mathbf{K}_{i-1} \mathbf{H}_{i-1}) \epsilon_{i-1}^b + \mathbf{M}_{i-1} \mathbf{K}_{i-1} \epsilon_{i-1}^o + \epsilon_{i-1}^m] + \mathbf{M}_i \mathbf{K}_i \epsilon_i^o + \epsilon_i^m \\
 &= \mathbf{T}_2 \epsilon_{i-1}^b + \sum_{j=i-1}^i \mathbf{T}_{i-j} (\mathbf{M}_j \mathbf{K}_j \epsilon_j^o + \epsilon_j^m) \\
 &= \dots \\
 &= \mathbf{T}_{i+1} \epsilon_0^b + \sum_{j=0}^i \mathbf{T}_{i-j} (\mathbf{M}_j \mathbf{K}_j \epsilon_j^o + \epsilon_j^m)
 \end{aligned}$$

where, for  $j < i$ ,

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

and  $t_0$  is the beginning of the considered cycling period.

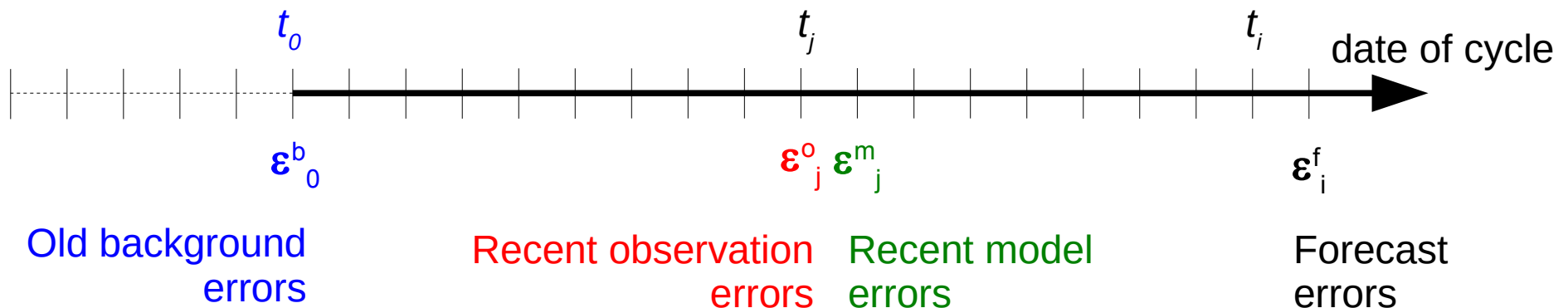
# Old and recent error contributions

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

with  $\mathbf{T}_{i-j} = \prod_{k=j+1}^i \mathbf{M}_k (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k)$  (= cycling operator).

OLD CYCLES

RECENT CYCLES



*How do these 3 error contributions compare, and how do they propagate & accumulate during the cycling ?*

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- Conclusions

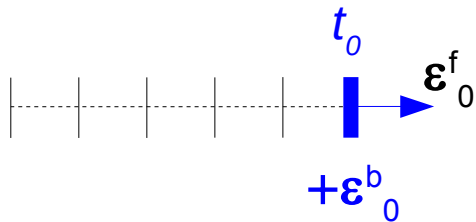
# Simulation of error contributions from an old background and from recent observations

- Baseline Ensemble DA experiment (EDA) : Arpege 4D-Var (global NWP), observation perturbations and multiplicative inflation, warm start on 9 January 2017 from operational EDA ; 6h cycling ; same  $\mathbf{B}_j$  (provided by operational EDA) for all xp's.
- To quantify contributions of  $\boldsymbol{\varepsilon}_0^b$  and  $\boldsymbol{\varepsilon}_j^o$ , variants of this EDA baseline are run, from 9 to 22 January 2017 (2 weeks), using **addition and propagation of specific perturbations**.
- Propagation of states is done non linearly (4D-Var + NL model) ; propagation of perturbations is interpreted using linear formalism.
- Evolution of global variance of error contributions for temperature (500 hPa) from corresponding ensemble spread<sup>2</sup>.

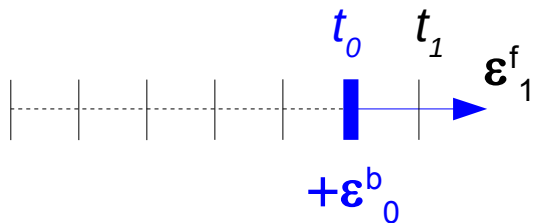
# Propagation of old background error

$\epsilon^b_0$  = background error at  $t_0$  simulated  
by warm start from operational EDA

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



Step  $t_0$  : add  $\epsilon^b_0$ , run analysis and forecast :  $\epsilon^f_0 = \mathbf{T}_1 \epsilon^b_0$

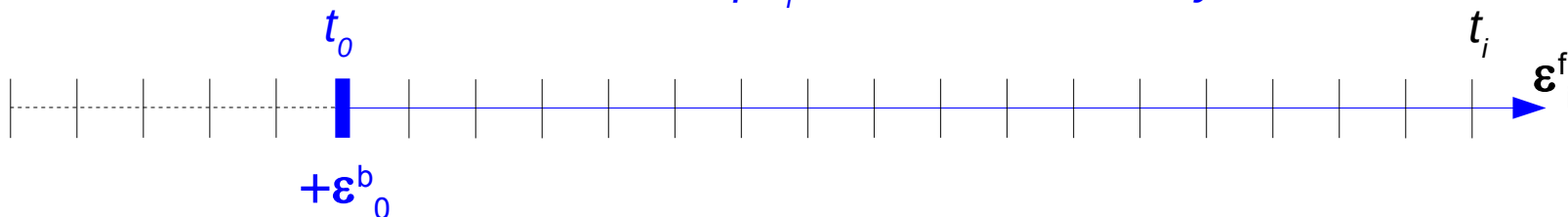


Step  $t_1$  : run analysis and forecast :  $\epsilon^f_1 = \mathbf{T}_2 \epsilon^b_0$

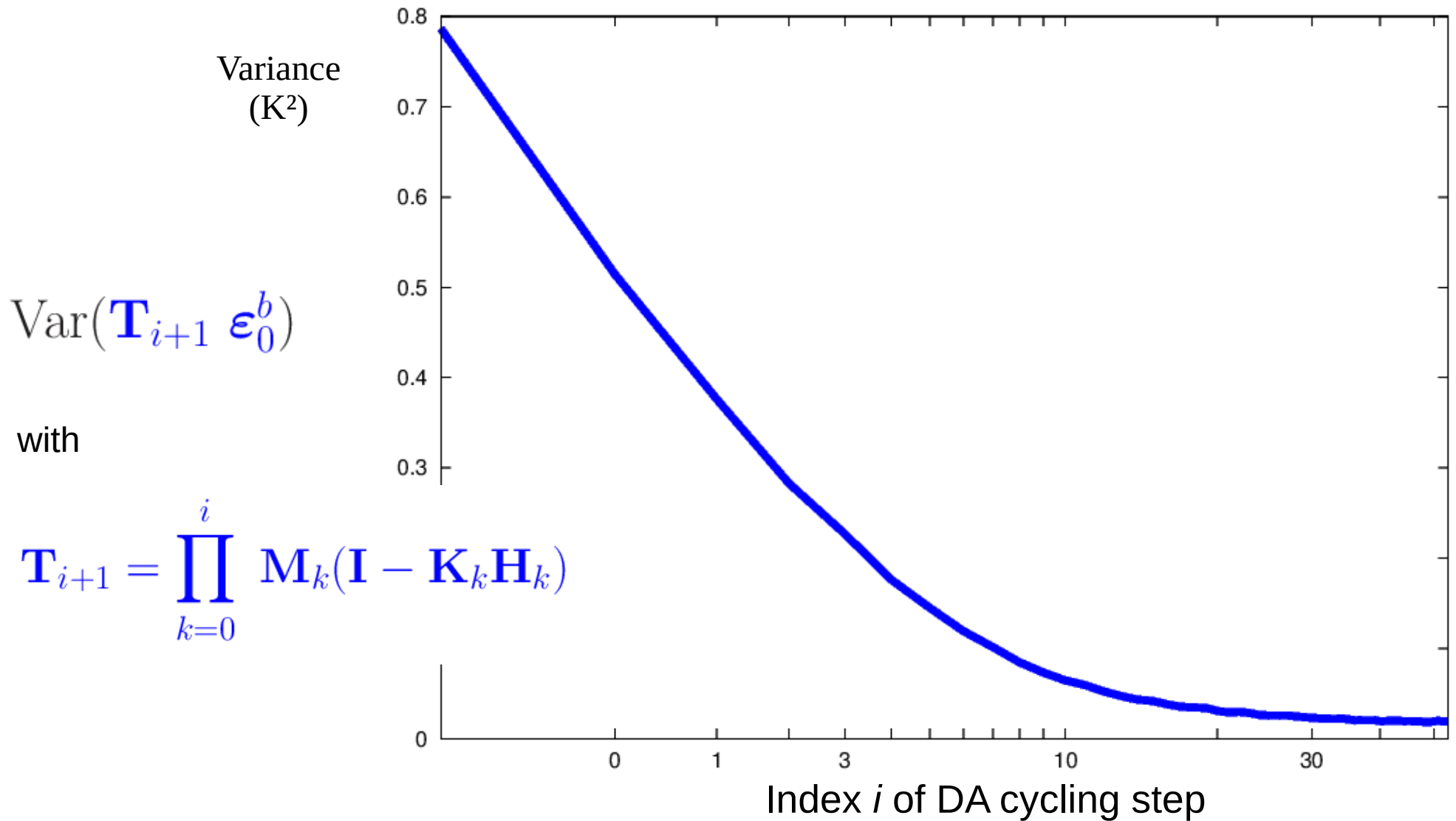
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Step  $t_i$  : run analysis and forecast :  $\epsilon^f_i = \mathbf{T}_{i+1} \epsilon^b_0$

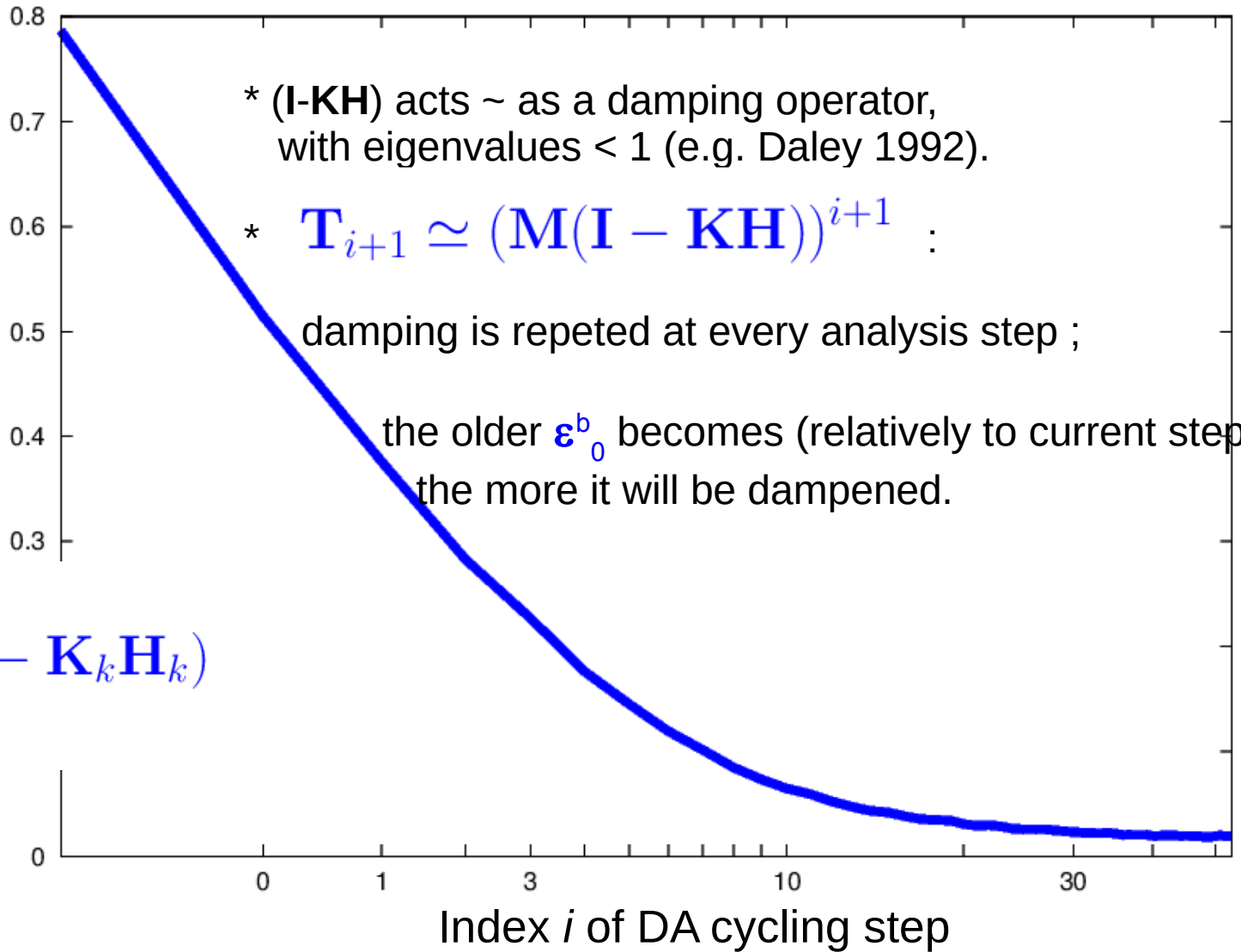


# Propagation of old background error



*Old background errors are dampened by successive DA steps (~ 4-day period).*

# Propagation of old background error



$$\text{Var}(\mathbf{T}_{i+1} \boldsymbol{\varepsilon}_0^b)$$

with

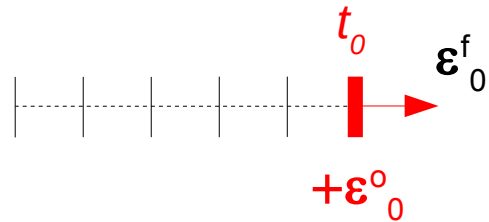
$$\mathbf{T}_{i+1} = \prod_{k=0}^i \mathbf{M}_k(\mathbf{I} - \mathbf{K}_k \mathbf{H}_k)$$

*Old background errors are dampened by successive DA steps (~ 4-day period).*

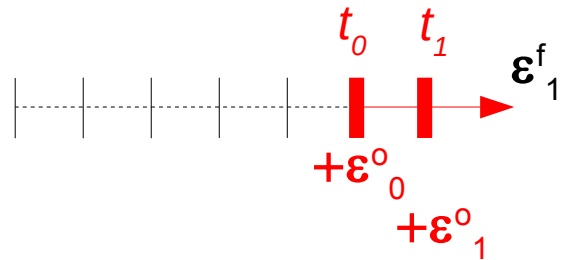
# Accumulation and propagation of recent observation errors

$$\text{Var}\left(\sum_{j=0}^i \mathbf{T}_{i-j} \mathbf{M}_j \mathbf{K}_j \boldsymbol{\varepsilon}_j^o\right)$$

$$\boldsymbol{\varepsilon}_j^o = \mathbf{R}^{1/2} \boldsymbol{\eta}$$



Step  $t_0$ : add  $\boldsymbol{\varepsilon}_0^o$ , run analysis and forecast:  $\boldsymbol{\varepsilon}_0^f = \mathbf{M}_0 \mathbf{K}_0 \boldsymbol{\varepsilon}_0^o$

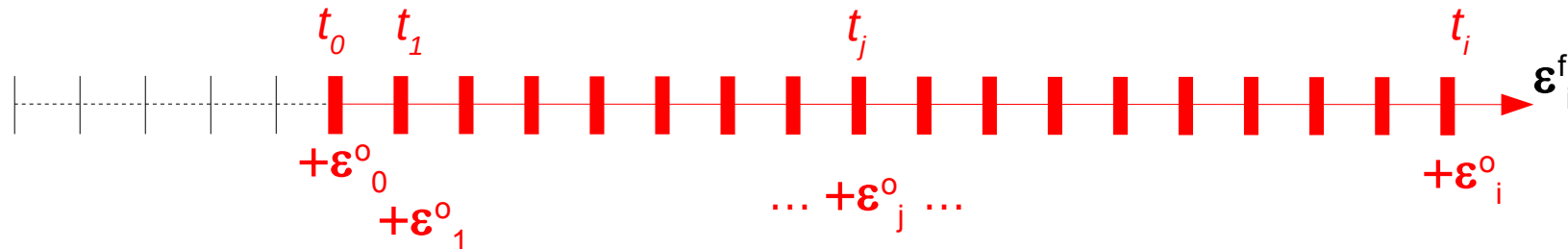


Step  $t_1$ : add  $\boldsymbol{\varepsilon}_1^o$ , run analysis and forecast:  $\boldsymbol{\varepsilon}_1^f = \mathbf{T}_1 \mathbf{M}_0 \mathbf{K}_0 \boldsymbol{\varepsilon}_0^o + \mathbf{M}_1 \mathbf{K}_1 \boldsymbol{\varepsilon}_1^o$

...

...

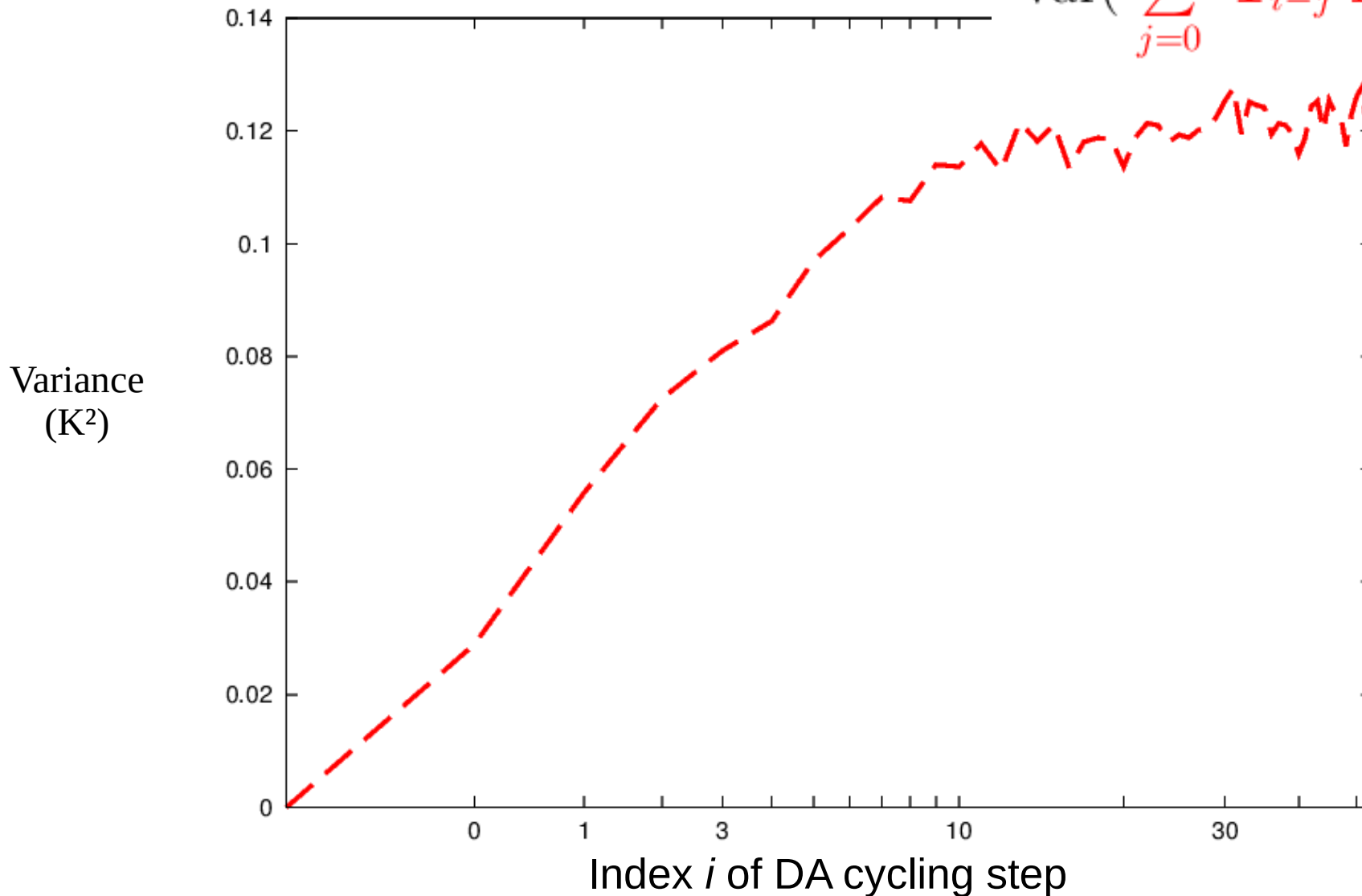
Step  $t_i$ : add  $\boldsymbol{\varepsilon}_i^o$ , run analysis and forecast:  $\boldsymbol{\varepsilon}_i^f = \sum_{j=0}^i \mathbf{T}_{i-j} \mathbf{M}_j \mathbf{K}_j \boldsymbol{\varepsilon}_j^o$





# Accumulation and propagation of recent observation errors

$$\text{Var}\left(\sum_{j=0}^i \mathbf{T}_{i-j} \mathbf{M}_j \mathbf{K}_j \boldsymbol{\varepsilon}_j^o\right)$$



*Recent observation errors are accumulated and dampened by successive DA steps.*

# Why does it converge like this ?

Spectral interpretation of the convergence of  $\text{Var}\left(\sum_{j=0}^i \mathbf{T}_{i-j} \mathbf{M}_j \mathbf{K}_j \boldsymbol{\varepsilon}_j^o\right)$  as a power series

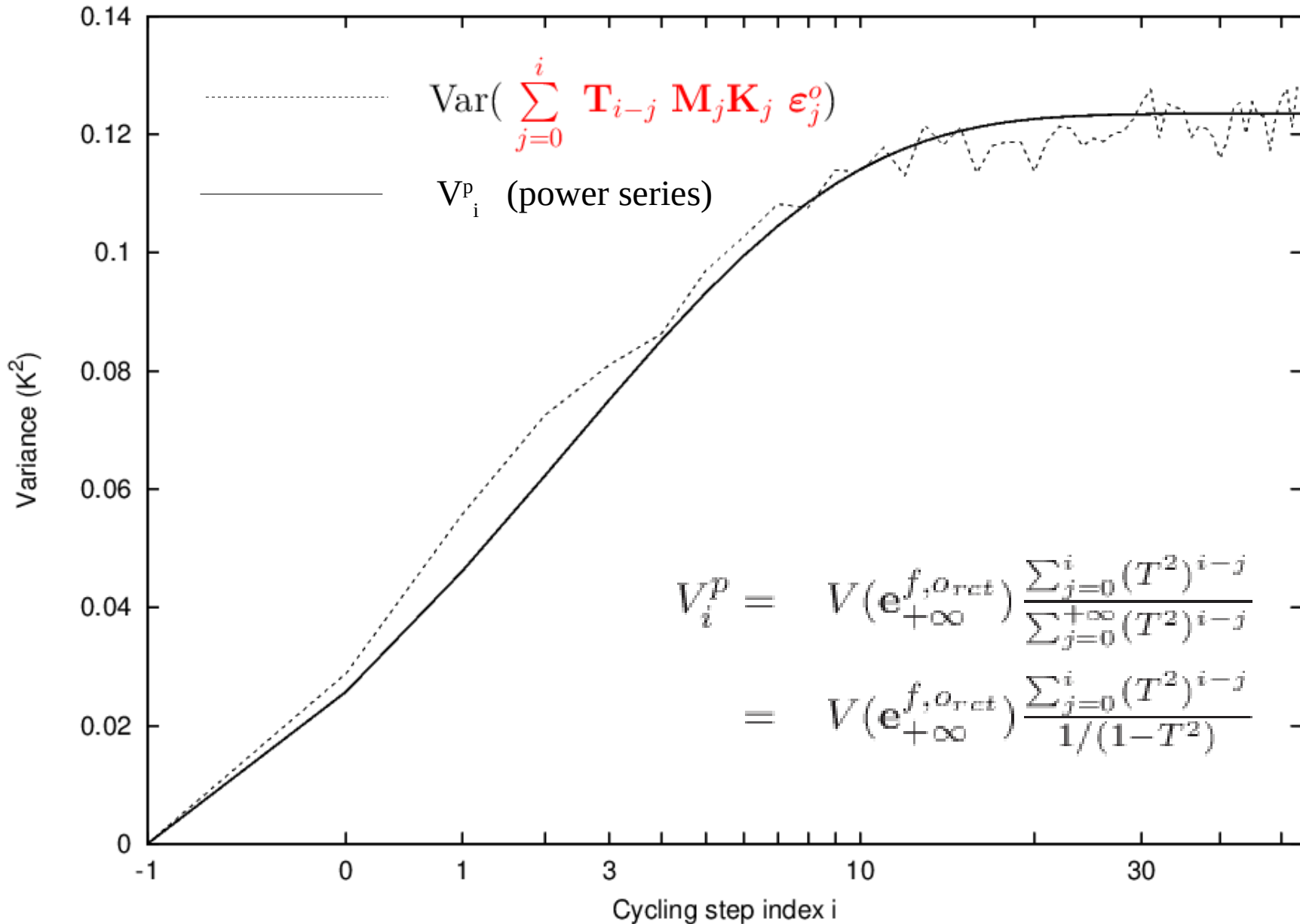
Spectral variance (for a given wave vector  $\vec{m}$ ):  $V[e_{i, \vec{m}}^{f, o_{rect}}] = \sum_{j=0}^i (|T_{\vec{m}}|^2)^{i-j} V[\tilde{e}_{\vec{m}}^{f, o_j}]$   
 for homogeneous and static covariances, etc.

$$= V[\tilde{e}_{\vec{m}}^{f, o}] \sum_{j=0}^i (|T_{\vec{m}}|^2)^{i-j}$$

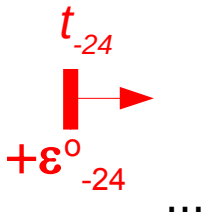
Convergence of power series :  $\lim_{i \rightarrow +\infty} \sum_{j=0}^i (|T_{\vec{m}}|^2)^{i-j} = \sum_{j'=0}^{+\infty} (|T_{\vec{m}}|^2)^{j'} = \frac{1}{1 - |T_{\vec{m}}|^2}$   
 ( if  $|T_{\vec{m}}|^2 < 1$  )

Weighted sum of power series :  $V(e_{+\infty}^{f, o_{rect}}) = \sum_{\vec{m}} \frac{|(MK)_{\vec{m}}|^2}{1 - |(MK')_{\vec{m}}|^2} V(e_{\vec{m}}^o)$   
 ( with  $\mathbf{K}' = \mathbf{I} - \mathbf{KH}$  )

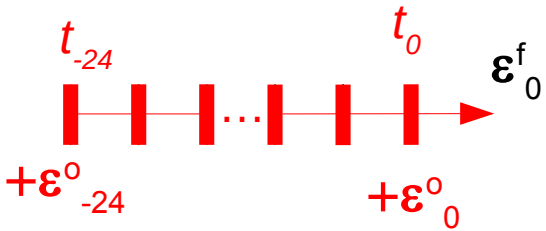
# Spectral interpretation of the convergence as a power series



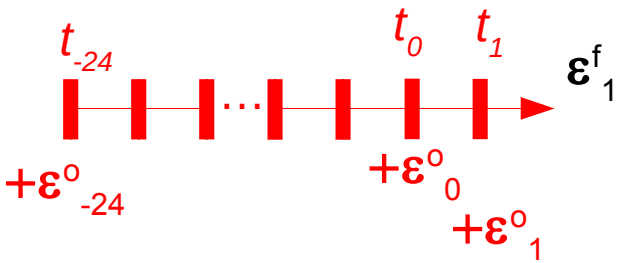
# Accumulation and propagation of old+recent observation errors



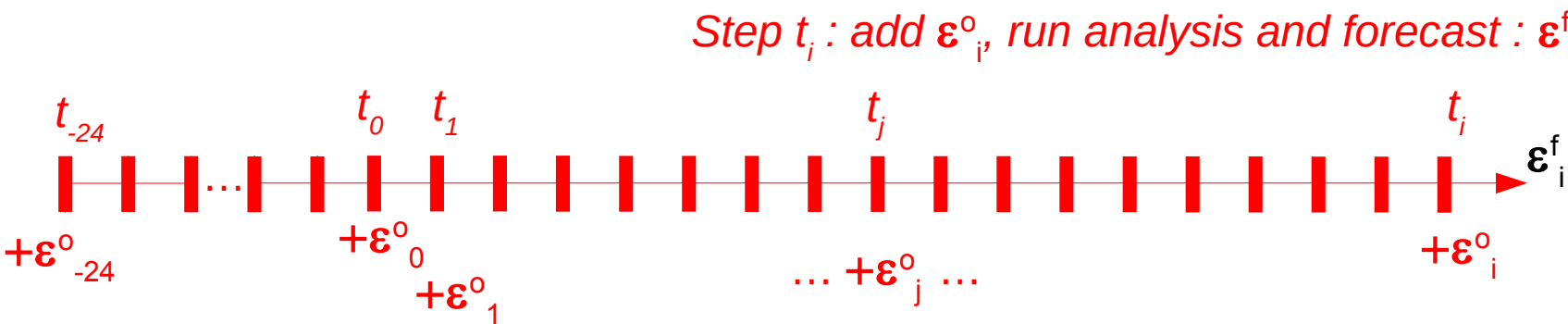
Step  $t_{-24}$  : add  $\epsilon^0_{-24}$ , run analysis and forecast ( 6 days before  $t_0$  )



Step  $t_0$  : add  $\epsilon^0_0$ , run analysis and forecast

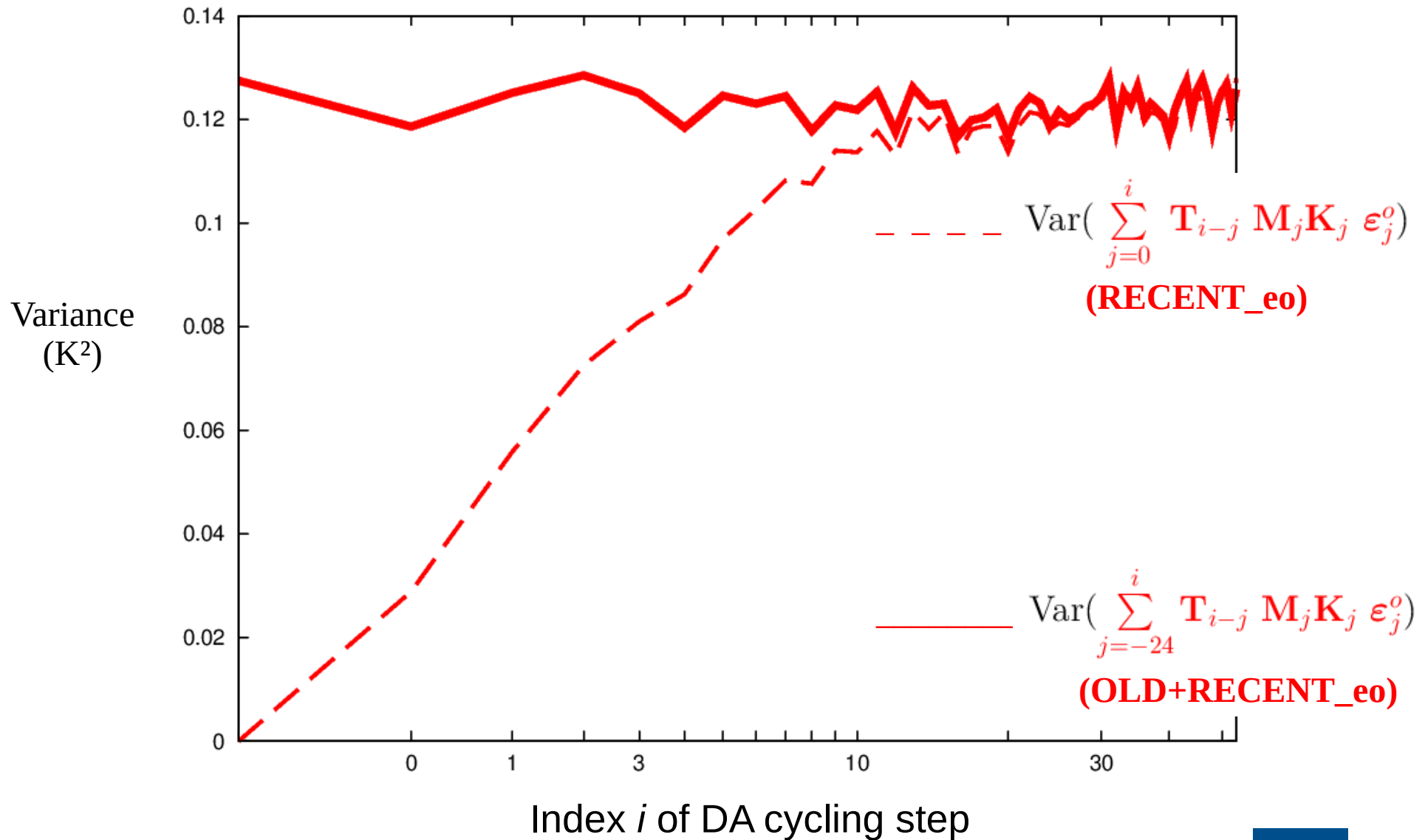


Step  $t_1$  : add  $\epsilon^0_1$ , run analysis and forecast



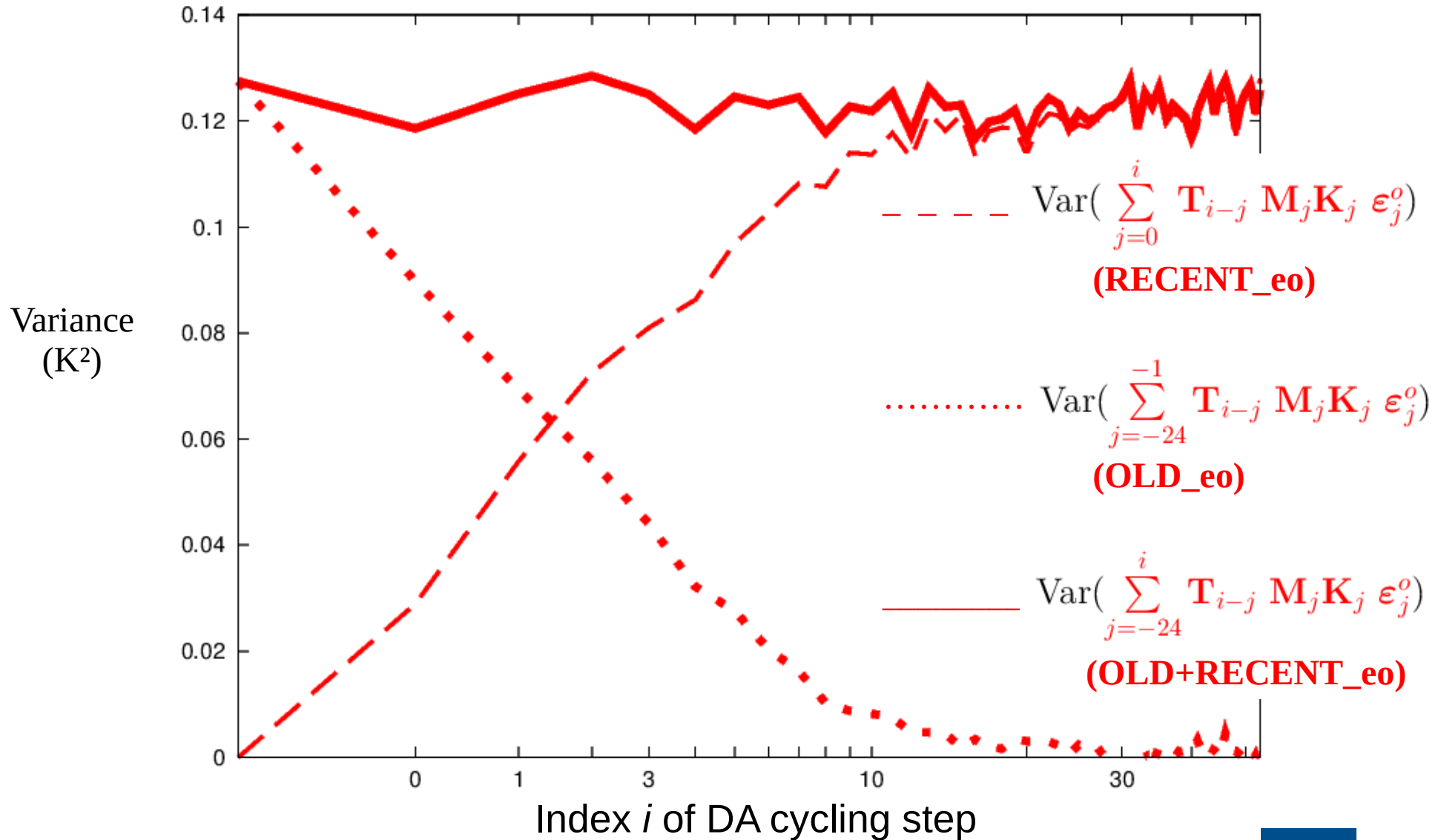
Step  $t_i$  : add  $\epsilon^0_i$ , run analysis and forecast :  $\epsilon^f_i = \sum_{j=-24}^i \mathbf{T}_{i-j} \mathbf{M}_j \mathbf{K}_j \epsilon^0_j$

# Accumulation and propagation of old+recent observation errors



*Total (old+recent) contribution is stable.*

# Evolution of old & recent observation error contributions



*Total (old+recent) contribution is stable : compensation between damping of old errors and accumulation of recent errors.*

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# Contributions to forecast error variance

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

with

$$\text{Var}(\mathbf{T}_{i+1} \boldsymbol{\epsilon}_0^b) \simeq 0 \quad \text{for } i \gtrsim \tau^T,$$

where  $\tau^T \simeq 4$  days is the timescale over which old errors vanish,

$$\text{Cov}(\boldsymbol{\epsilon}_0^b, \boldsymbol{\epsilon}_j^o) = 0 \quad \text{for time uncorrelated random observation errors,}$$

$$\text{Cov}(\mathbf{T}_{i+1} \boldsymbol{\epsilon}_0^b, \mathbf{T}_{i-j} \boldsymbol{\epsilon}_j^m) \simeq 0 \quad \text{when } i \gtrsim \max(\tau^T, \tau^m)$$

where  $\tau^m$  is the correlation timescale of random model errors.

for  $i \gtrsim \max(\tau^T, \tau^m)$  :

$$\text{Var}(\boldsymbol{\epsilon}_i^f) = \text{Var}\left(\sum_{j=0}^i \mathbf{T}_{i-j} \mathbf{M}_j \mathbf{K}_j \boldsymbol{\epsilon}_j^o\right) + \text{Var}\left(\sum_{j=0}^i \mathbf{T}_{i-j} \boldsymbol{\epsilon}_j^m\right)$$



# Diagnosis of recent model error contributions

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Contributions to forecast error variance :

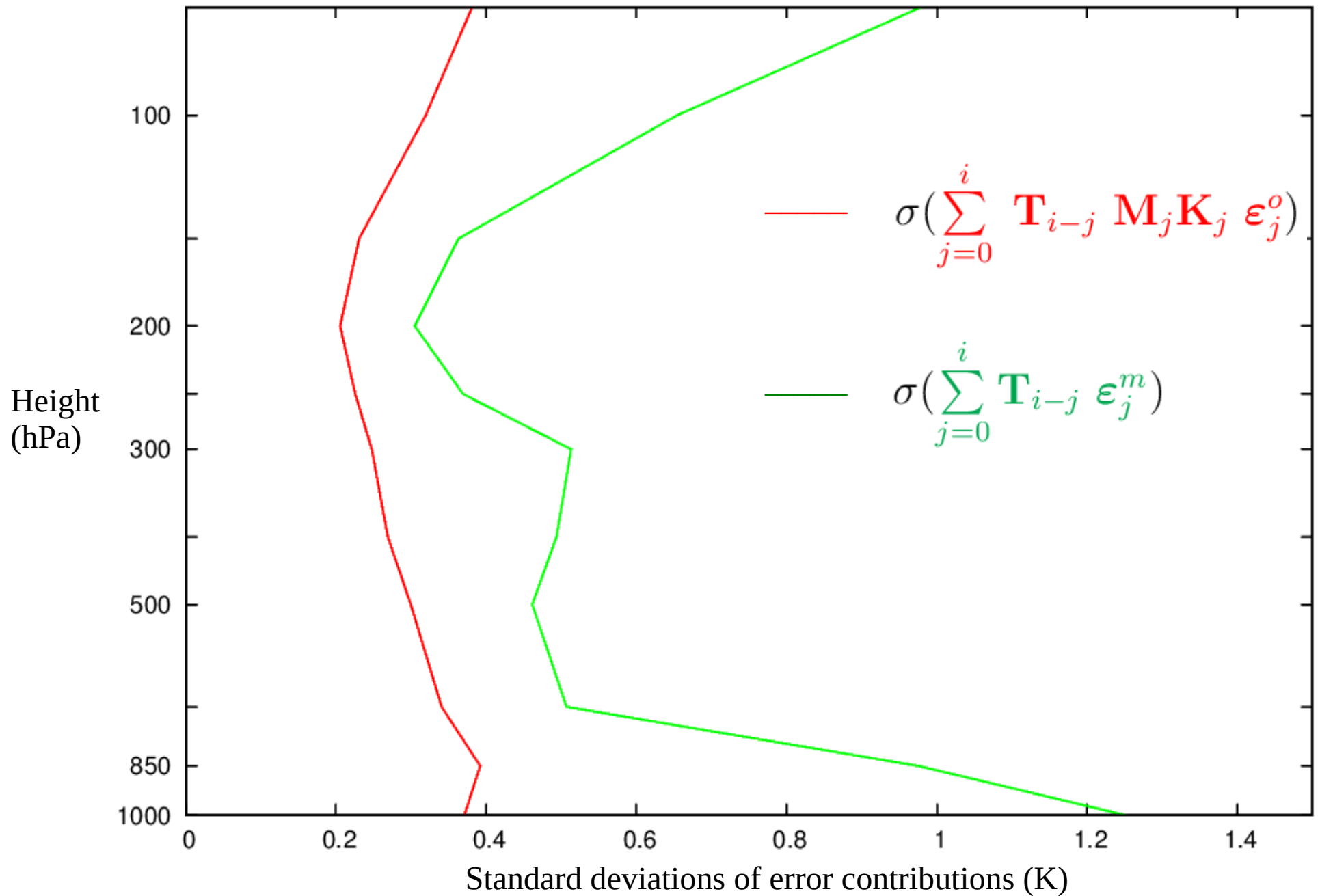
$$\text{Var}(\boldsymbol{\epsilon}_i^f) = \text{Var}\left(\sum_{j=0}^i \mathbf{T}_{i-j} \mathbf{M}_j \mathbf{K}_j \boldsymbol{\epsilon}_j^o\right) + \text{Var}\left(\sum_{j=0}^i \mathbf{T}_{i-j} \boldsymbol{\epsilon}_j^m\right)$$

which leads to the following estimation approach

(e.g. at day 4, considering  $\max(\tau^T, \tau^m) \simeq 4$  days) :

- $\text{Var}(\boldsymbol{\epsilon}_i^f)$  estimated by innovation-based diagnostics (e.g. Desroziers et al 2005);
- $\text{Var}\left(\sum_{j=0}^i \mathbf{T}_{i-j} \mathbf{M}_j \mathbf{K}_j \boldsymbol{\epsilon}_j^o\right)$  estimated by EDA with observation perturbations only ;
- $\text{Var}\left(\sum_{j=0}^i \mathbf{T}_{i-j} \boldsymbol{\epsilon}_j^m\right) = \text{Var}(\boldsymbol{\epsilon}_i^f) - \text{Var}\left(\sum_{j=0}^i \mathbf{T}_{i-j} \mathbf{M}_j \mathbf{K}_j \boldsymbol{\epsilon}_j^o\right)$

# Diagnosis of model error contributions versus observation error contributions



# Conclusions

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- Linear forecast error expansion to diagnose background, observation and model error contributions, with different ages.
- Global forecast error variance tends to be stable : compensation between damping of old errors (by successive analyses, within 4 days) and accumulation of recent errors (like a power series).
- Observation error contributions are significant, and model error contributions seem to be even larger.
- Extend this study to spatial correlation aspects, regional variations, etc. Possible use for calibration of model error representations.

# Thank you for your attention

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