Data assimilation of tree-ring-width-like observations using ensemble Kalman filtering techniques

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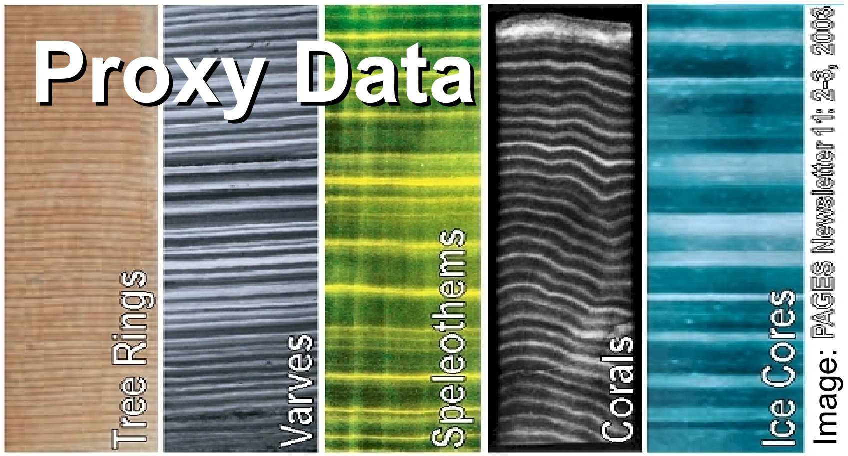
Traditional climate reconstruction methods

Statistical Approach



Statistical Model

Some Climate fields

Simulation Approach

Plausible Initial Climate State

Climate Model

Historical Forcings

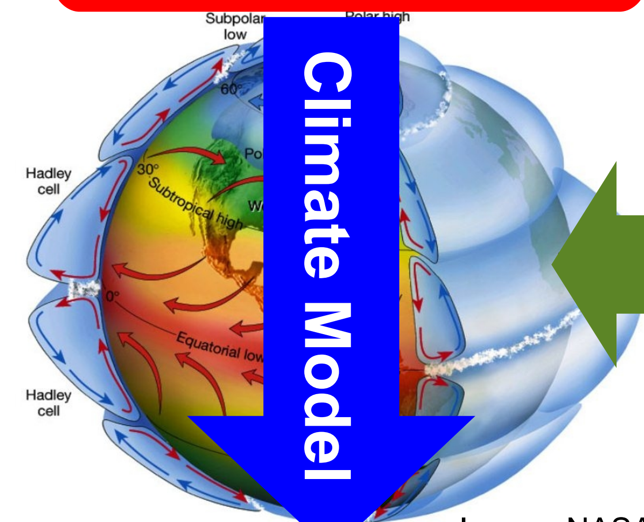


Image: NASA

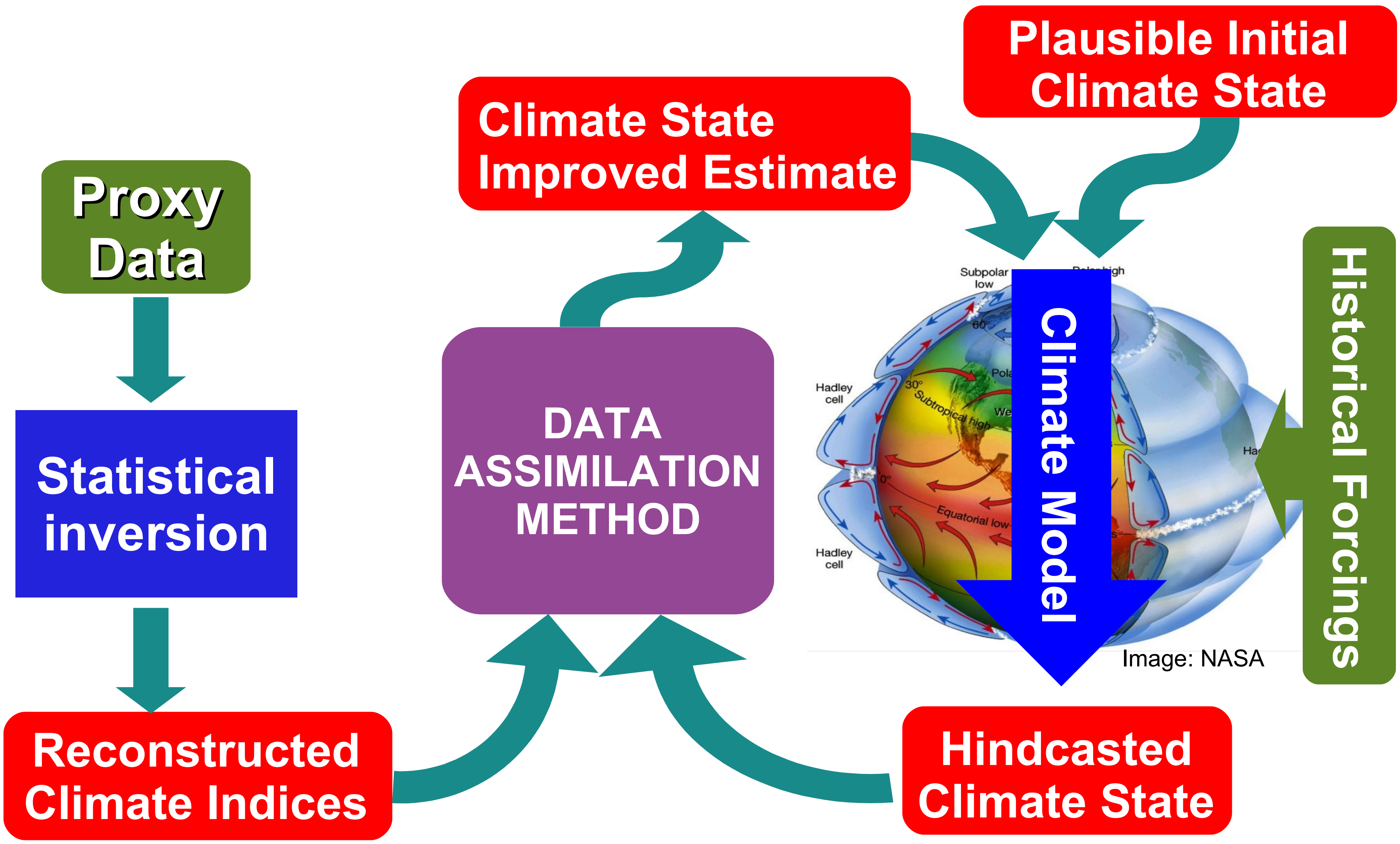
"Complete" Climate State

Weak points

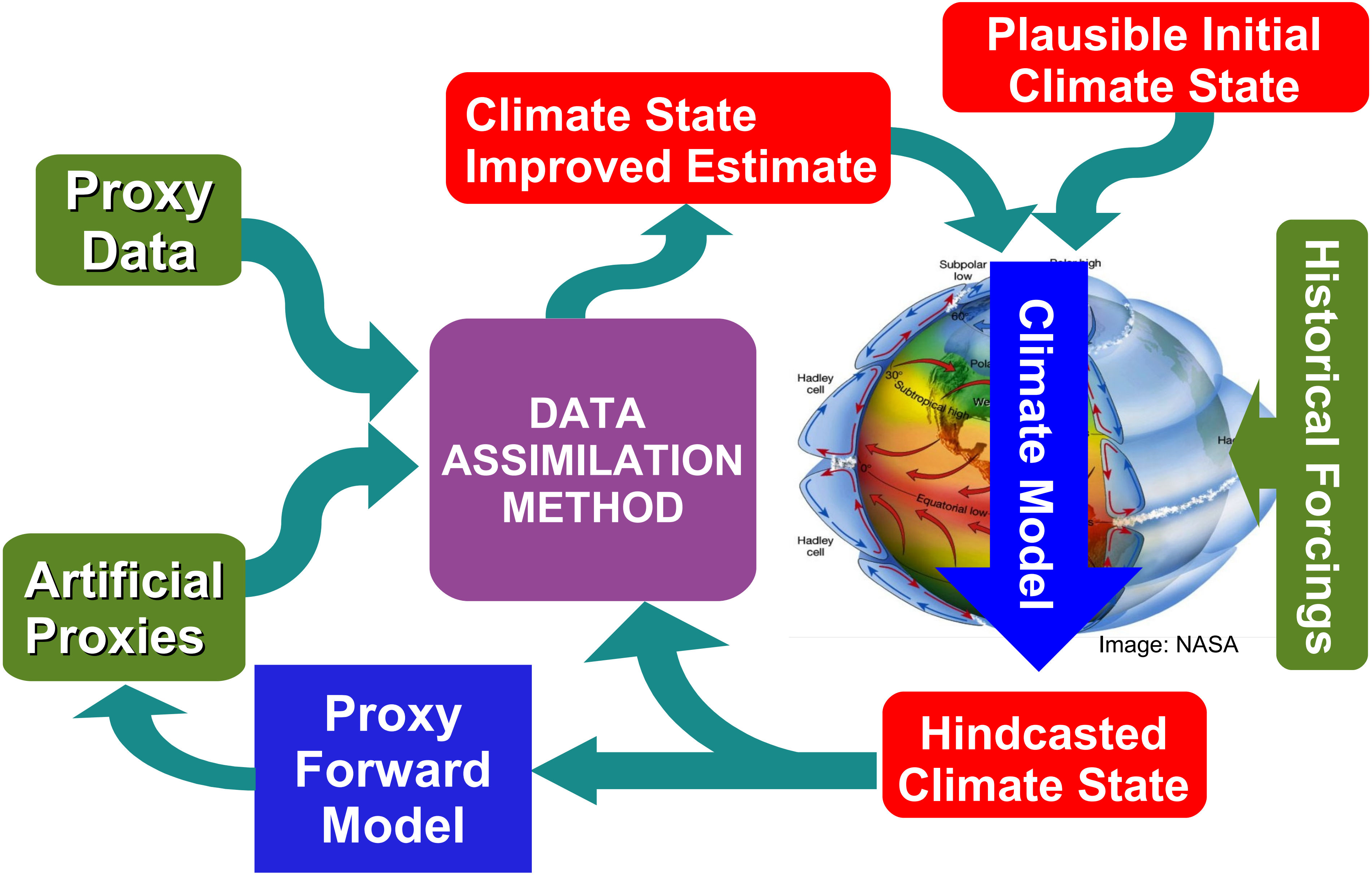
- Completely data driven
- VERY different proxy data treated indifferently

- Loosely linked to observations (internal variability unconstrained)
- Forcings quite uncertain

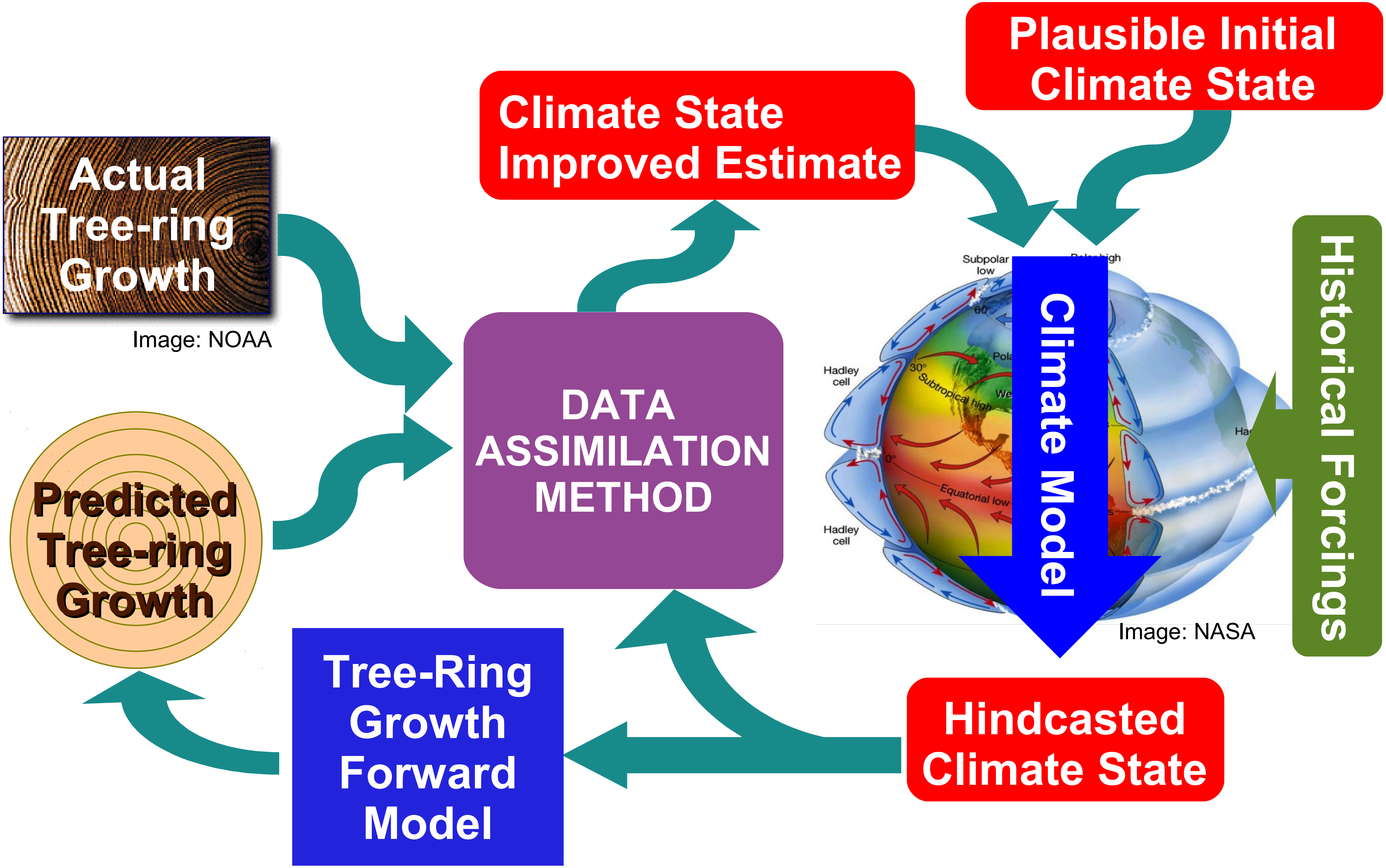
Data assimilation approach



Data assimilation approach

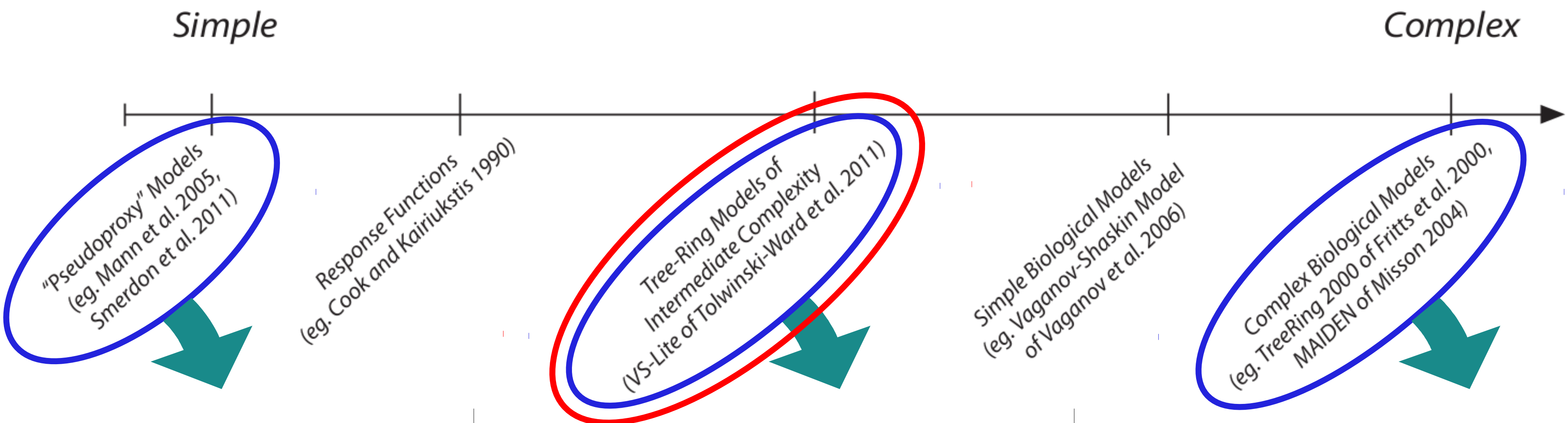


Data assimilation approach



Spectrum of tree-ring growth forward models

(Tolwinsky-Ward 2012)



Pseudo-proxy

Tree-ring
Chronology
||
Climate Index
\+
Noise

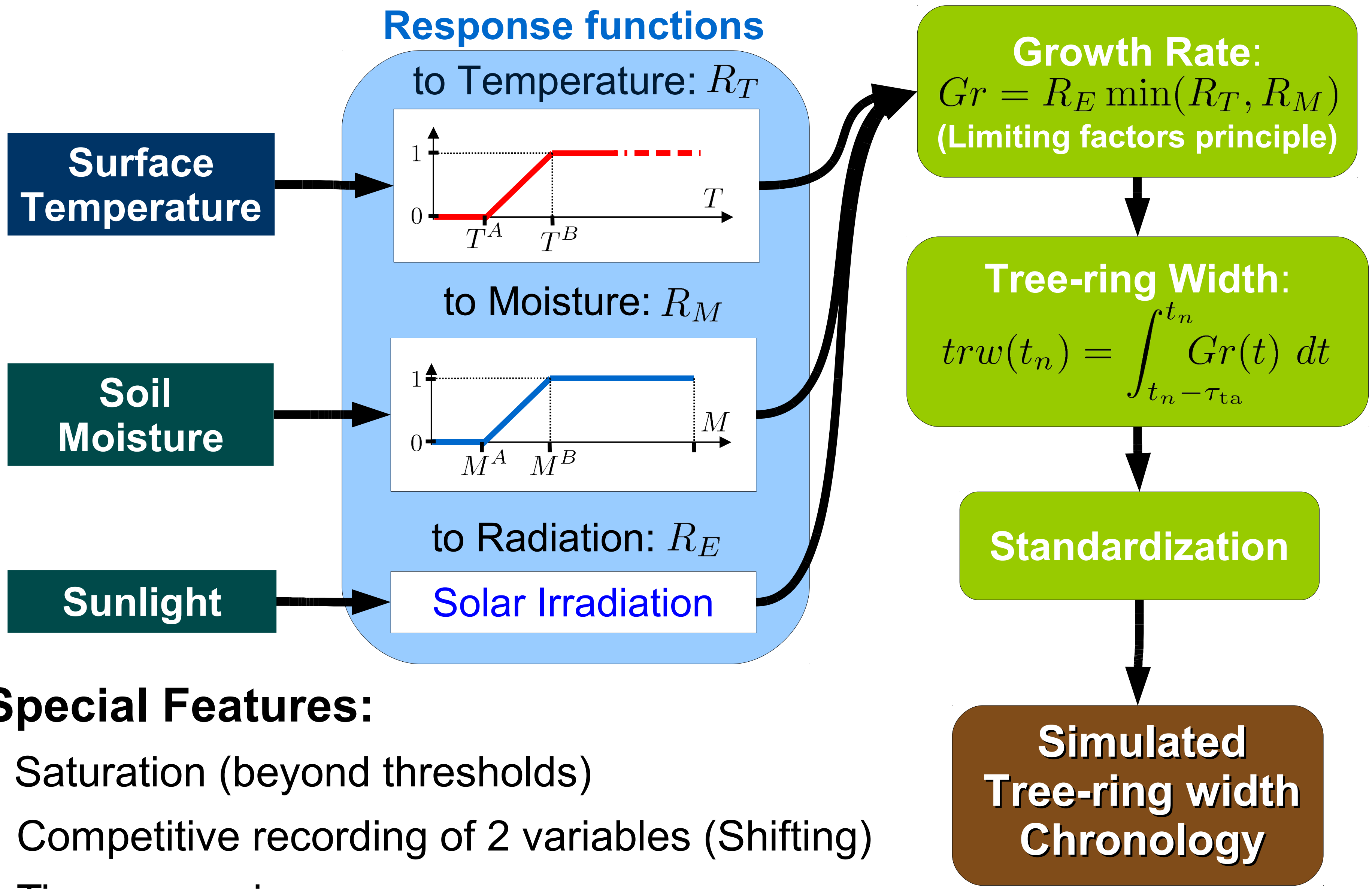
VS-Lite Model[1]

Tree growth driven by
- Limiting factors:
  - Surface temperature
  - Soil moisture
- Modulating factor
  - Sunshine

TreeRing Model

Simulates:
Tree water balance,
Photosynthesis,
Carbon allocation,
Crown growth
Cambial Activity

Vaganov-Shashkin-Lite model scheme[1]



Special Features:

- Saturation (beyond thresholds)
- Competitive recording of 2 variables (Shifting)
- Time-averaging

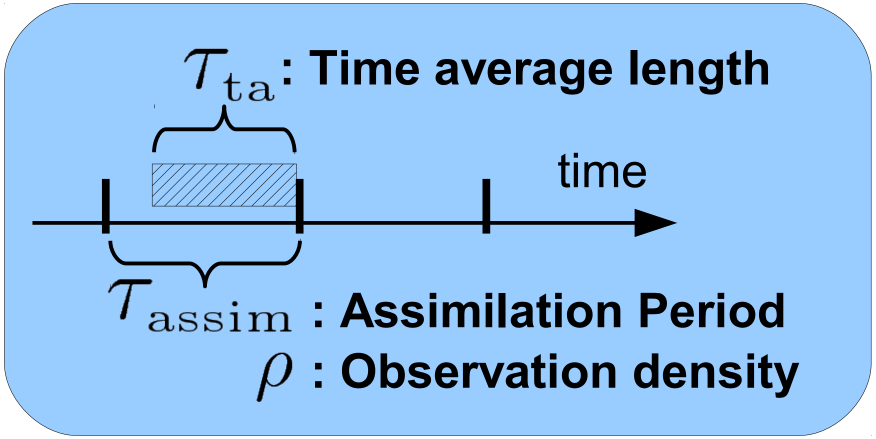
Time-averaged Data Assimilation[2]

- **Time average decomposition**

$$\mathbf{X}^b(t_n) = \overline{\mathbf{X}}^b(t_n) + \widetilde{\mathbf{X}}^b(t_n)$$

where

$$\overline{\mathbf{X}}^b(t_n) = \frac{1}{\tau_{\mathrm{ta}}} \int_{t_n-\tau_{\mathrm{ta}}}^{t_n} \mathbf{X}^b(t')\, dt'$$



- **Observation generation**

$$\mathbf{trw}(t_n) = \int_{t_n-\tau_{\mathrm{ta}}}^{t_n} \mathbf{Gr}(\mathbf{X}^b(t'))\, dt'$$

! VS-Lite growth rate is Non-linear and thus does not Commute with the time integral !

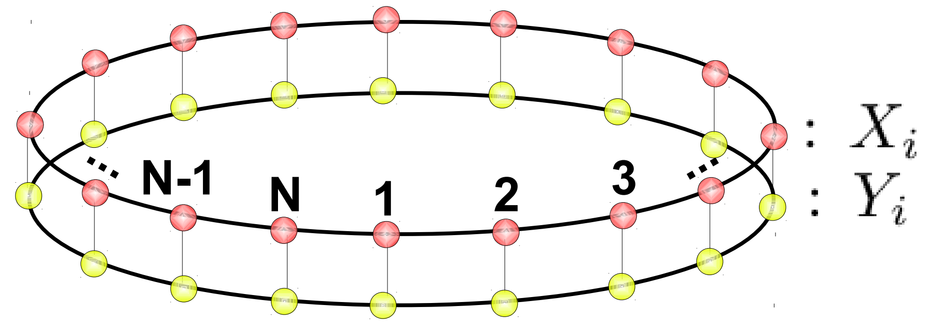
- **Assimilation step**

$\overline{\mathbf{X}}^a(t_n)$ is the update of $\overline{\mathbf{X}}^b(t_n)$ given $\mathbf{trw}(t_n)$ using **EnKF**[3] and **EnKBF**[4]

- **Time average recomposition** $\mathbf{X}^a(t_n) = \overline{\mathbf{X}}^a(t_n) + \widetilde{\mathbf{X}}^b(t_n)$

Lorenz 96 model with 2 components[5]

2 components with equal spatial and time scales



Model equations :

$$
\begin{aligned}
dX_i/dt &= X_{i-1}(X_{i+1} - X_{i-2}) - X_i + Y_i + F, \\
dY_i/dt &= Y_{i+1}\,(Y_{i-1} - \,Y_{i+2}\,) - Y_i\; - X_i,\;\; i = 1\ldots 40.
\end{aligned}
$$

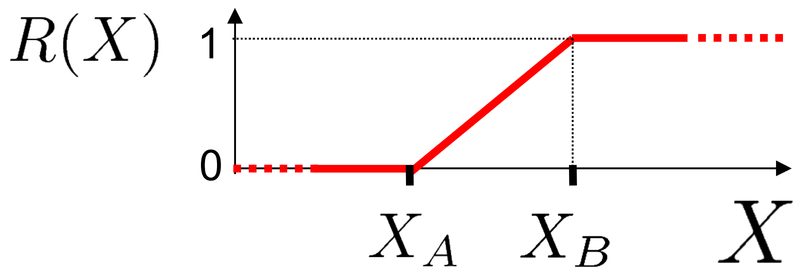
Tree-Ring-Width:

$$trw(t_n) = \int_{t_n - \tau_{\mathrm{ta}}}^{t_n} Gr(t)\; dt$$

Growth Rate:

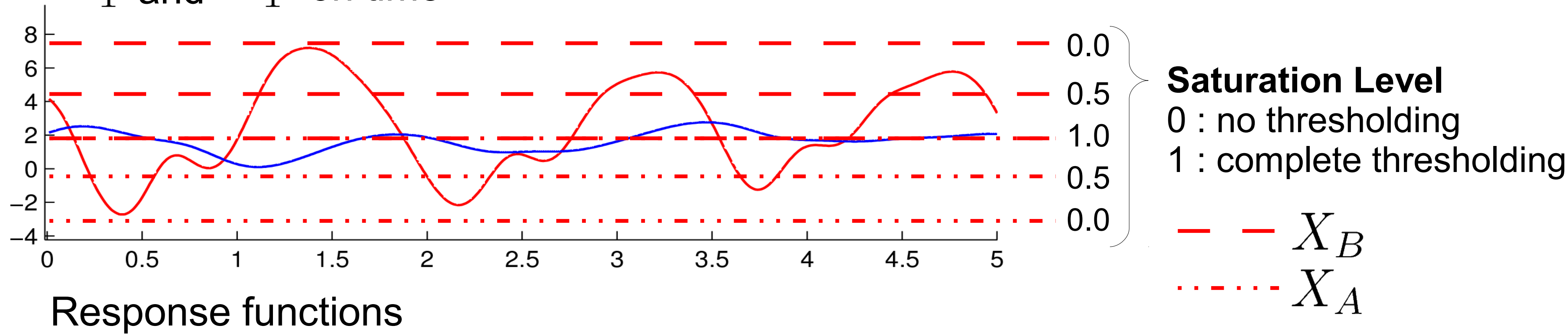
$$Gr_i = \min(R(X_i), R(Y_i))$$

Response functions:

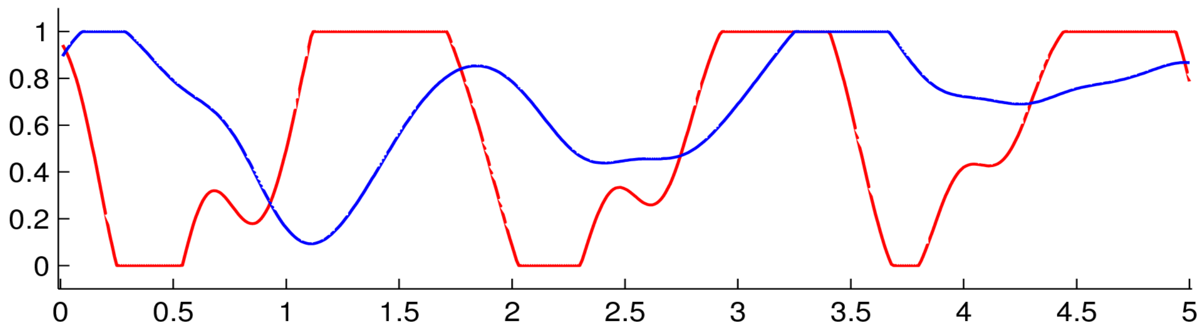


Observation generation

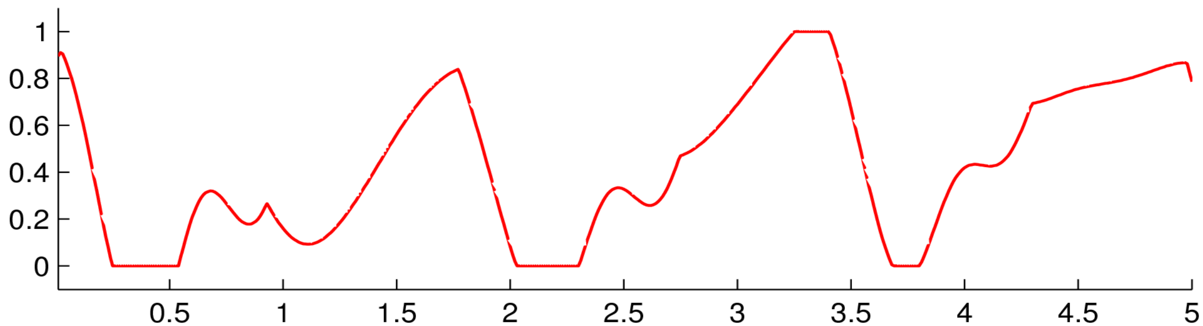
X_1 and Y_1 on time



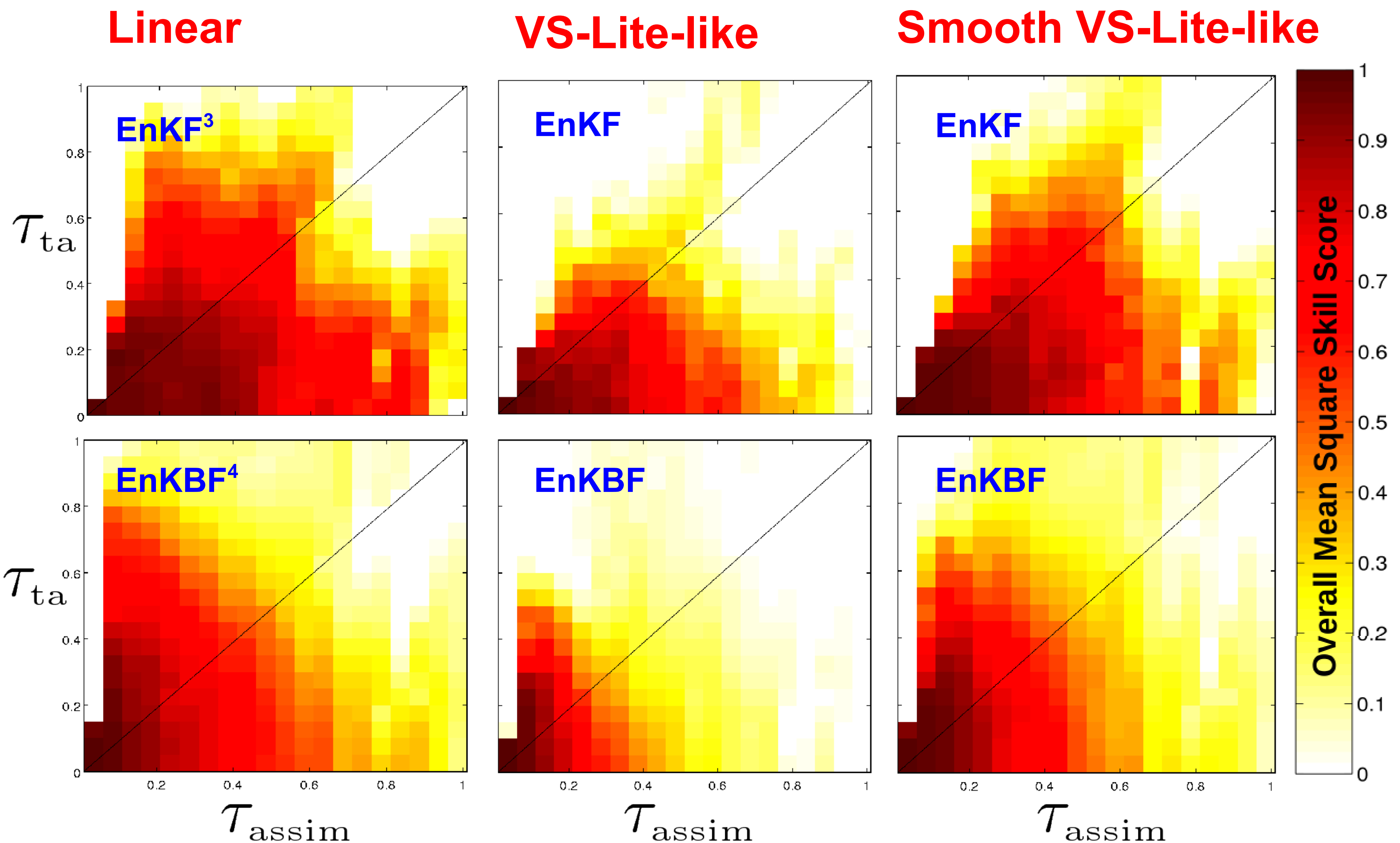
Response functions



“Growth Rate”

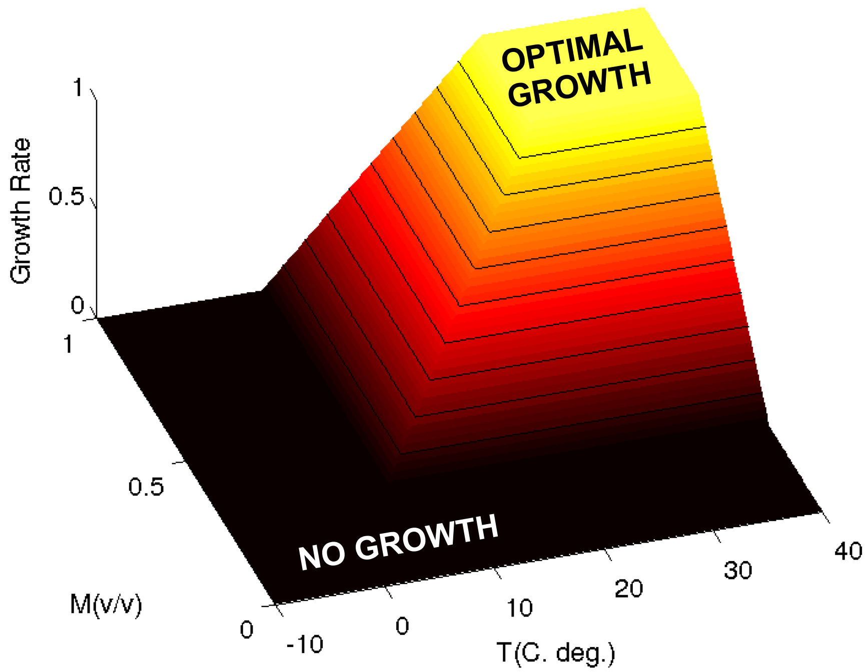


Filter Skill vs observation operator



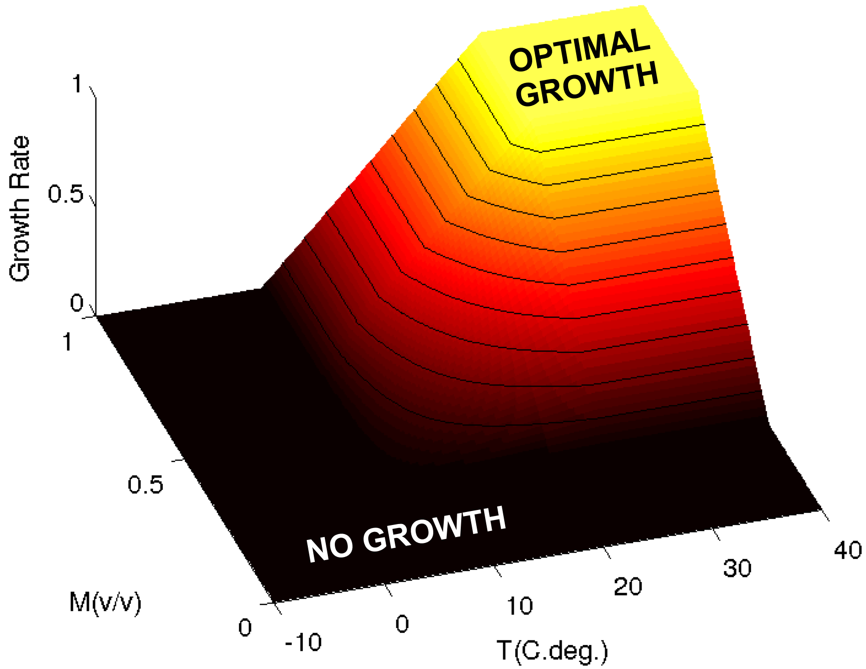
Instantaneous Observation operator

$$Gr_i = \min(R(X_i), R(Y_i))$$



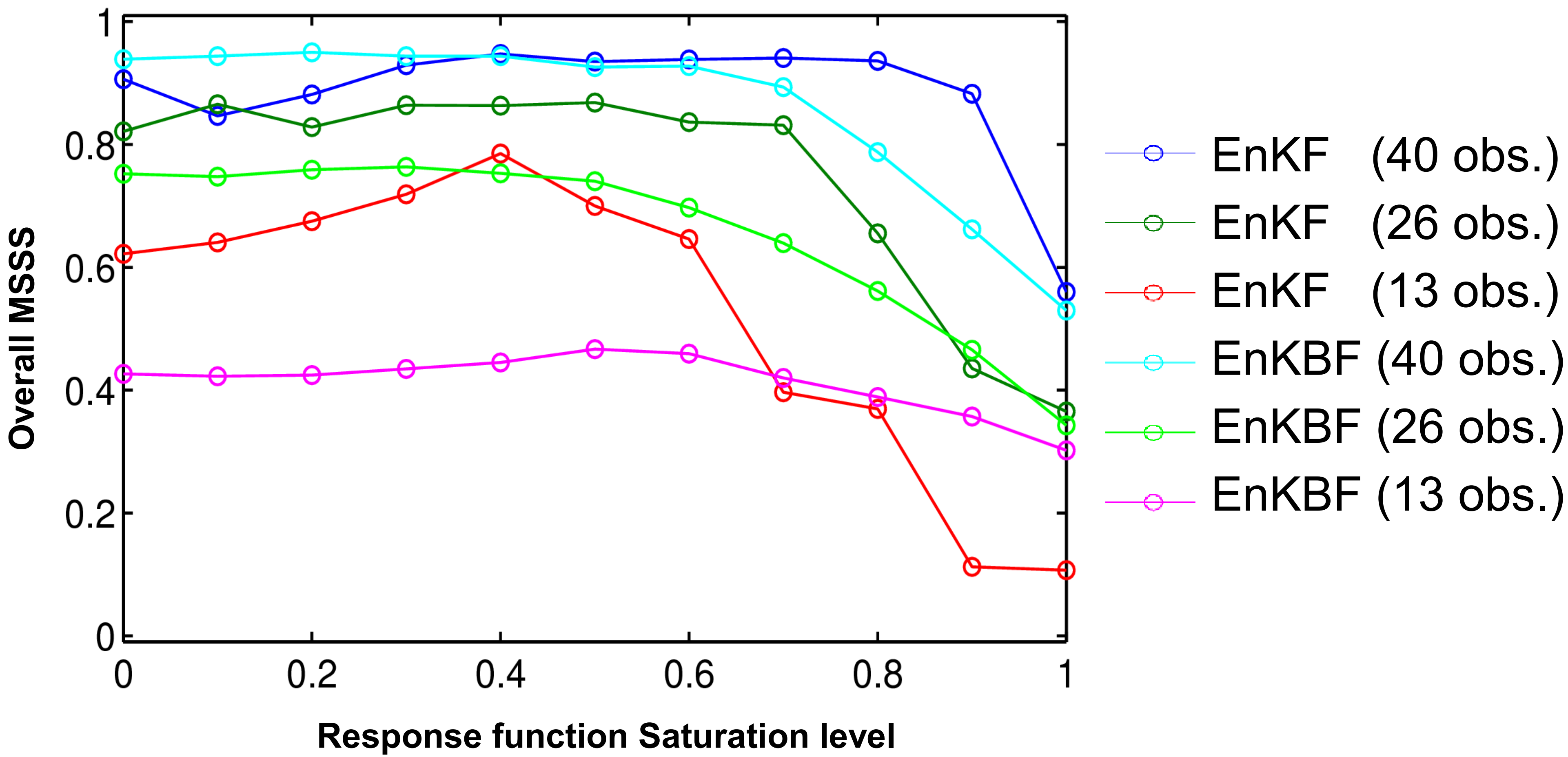
VS-Lite growth rate function

$$Gr_i = R(X_i) \cdot R(Y_i)$$



VS-Lite growth rate function with smooth shifting of recorded variable

Saturation level dependency



Preliminary findings and prospect

- VS-Lite non-linearities substantially deteriorate filter performance
- Smoother switching of recorded variable recovers most of the lost skill
- Filter performance was very robust to VS-lite response function saturation.
- Currently carrying out tree-ring DA experiments for the simplified parametrization GCM SPEEDY[6] using SPEEDY-LETKF code[7]
- Planning to extend experiments to a coupled atmosphere-land model

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- **[2a]** Dirren S. & Hakim G. (2005): *Toward the assimilation of time averaged observations, Geophys. Res. Lett.* 32 (4), L04804.

  [2b] Huntley H. & Hakim G. (2010): *Assimilation of time-averaged observations in a quasi-geostrophic atmospheric jet model*, Clim Dyn 35:995–1009.

  [2c] Perdergrass A. et al (2012): *Coupled Air–Mixed Layer Temperature Predictability for Climate Reconstruction*. Journal of climate 25: 459–472.

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  [3b] Burgers, G. et al. (1998): *Analysis scheme in the ensemble Kalman filter.* Mon. Wea. Rev. 126, 1719-1724.

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- **[4a]** Bergemann K. and Reich S. (2010): *A localization technique for ensemble Kalman filters*. Q. J. R. Meteorol. Soc., 136, 701-707.

  [4b] Bergemann K. and Reich S. (2012): *An ensemble Kalman-Bucy filter for continuous data assimilation*. Meteorolog. Zeitschrift, 21 , 213-219.

- **[5]** Lorenz, E. (1996): *Predictability - a problem partly solved*, in: Predictability, (Ed) Palmer, T., ECMWF, Reading UK.

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Thanks for your attention !!