

Multivariate estimations of Equilibrium Climate Sensitivity

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Current work

- Postdoc @ Utrecht University
(with Anna von der Heydt & Henk Dijkstra)
- Within H2020 project TiPES: Tipping Points in the Earth System
- Work on **Climate Sensitivity**:
*If we increase the atmospheric CO₂ concentration,
how much warmer does the Earth get?*

Climate response and sensitivity metrics

Climate response is the change (response) in an observable due to increase in forcing

Two common metrics:

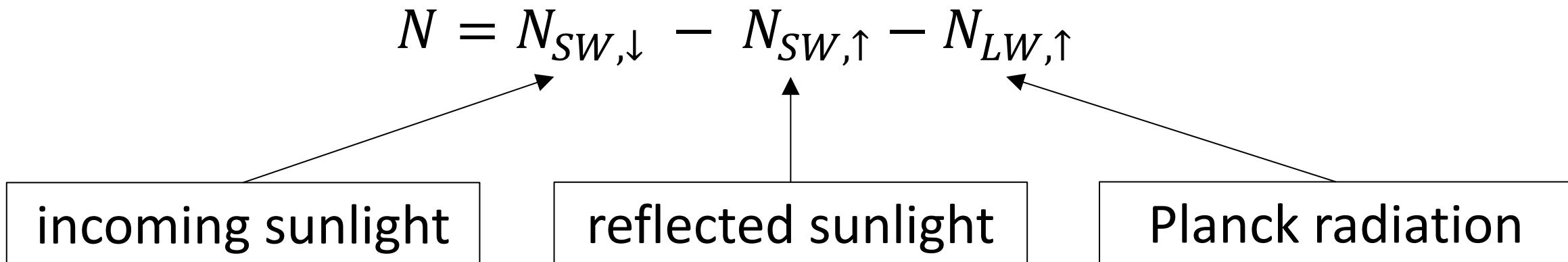
- **Equilibrium Climate Sensitivity:** change in equilibrium temperature due to (instantaneous) doubling of atmospheric CO₂
- **Transient Climate Response:** change in temperature after 100 years with 1% CO₂ increase per year (until doubling)

Equilibrium Climate Sensitivity

- Derived from dedicated experiments with climate models
 - Start from equilibrium with pre-industrial levels of CO₂
 - Instantaneous increase in CO₂
 - Monitor change in observables compared to a control run
- However: equilibrating climate models takes very, very long
- Need for techniques to estimate equilibrium temperature
- Mathematical context: $y' = f(y; \mu)$

Idea behind warming estimation techniques

Warming is due to net positive radiative imbalance



When $N = 0$ no more warming:

→ equilibrium warming $\Delta T_* = T_* - T_0$

Basic idea of Gregory method

Express imbalance as function of system state

$$N(t) = N(y(t))$$

Close to equilibrium y_* , Taylor expansion gives approximation

$$N(t) = N(y_*) + \sum_{j \in \mathcal{F}} \frac{\partial N}{\partial y_j}(y_*) [y_j(t) - y_{j*}]$$

Close to equilibrium, state variables $y_j(t) = y_j(T(t))$

Thus, another Taylor expansion yields

$$N(t) = \left\{ \frac{\partial N}{\partial T} + \sum_{j \in \mathcal{F}} \frac{\partial N}{\partial y_j} \frac{\partial y_j}{\partial T} \right\} [T(t) - T_*]$$

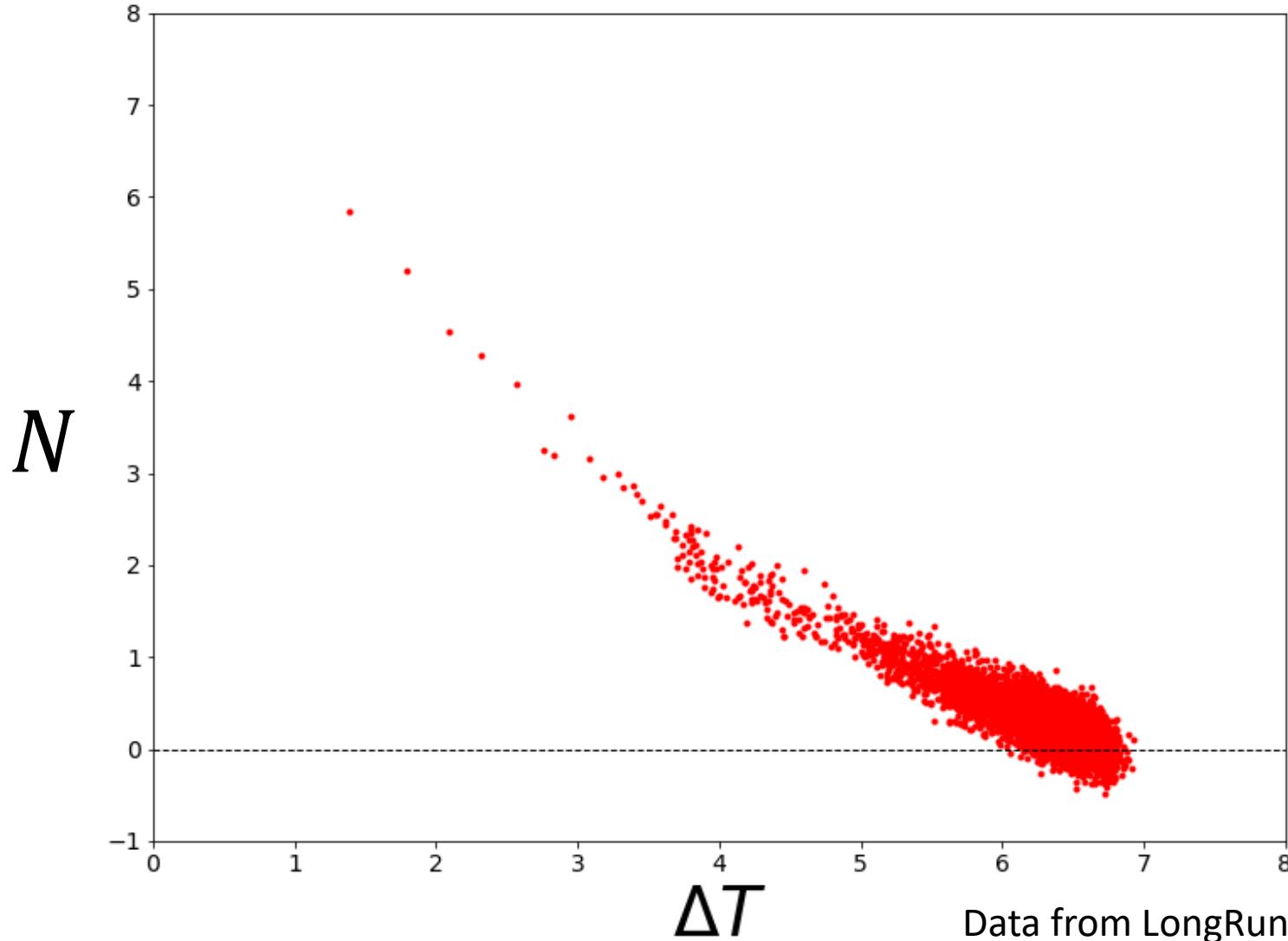
Rewriting $T = T_0 + \Delta T$ gives:

$$N(t) = a \Delta T(t) - a \Delta T_*$$

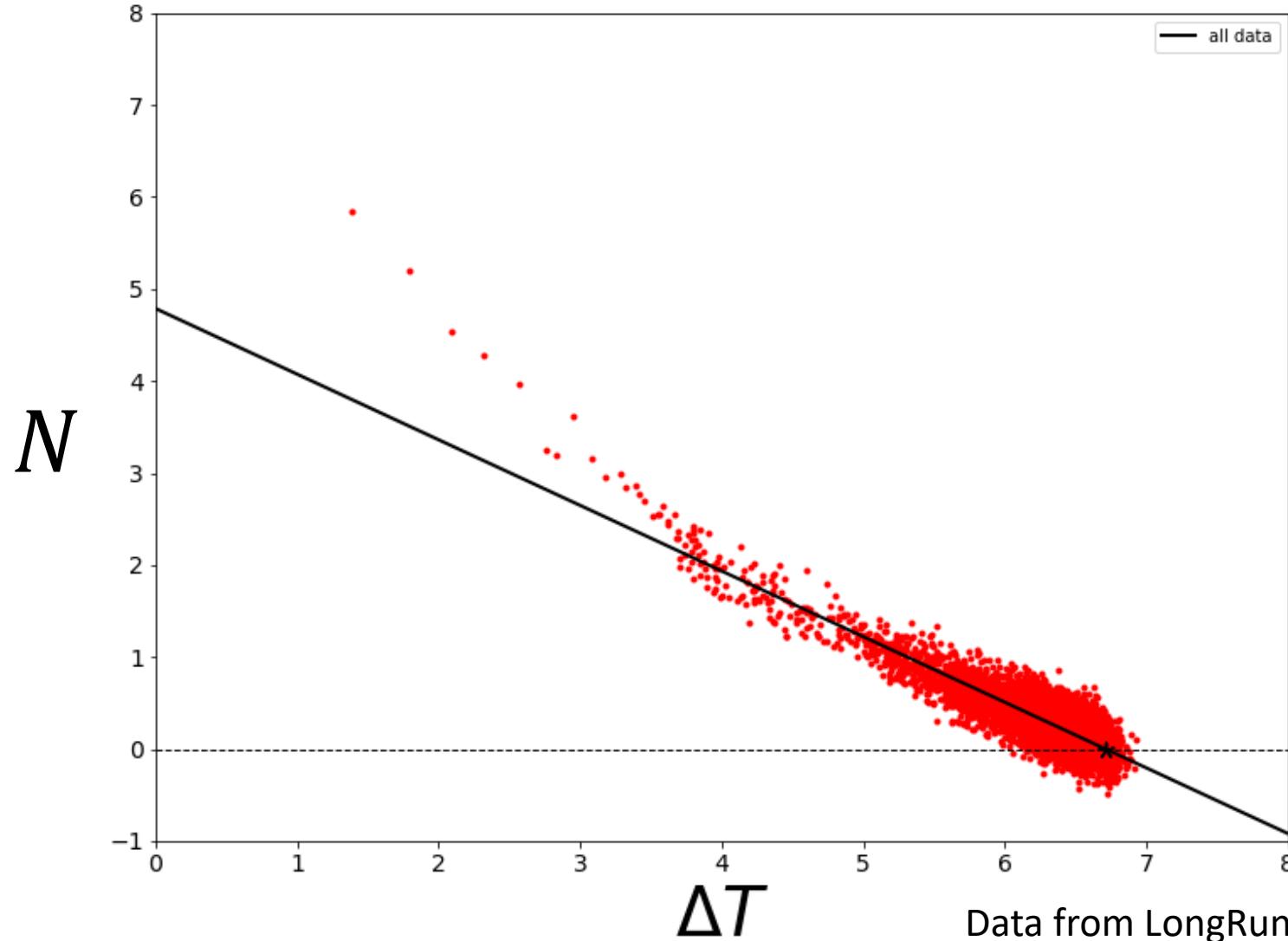
Linear regression on data:

$$N(t) = a \Delta T(t) + f \rightarrow \Delta T_*^{est} = -a^{-1} f$$

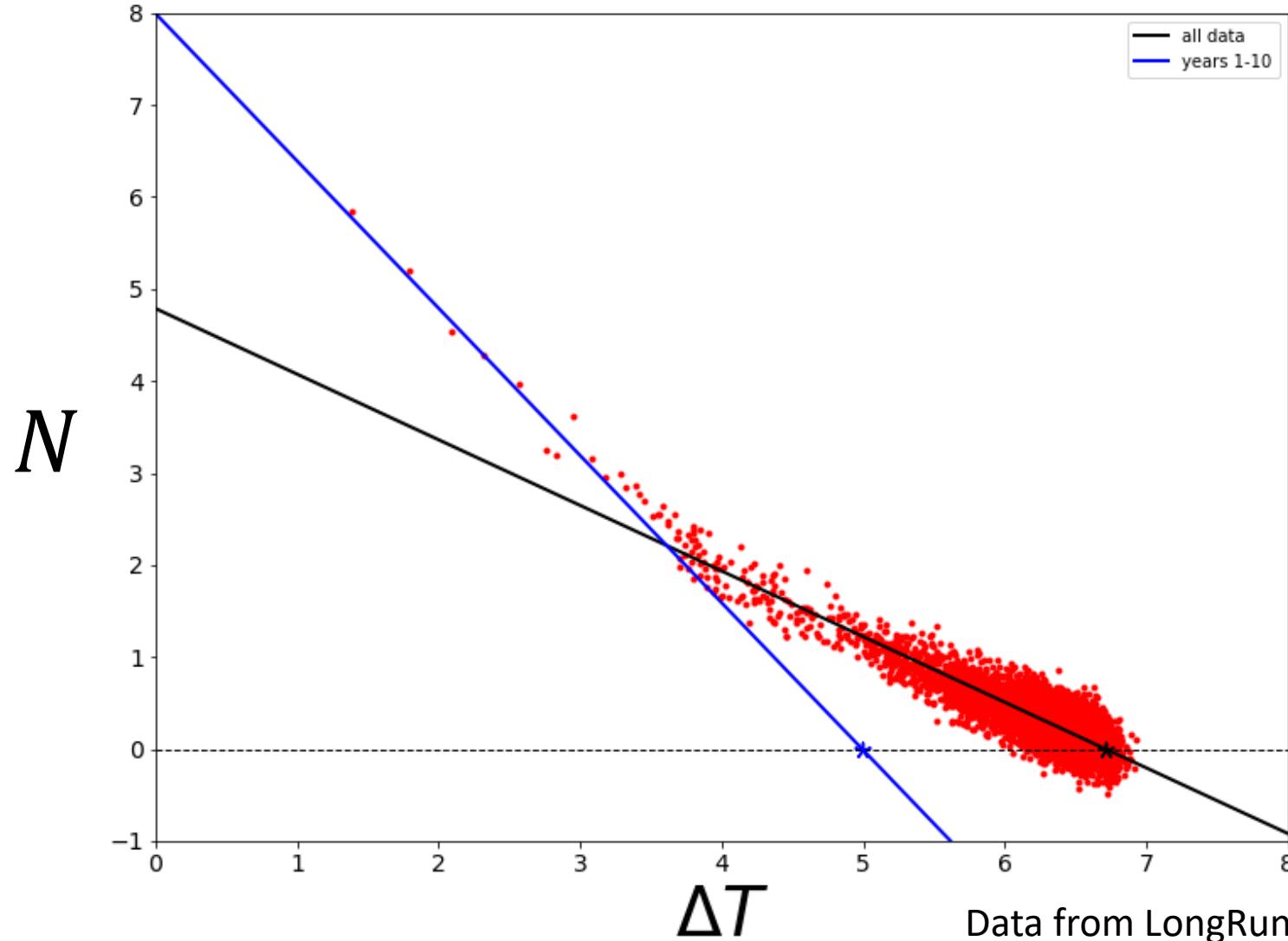
Gregory Plot for CESM 1.0.4



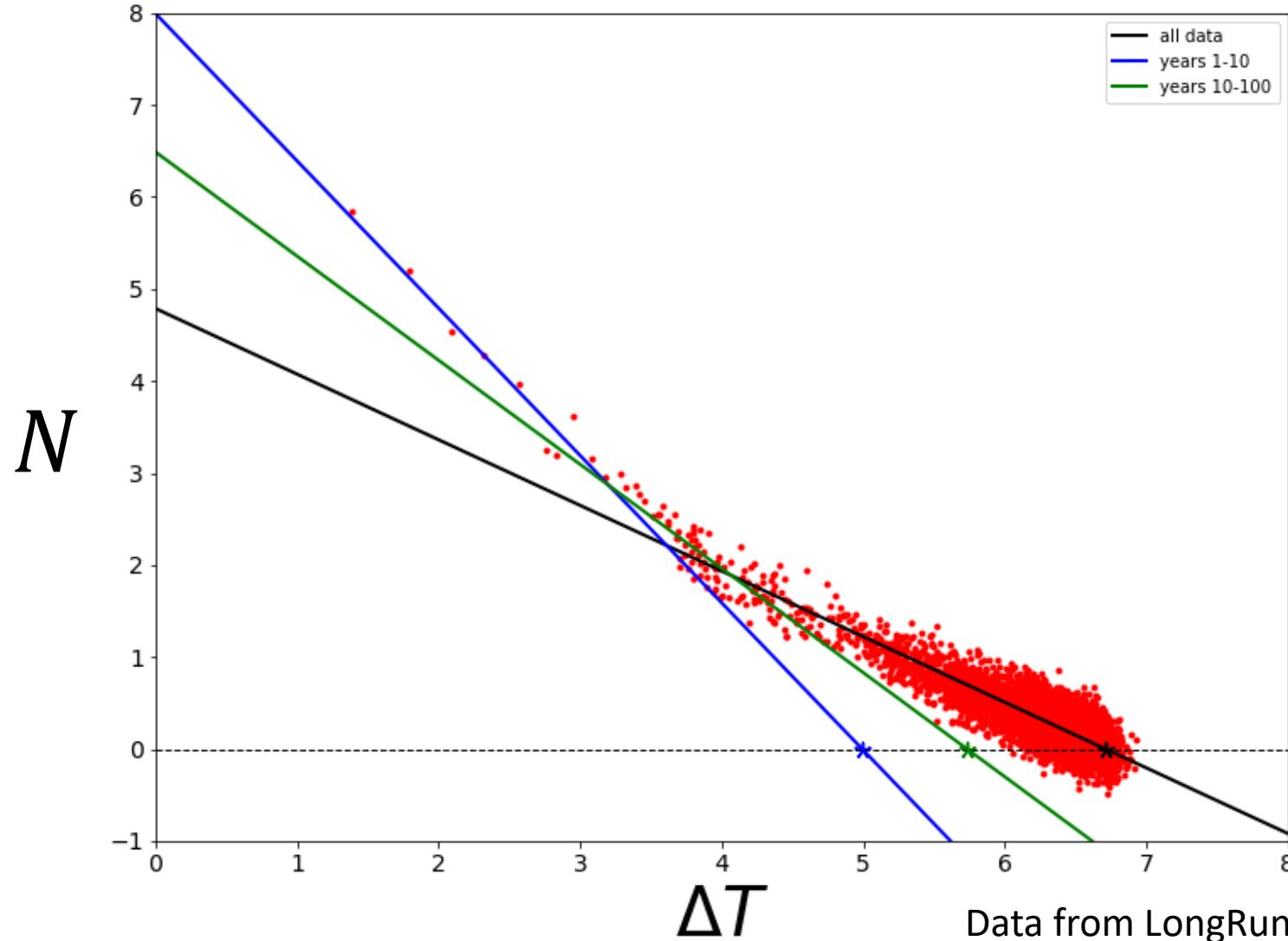
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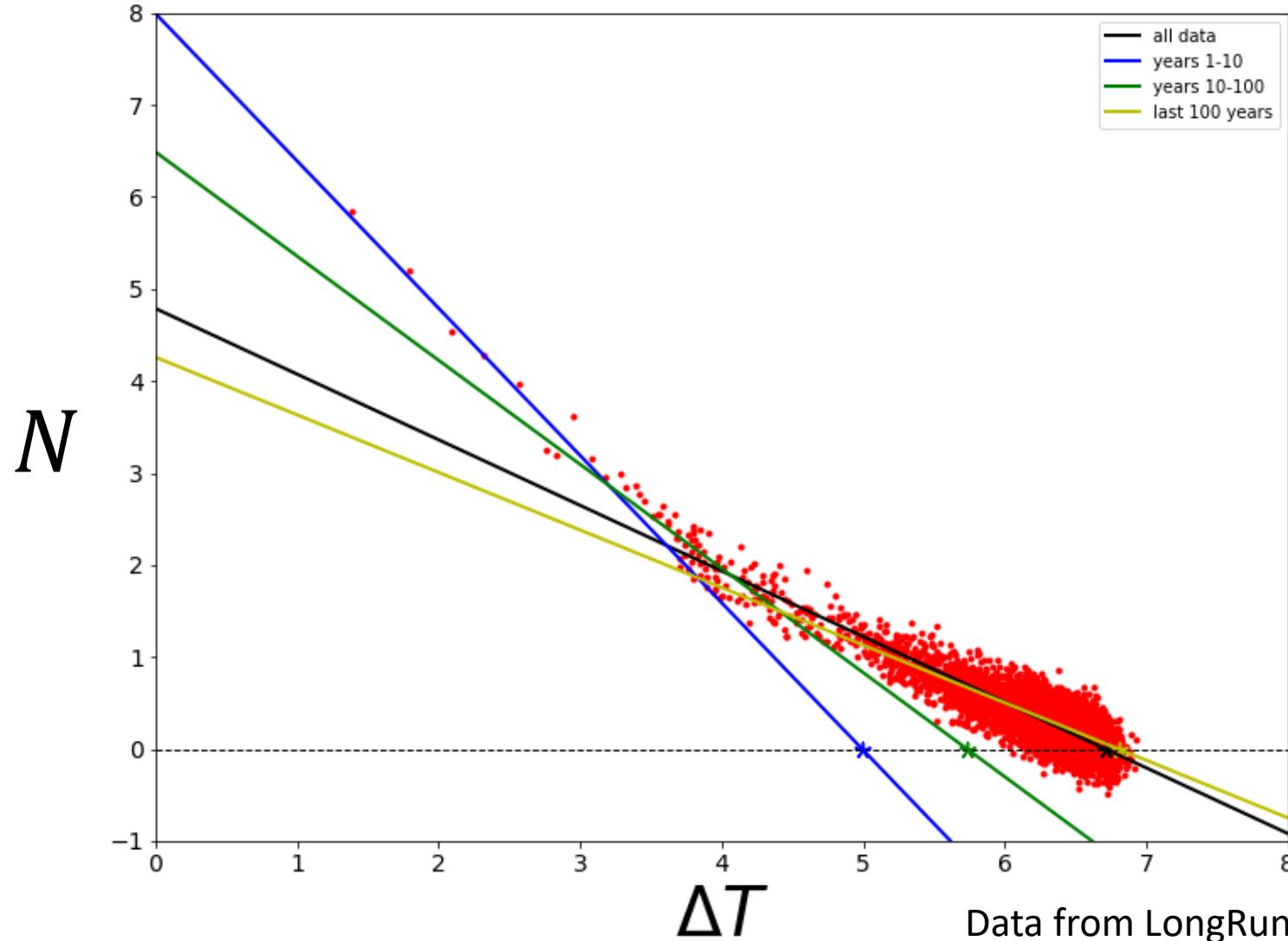
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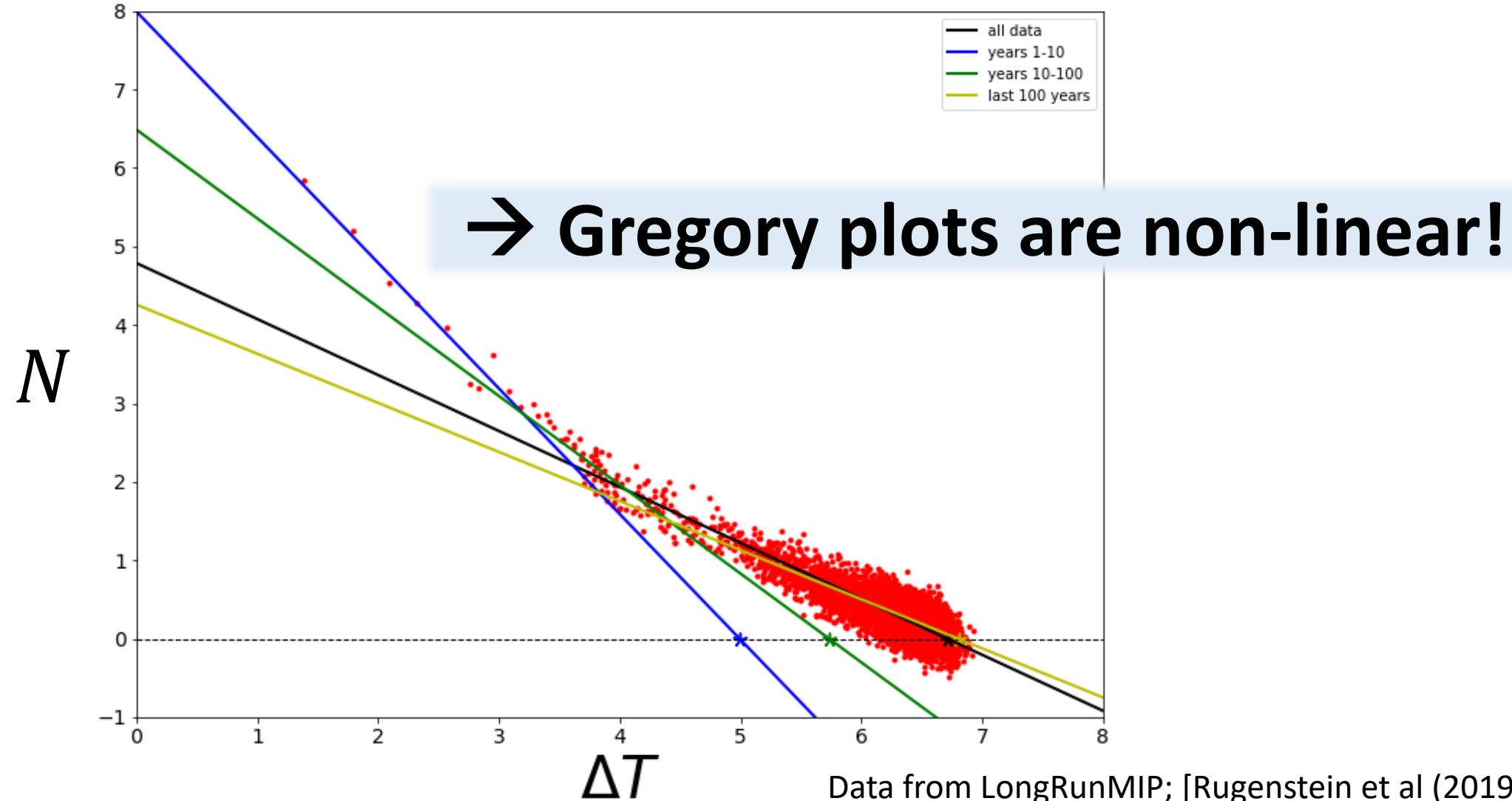
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Step back: dynamical system point of view

$$y' = f(y)$$

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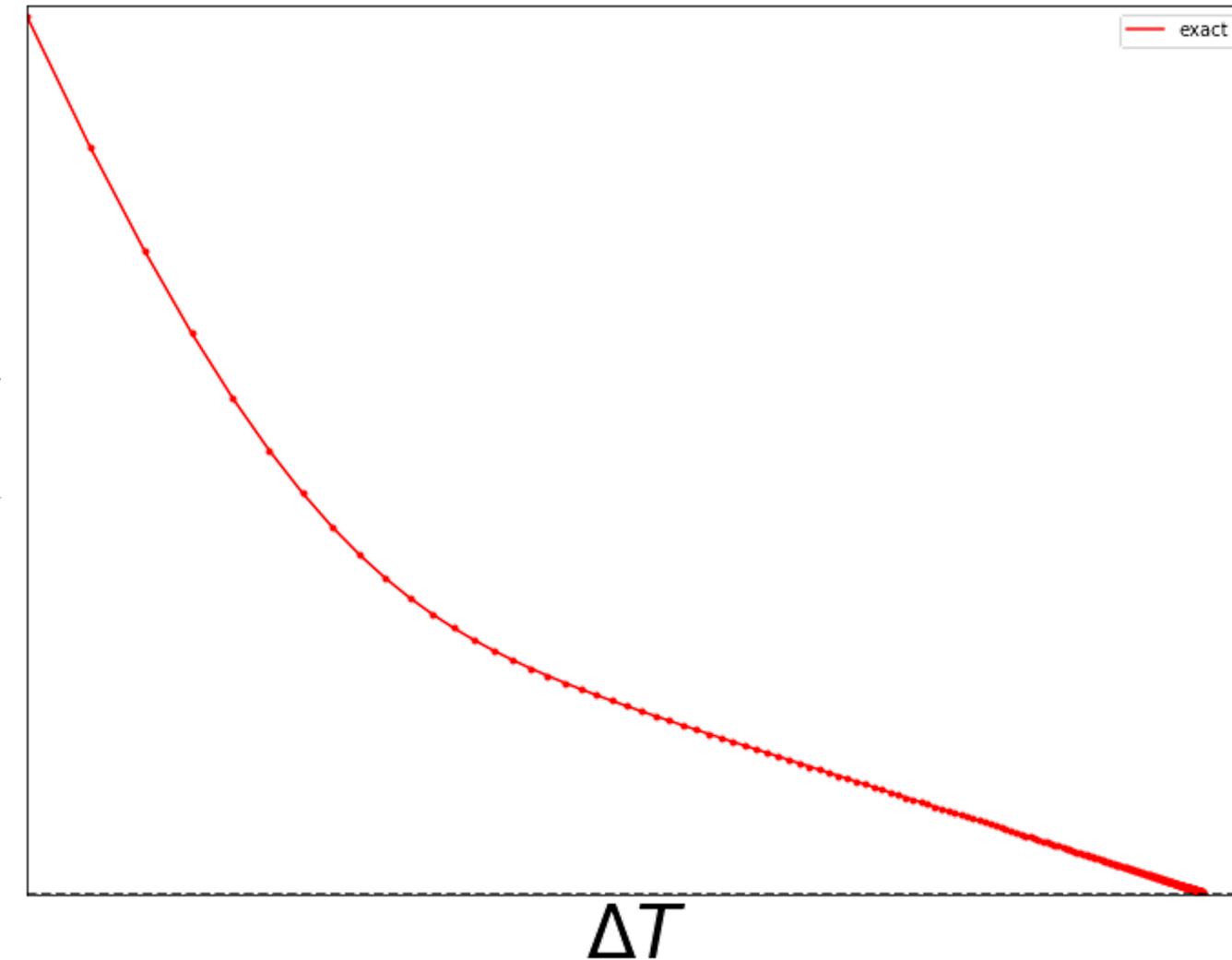
$$\Delta y' = Df(y_*) \Delta y + F$$

N

Solutions sum of exponentials

$$\Delta y(t) - \Delta y_* = \sum_{j=1}^n c_j v_j e^{\lambda_j t}$$

(v_j eigenvectors, λ_j eigenvalues of A)



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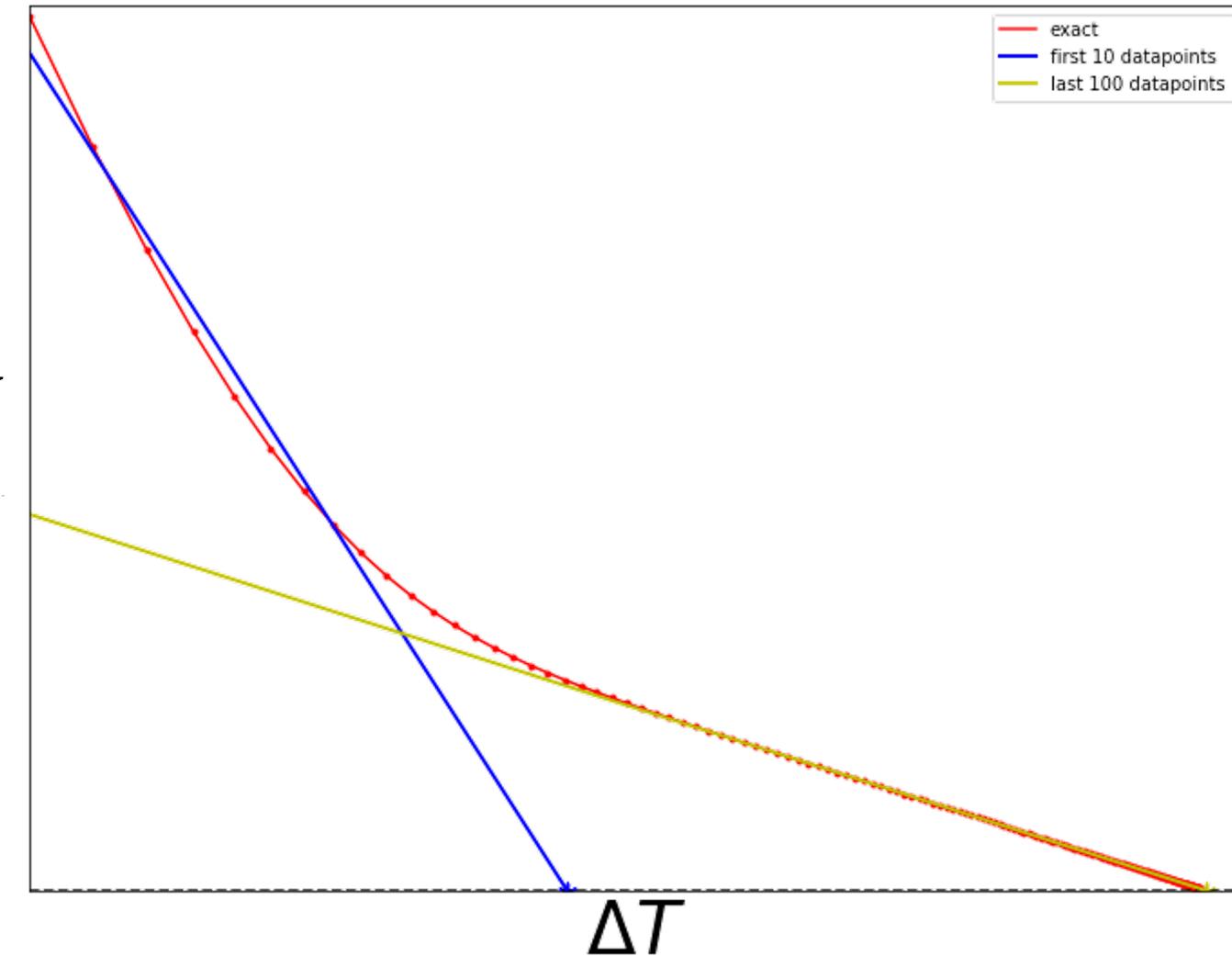
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We need as many
observables as relevant
eigenmodes

$$y_j(t) = y_j(T(t), \dots)$$

The problem with classical method

In linear regime of decay to equilibrium:

$$N(t) - N_* = \sum_m \beta_m^{[N]} e^{\lambda_m t}$$

$$\Delta T(t) - \Delta T_* = \sum_m \beta_m^{[T]} e^{\lambda_m t}$$

If only one eigenmode present:

$$[N(t) - N_*] = \frac{\beta_1^{[N]}}{\beta_1^{[T]}} [\Delta T(t) - \Delta T_*]$$

Since $N_* = 0$ this leads to Gregory method:

$$N(t) = a \Delta T(t) + f$$

Idea:

A Multi-Component Linear Regression (MC-LR):

$$Y = A X + F \rightarrow X_*^{est} = -A^{-1} F$$

Y :

M observables that tend to 0 in equilibrium

X :

M observables that are estimated in equilibrium

Example:

$$\begin{bmatrix} N \\ \Delta\alpha' \\ \Delta\varepsilon' \end{bmatrix} = A \begin{bmatrix} \Delta T \\ \Delta\alpha \\ \Delta\varepsilon \end{bmatrix} + F$$

α : effective top-of-atmosphere short-wave albedo

$$\alpha = \frac{N_{SW,\uparrow}}{N_{SW,\downarrow}}$$

ε : effective top-of-atmosphere long-wave emissivity

$$\varepsilon = \frac{N_{LW,\uparrow}}{T^4}$$

Toy system – Model Equations

$$\left\{ C_T \frac{dT}{dt} = Q_0 (1 - \alpha) - \varepsilon \sigma T^4 + \mu \right.$$

Diagram illustrating the components of the model equation:

- incoming sunlight**: Represented by a red box with an upward-pointing arrow pointing to the term $Q_0 (1 - \alpha)$.
- reflected sunlight**: Represented by a red box with a downward-pointing arrow pointing to the term $\varepsilon \sigma T^4$.
- Planck radiation**: Represented by a red box with a diagonal arrow pointing to the term $\varepsilon \sigma T^4$.
- effect of CO₂**: Represented by a red box with a red arrow pointing to the term μ .

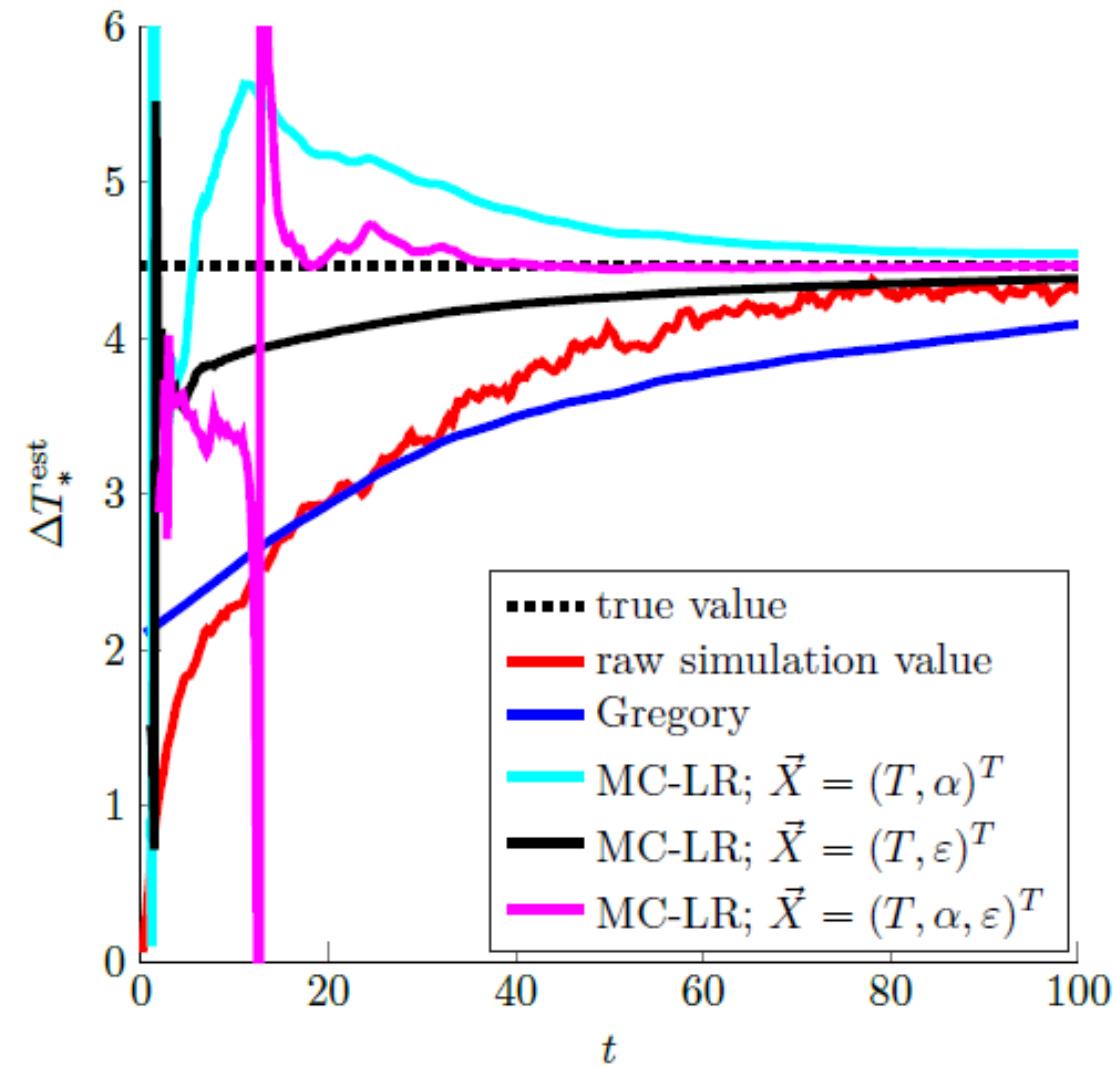
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$$\left\{ \begin{array}{l} C_T \frac{dT}{dt} = Q_0 (1 - \alpha) - \varepsilon \sigma T^4 + \mu \\ \frac{d\alpha}{dt} = -\delta_\alpha [\alpha - \alpha_0(T)]; \\ \frac{d\varepsilon}{dt} = -\delta_\varepsilon [\varepsilon - \varepsilon_0(T)]. \end{array} \right.$$

Toy system – Model Equations

$$\left\{ \begin{array}{l} C_T \frac{dT}{dt} = Q_0 (1 - \alpha) - \varepsilon \sigma T^4 + \mu + \nu \xi(t); \\ \frac{d\alpha}{dt} = -\delta_\alpha [\alpha - \alpha_0(T)]; \\ \frac{d\varepsilon}{dt} = -\delta_\varepsilon [\varepsilon - \varepsilon_0(T)]. \end{array} \right.$$

Toy system – Results

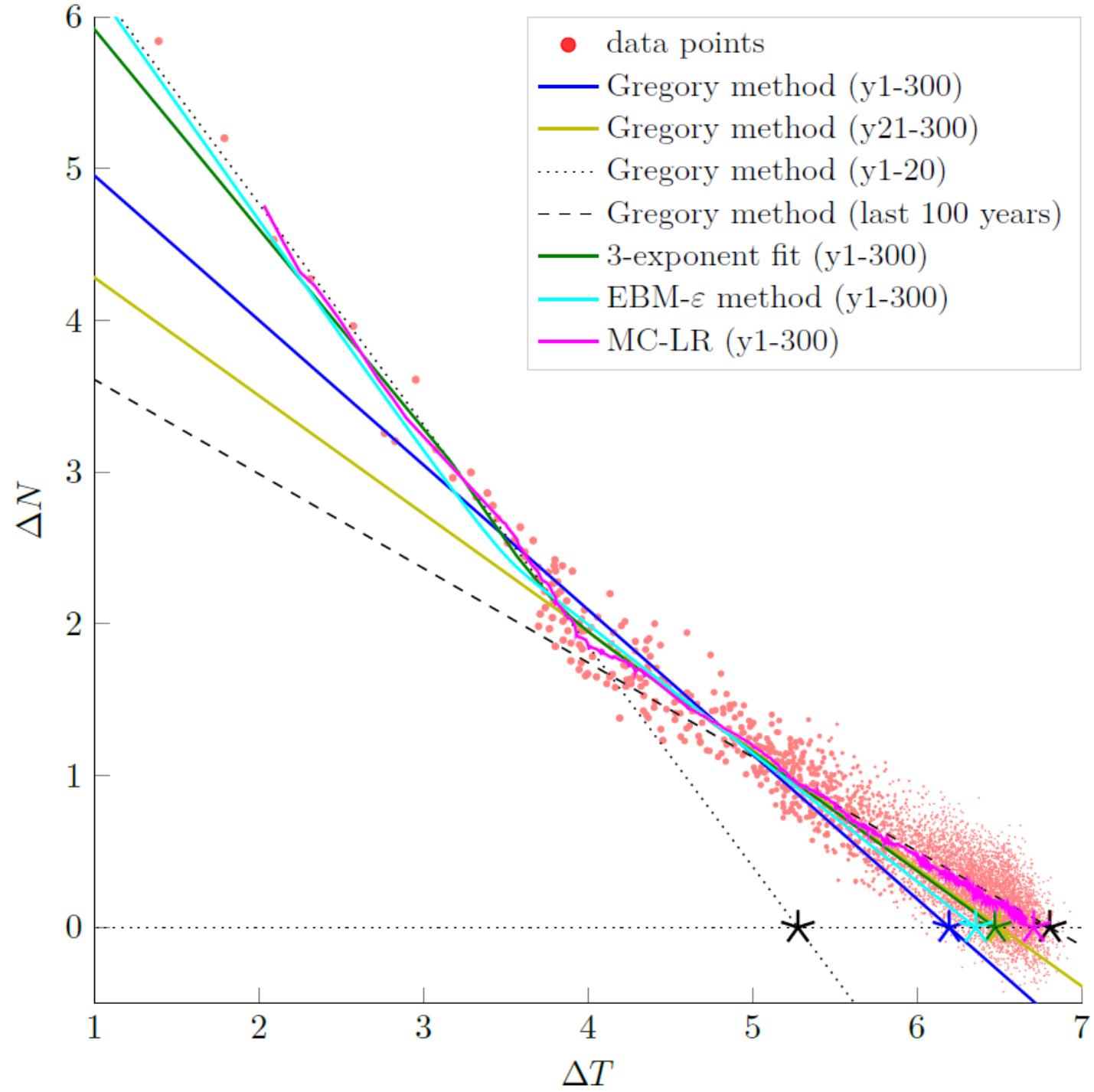


Testing on LongRunMIP data

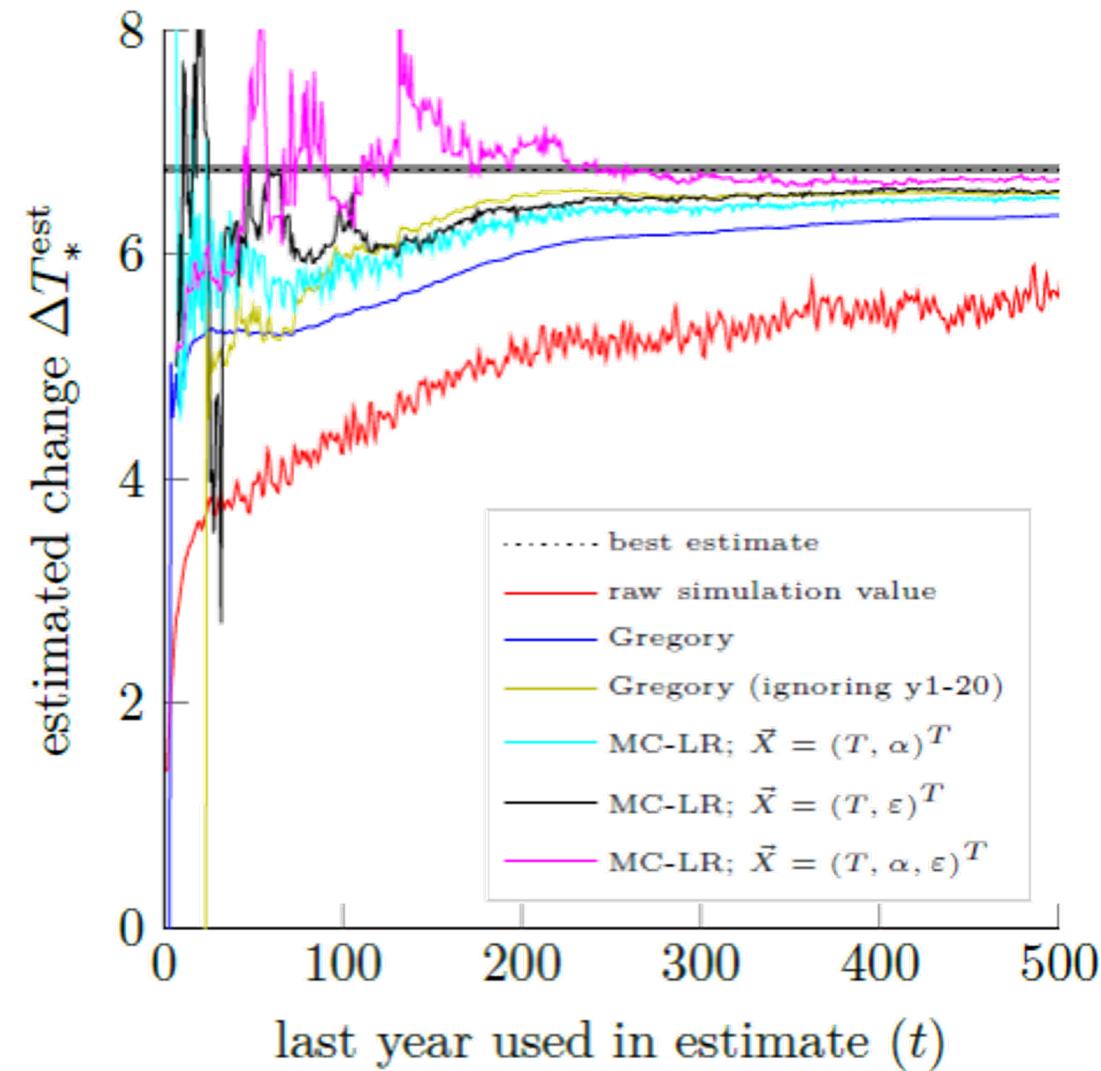
- Models run to ‘equilibrium’ (practice: runs of at least 1,000 years)
- Work with ‘abrupt-4xCO₂’ forcing experiments

Experiment

- Run estimation technique with data up to time t
- Compare with ‘equilibrium value’
- Determine effectiveness of techniques for time frame



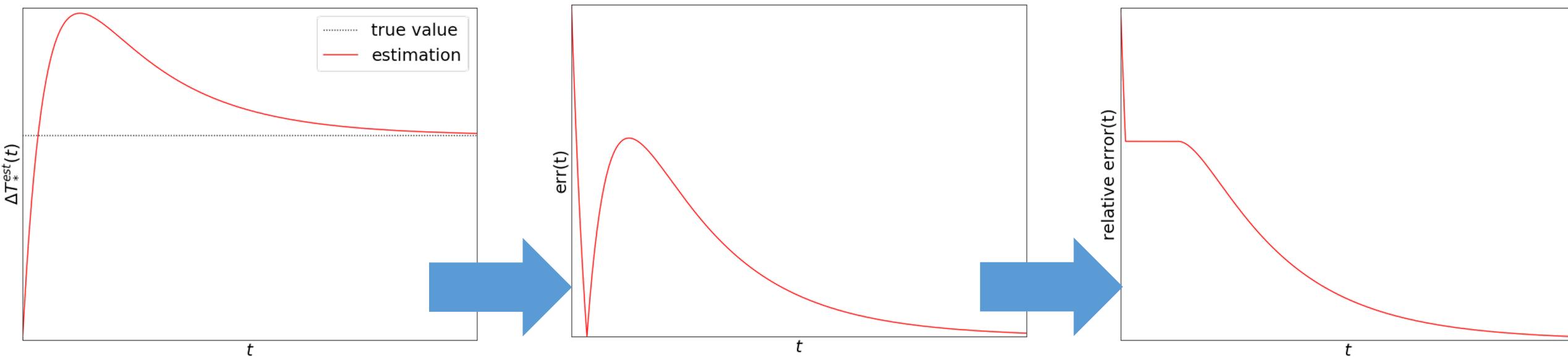
Results for CESM 1.0.4



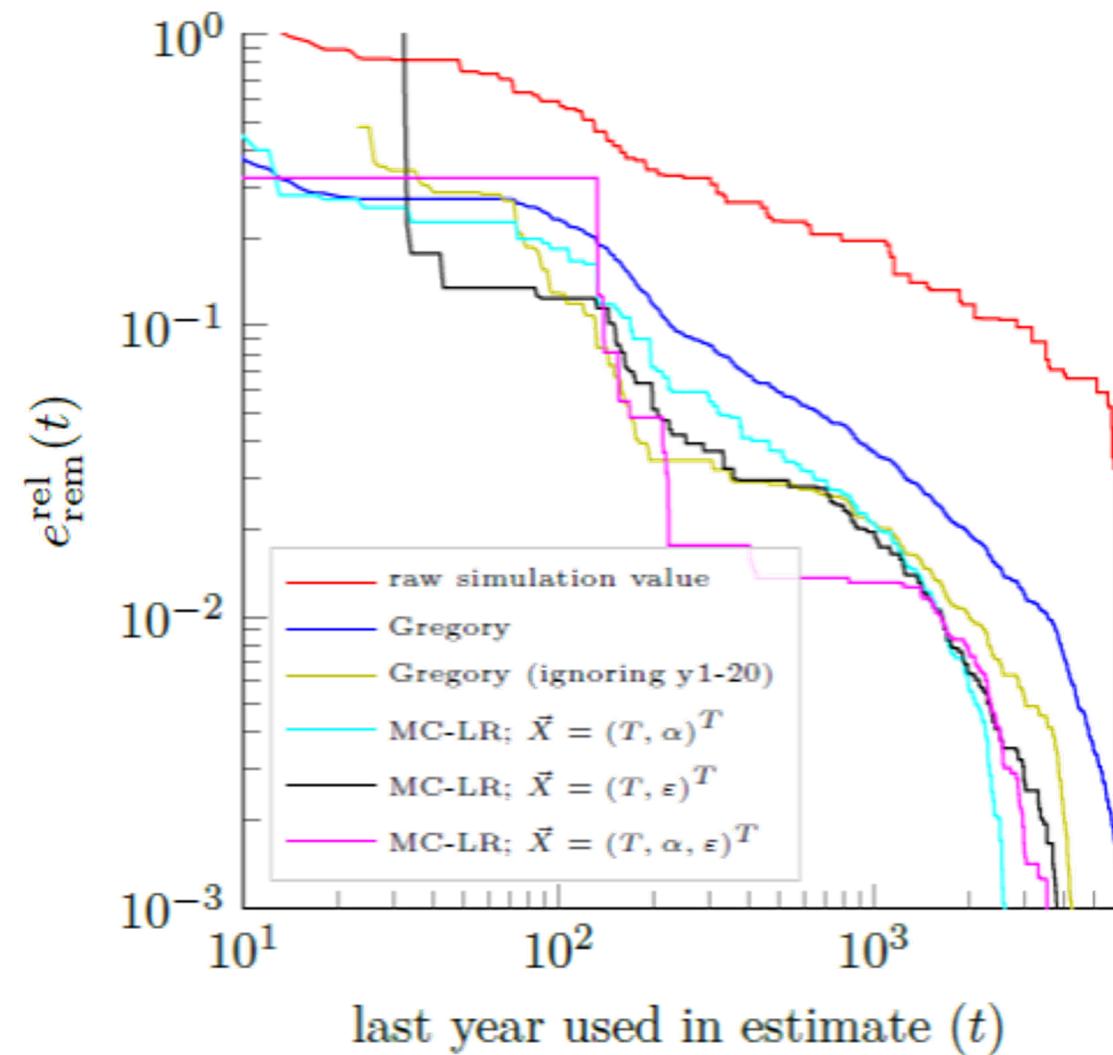
Measure for effectiveness

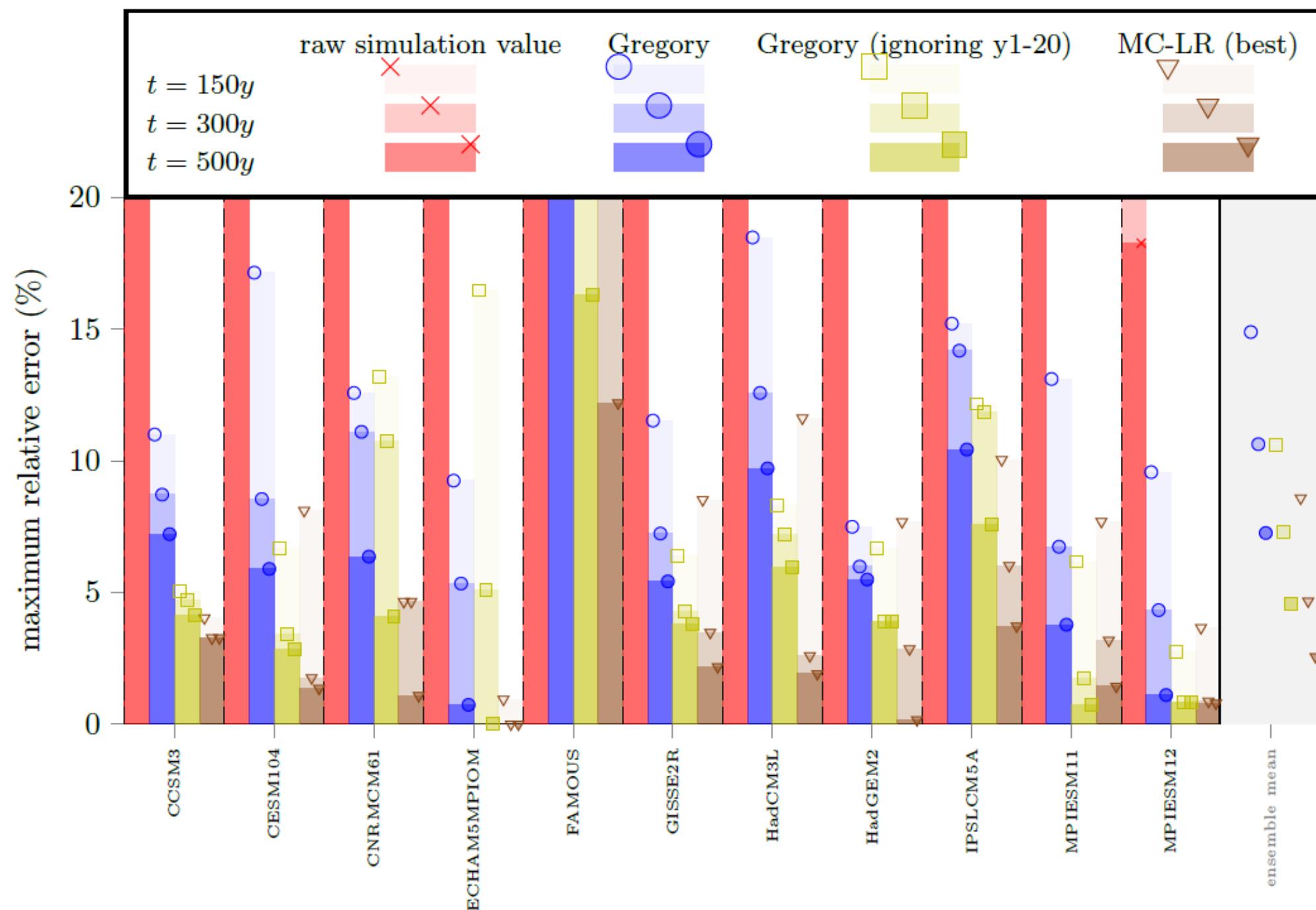
- Denote ‘equilibrium’ warming by ΔT_*
- Measure for maximum of relative error one ought to expect

$$\text{relative error}(t) := \max_{s \geq t} \left| \frac{\Delta T_*^{\text{est}}(s) - \Delta T_*}{\Delta T_*^{\text{est}}(s)} \right|$$



Results for CESM 1.0.4





Conclusions

- Multi-component regression $Y = A X + F$ yields better results
 - especially for $t > 150$ years
 - depends on model characteristics
- Multivariate estimate $X_*^{est} = -A^{-1}F$ contains more than temperature
 - useful for estimating projections of climate subsystems
- Potential improvements:
 - more curated observables
 - dedicated ensemble of simulations

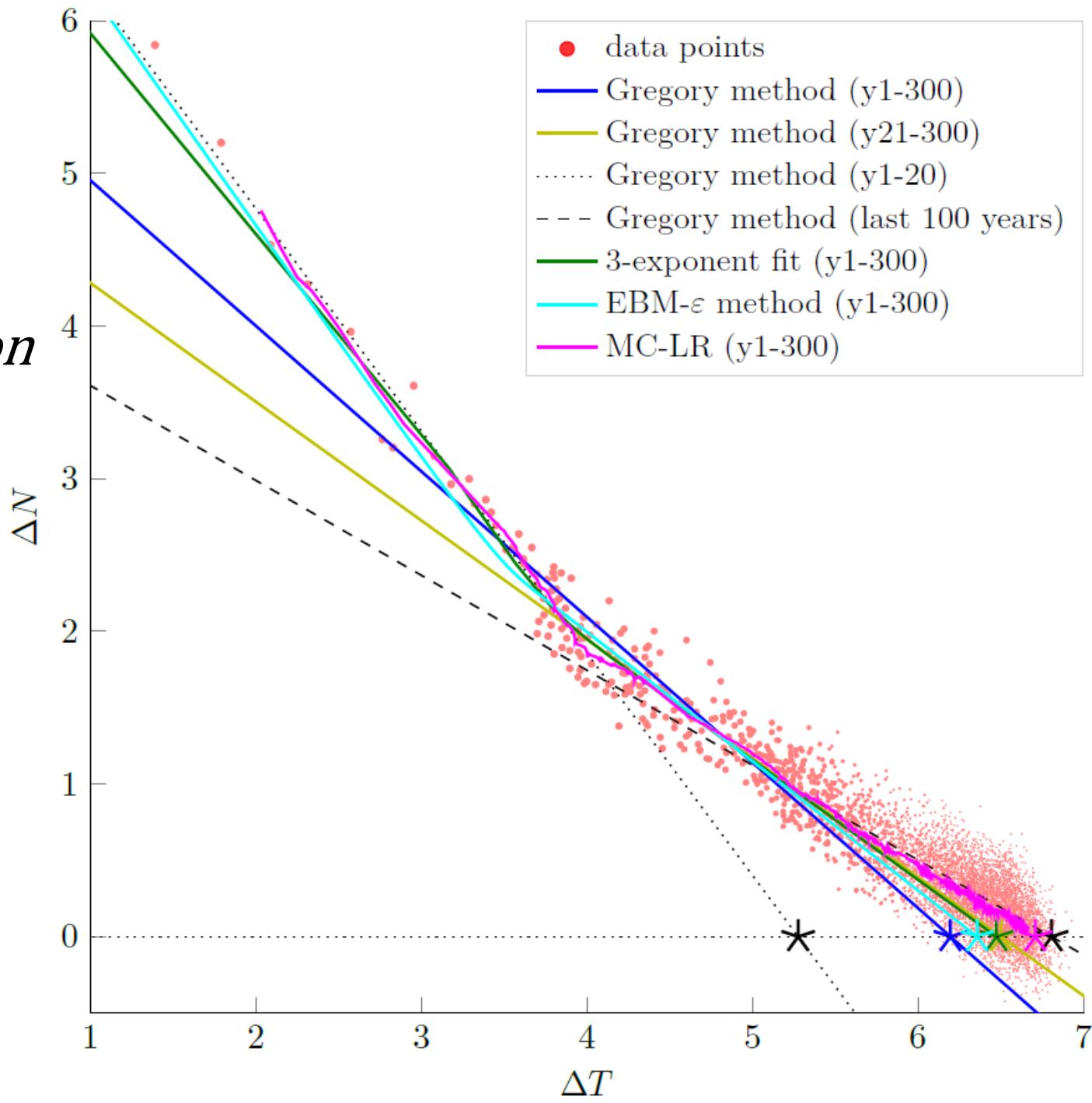
Multi-Component Linear Regression

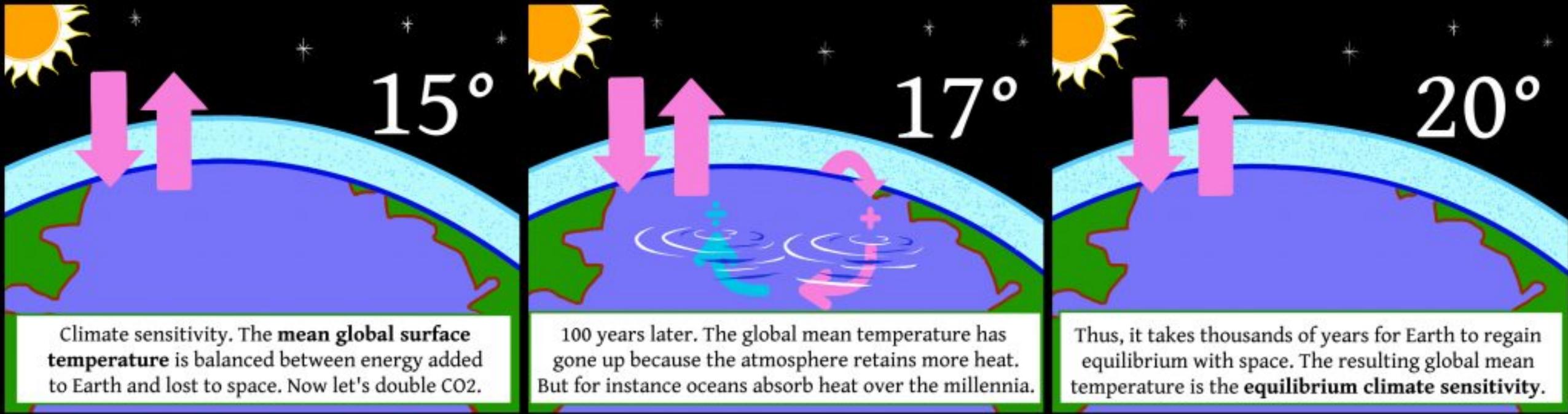
$$Y = A X + F$$

leads to

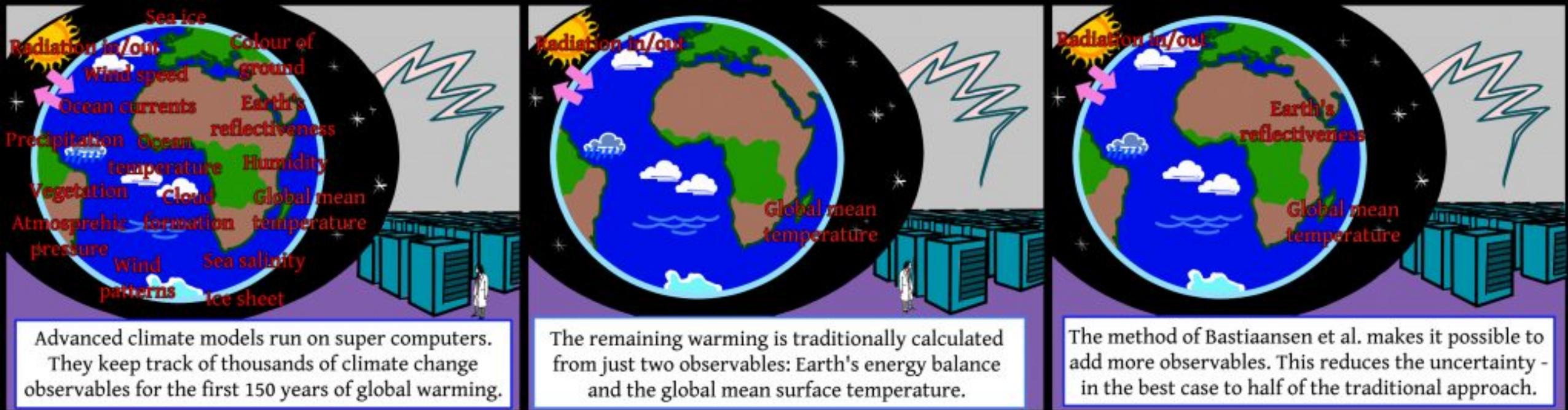
Multivariate Estimate

$$X_*^{est} = -A^{-1}F$$

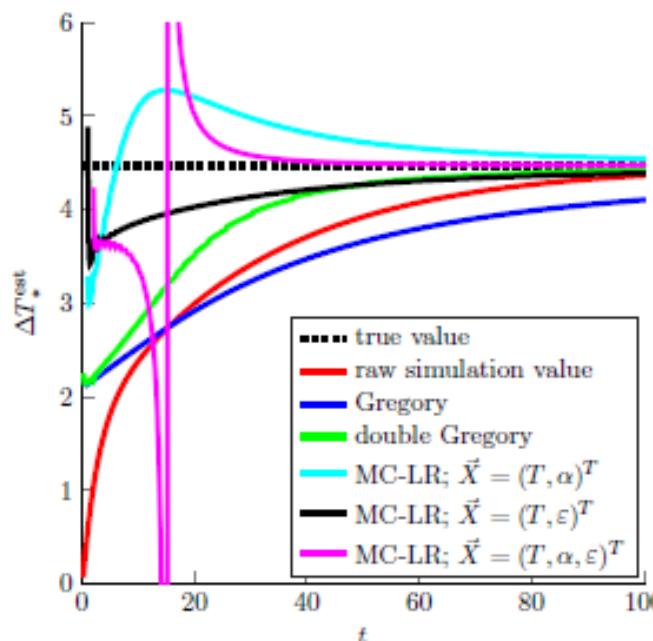




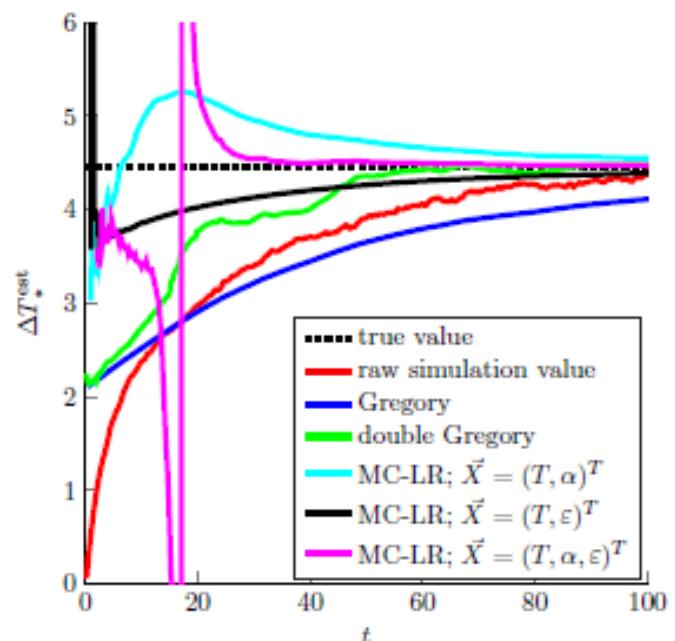
[Bastiaansen, Dijkstra, Von der Heydt (GRL, 2021). DOI: doi.org/10.1029/2020GL091090]



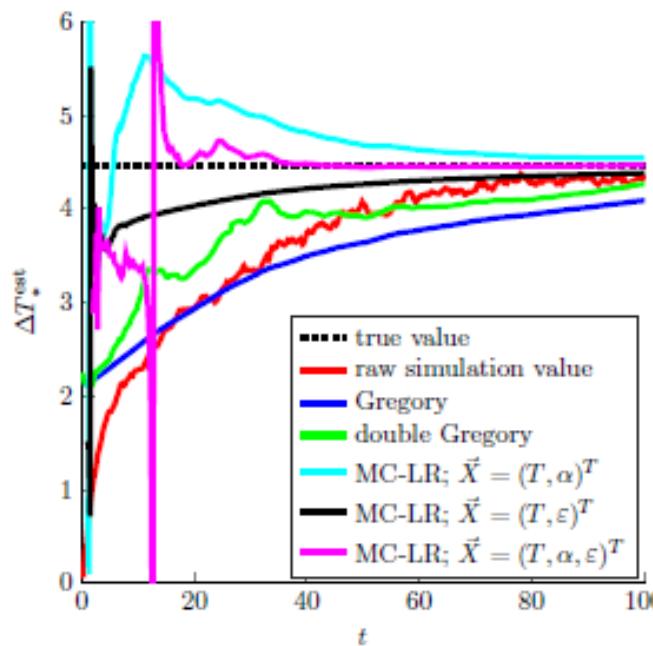
ADDITIONAL SLIDES



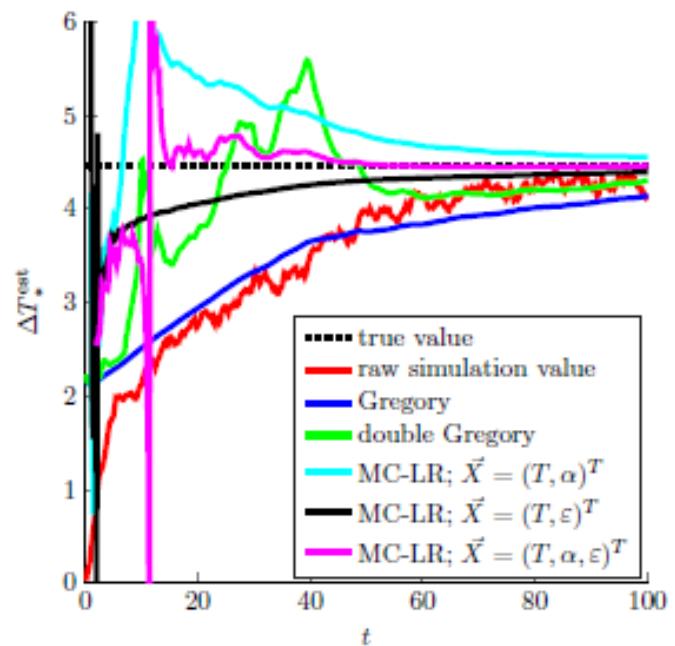
(a) $\nu = 0$



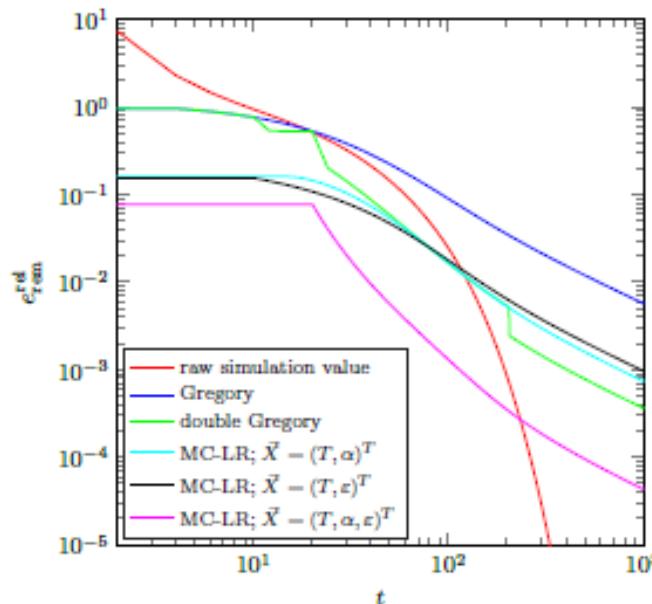
(b) $\nu = 0.25$



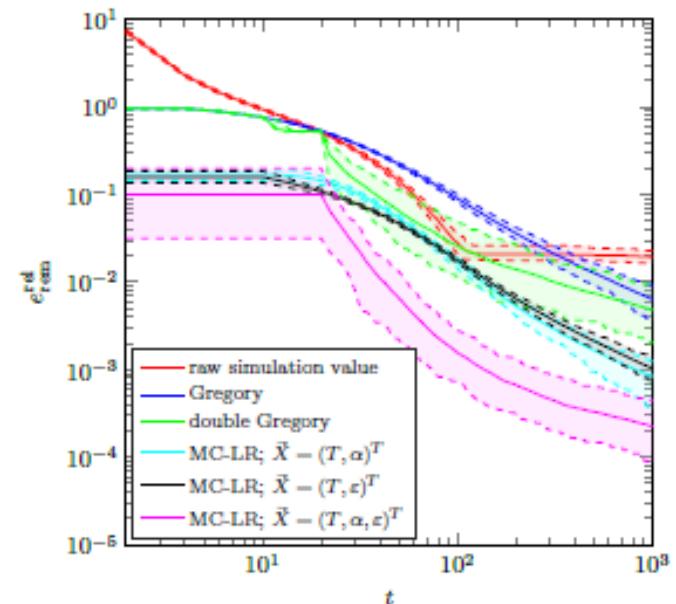
(c) $\nu = 0.5$



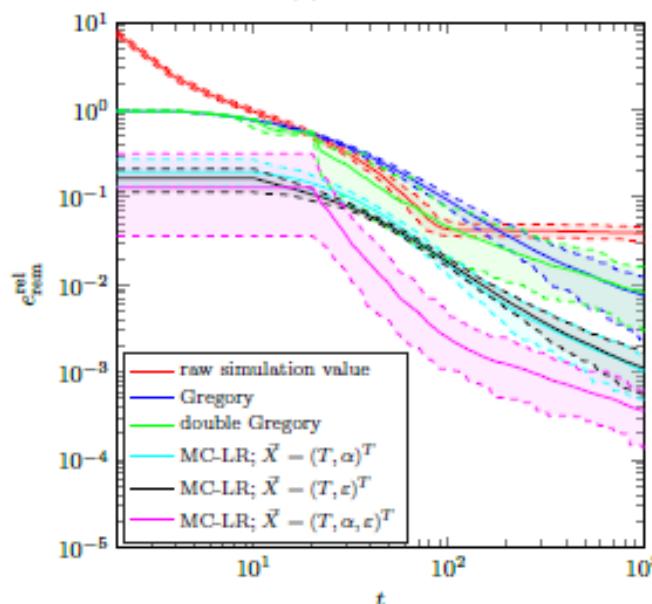
(d) $\nu = 1$



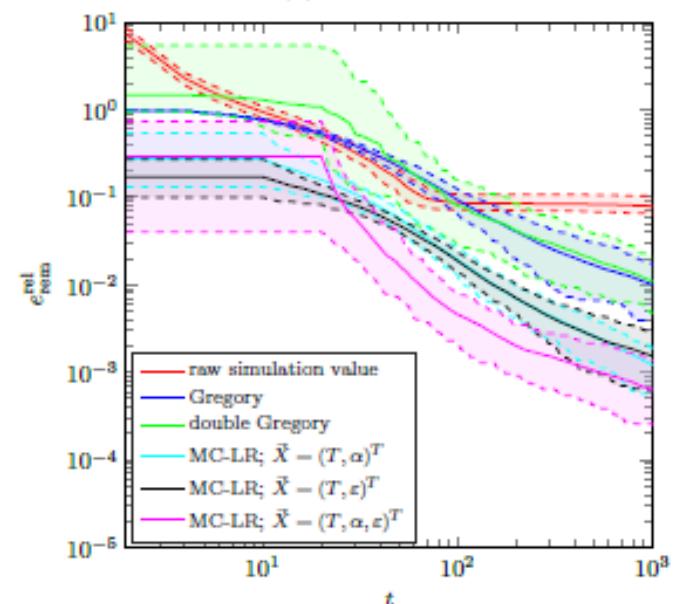
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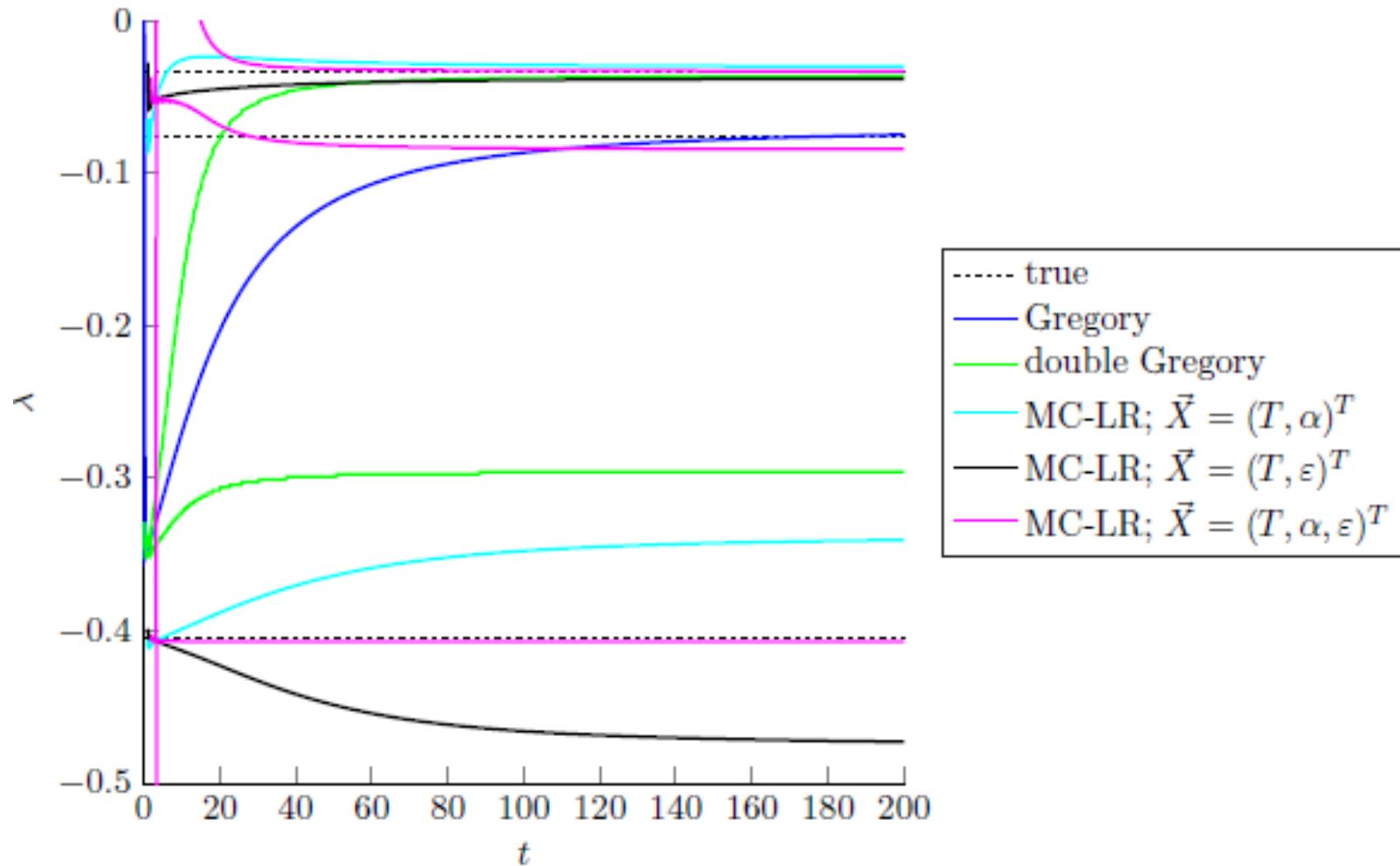


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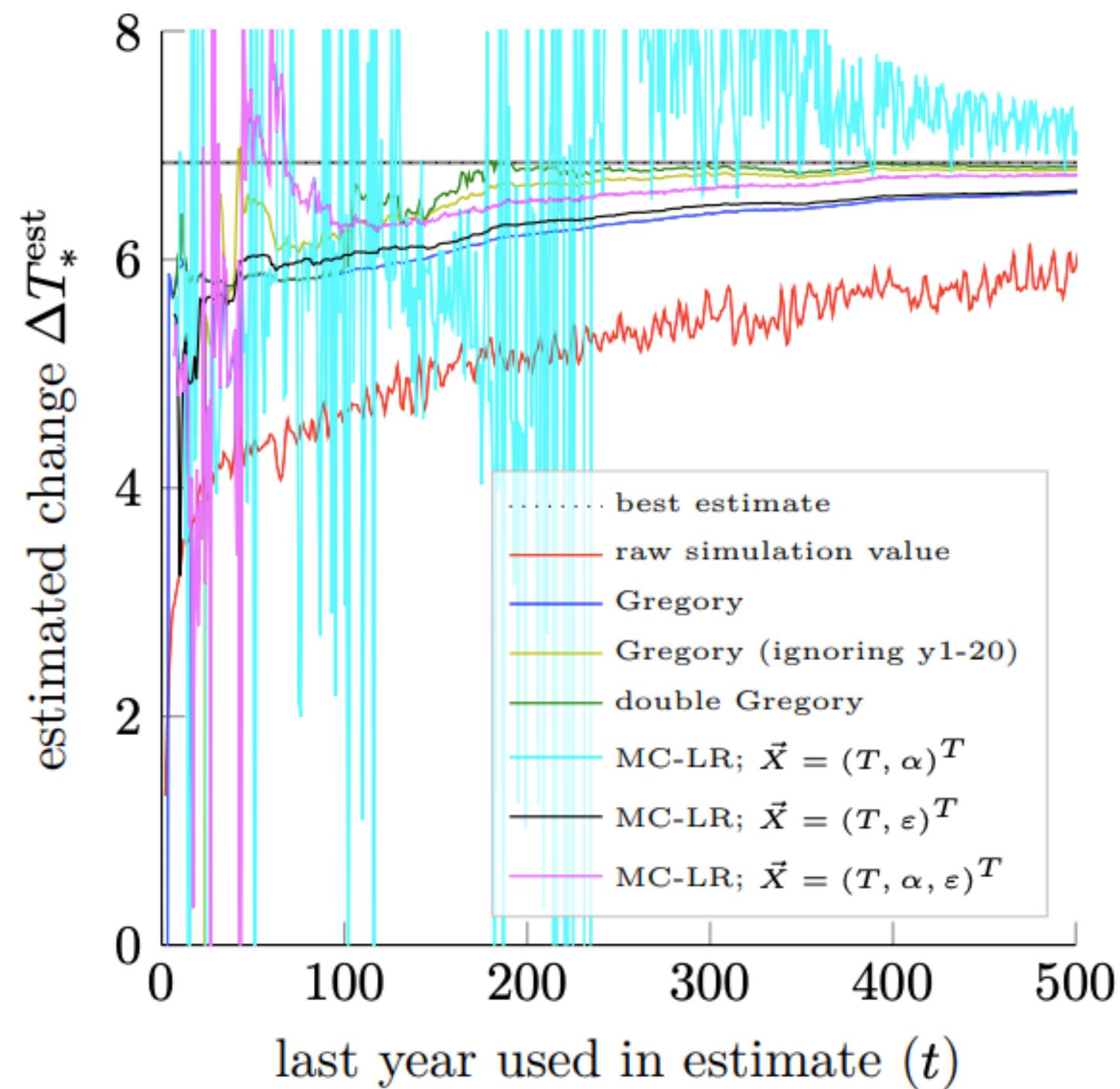


(d) $\nu = 1$

Toy model: Fitted eigenvalues



MPI-ESM 1.1



GISS-E2-R

