Advancing Deep-Time Climate Reconstruction with a New Online Paleoclimate Data Assimilation Approach in CESM

An Ongoing Research of the *paleoWeather* Project

***Feng Zhu*[1]**, *Dan Amrhein*[1], *Jiang Zhu*[1], *Jess Tierney*[2],
Anta-Clarisse Sarr[3], *Sophia Macarewich*[1], *Bette Otto-Bliesner*[1], *Chris Poulsen*[3],
Elke Zeller[2], *Maya Tessler*[2], *Dervla Meegan-Kumar*[4], *Jane W. Baldwin*[4], *and Ran Feng*[5]

1. NSF NCAR 2. U Arizona 3. U Oregon 4. UC Irvine 5. U Connecticut

Jun 11, 2025
CESM Workshop 2025

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The *paleoWeather* Project

How do weather extremes like tropical cyclones and atmospheric rivers behave in warm climates?

What are the limits of habitability?

image by Dan Amrhein

The *paleoWeather* Project

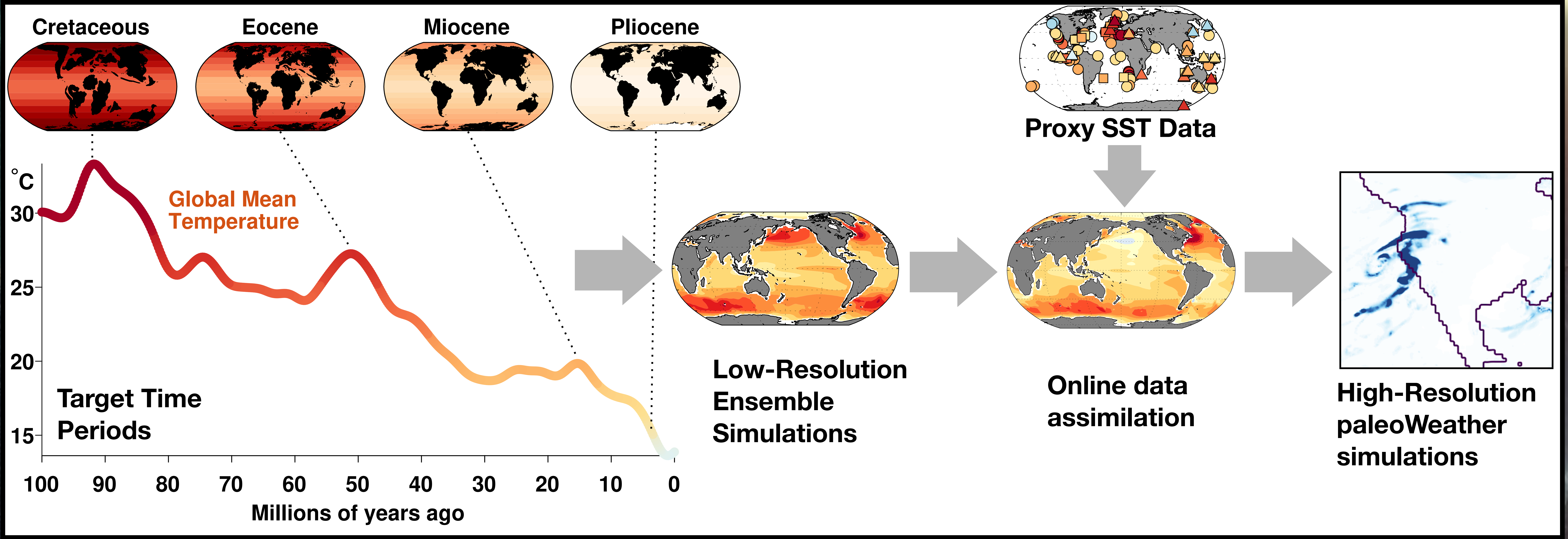

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image by Dan Amrhein

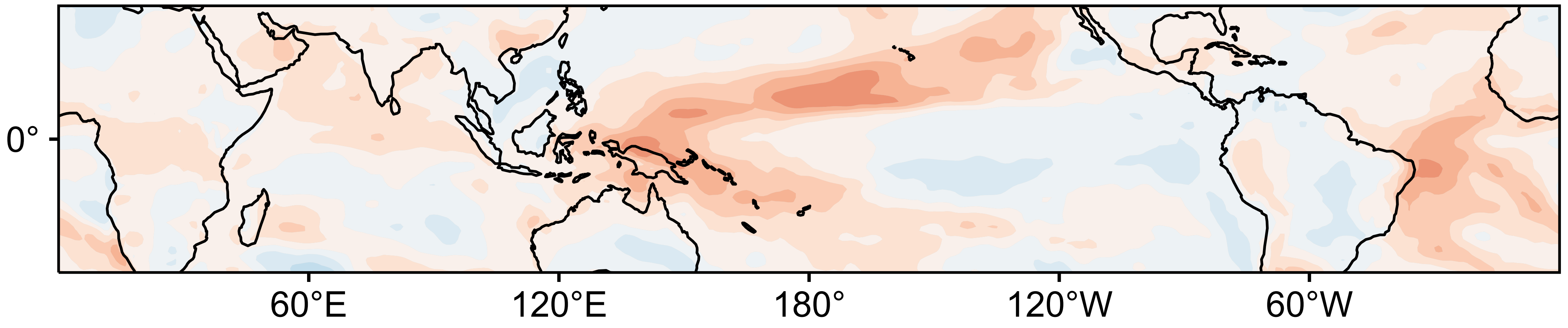
A Primer on Data Assimilation

A Bayesian Framework

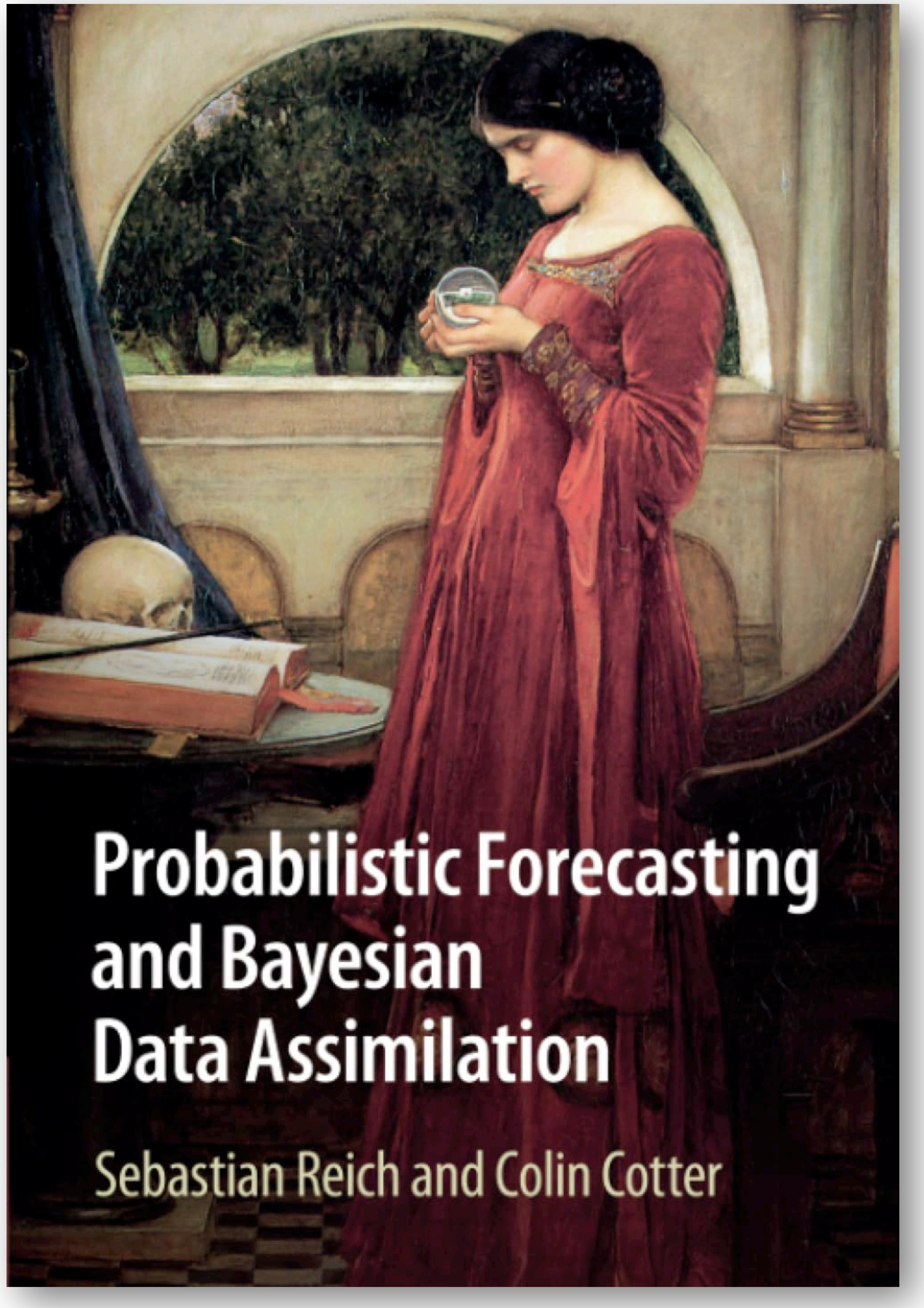
$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

prior
P(A)

corr(prior, truth), mean=0.05



Zhu et al. (2024, *GMD*)



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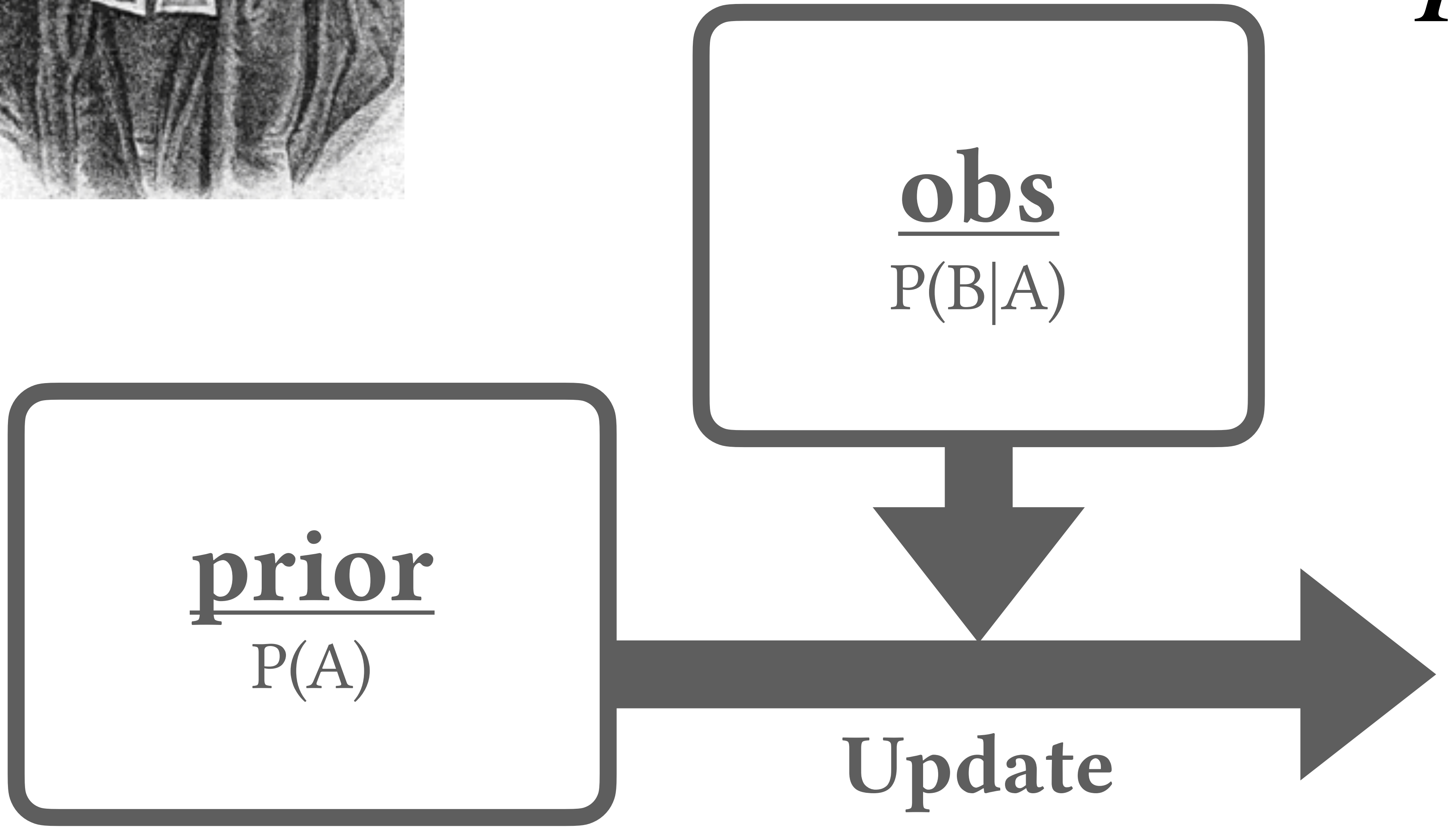

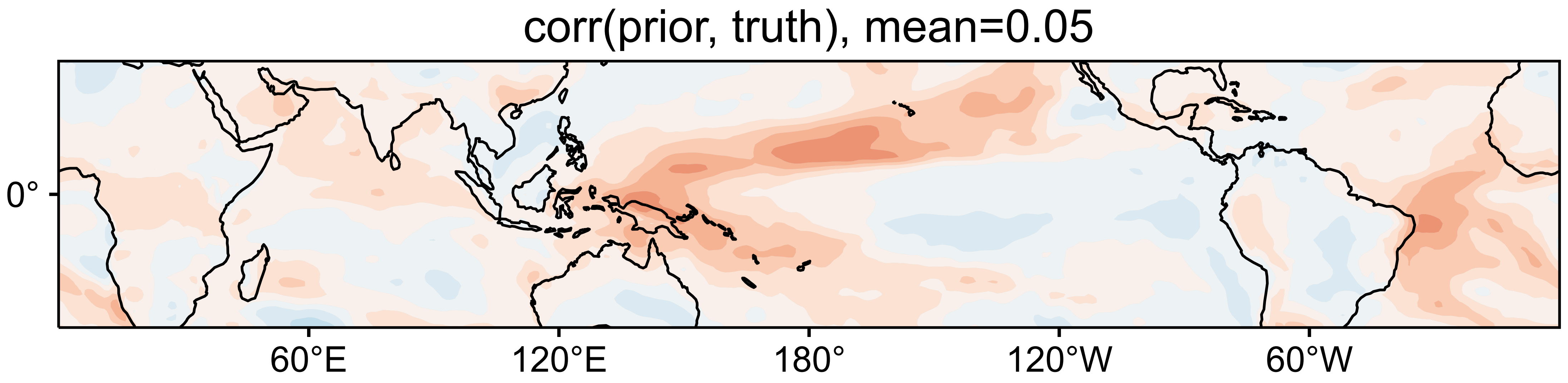

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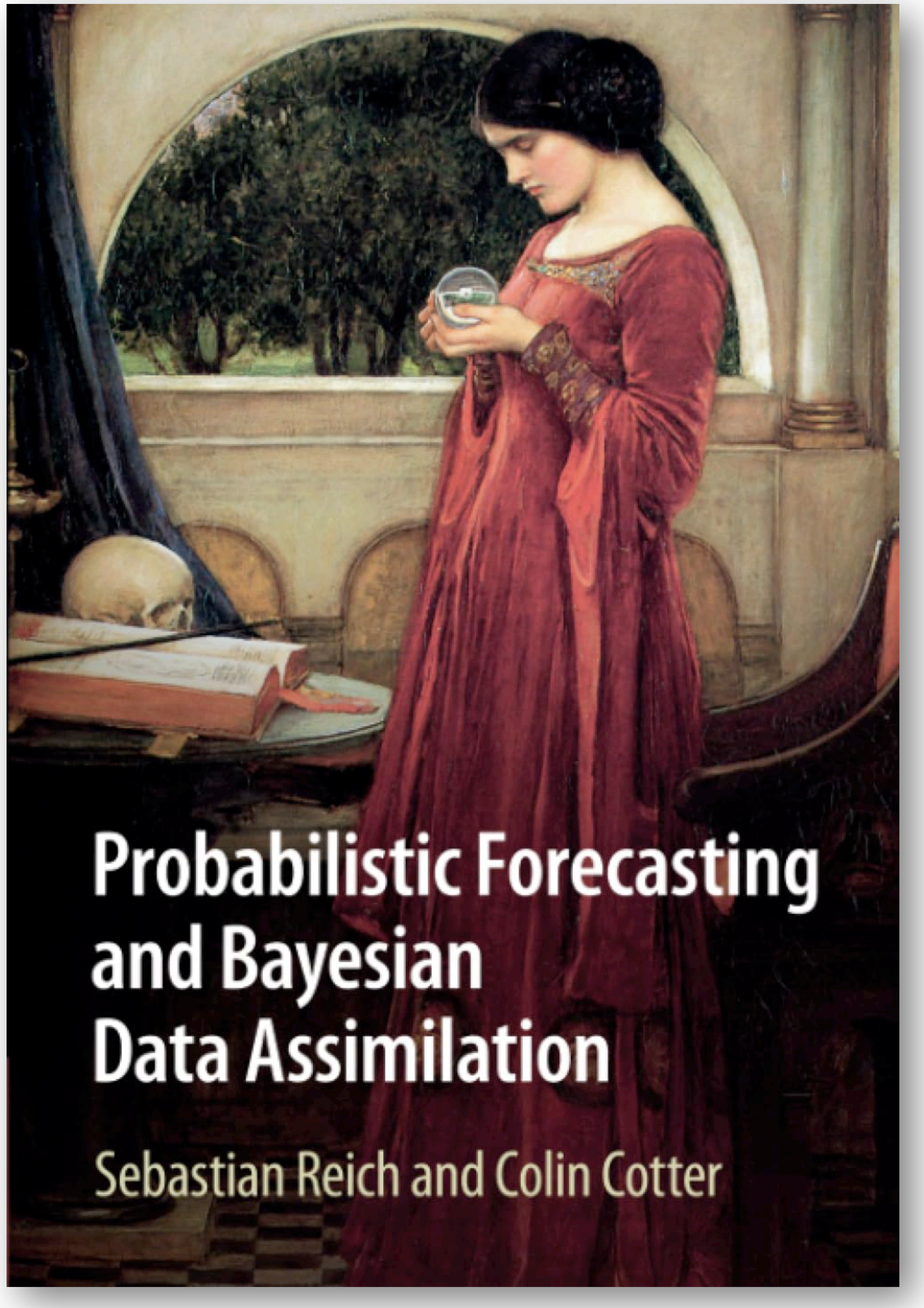

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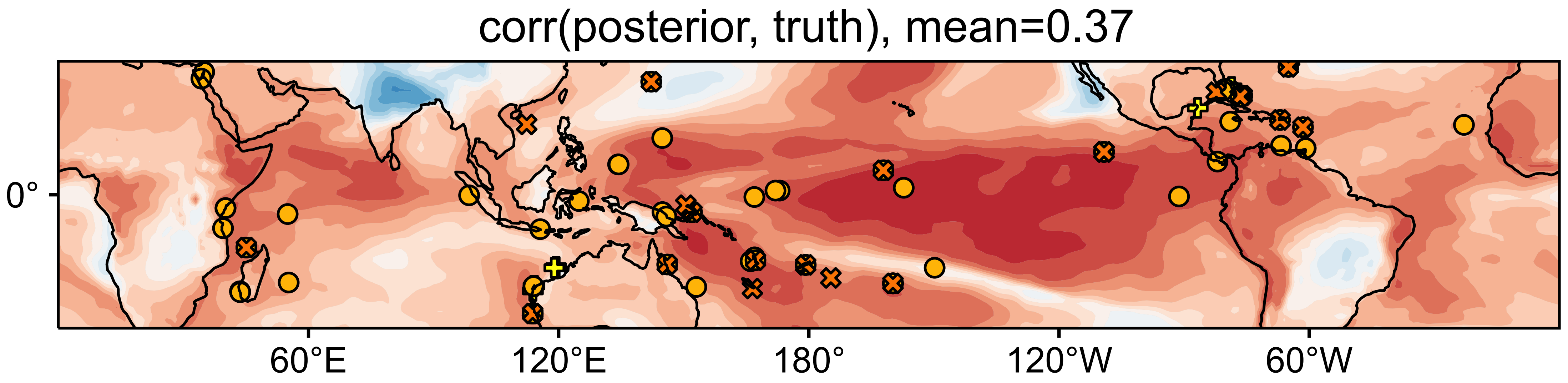
obs
P(B|A)

prior
P(A)

Update

posterior
P(A|B)



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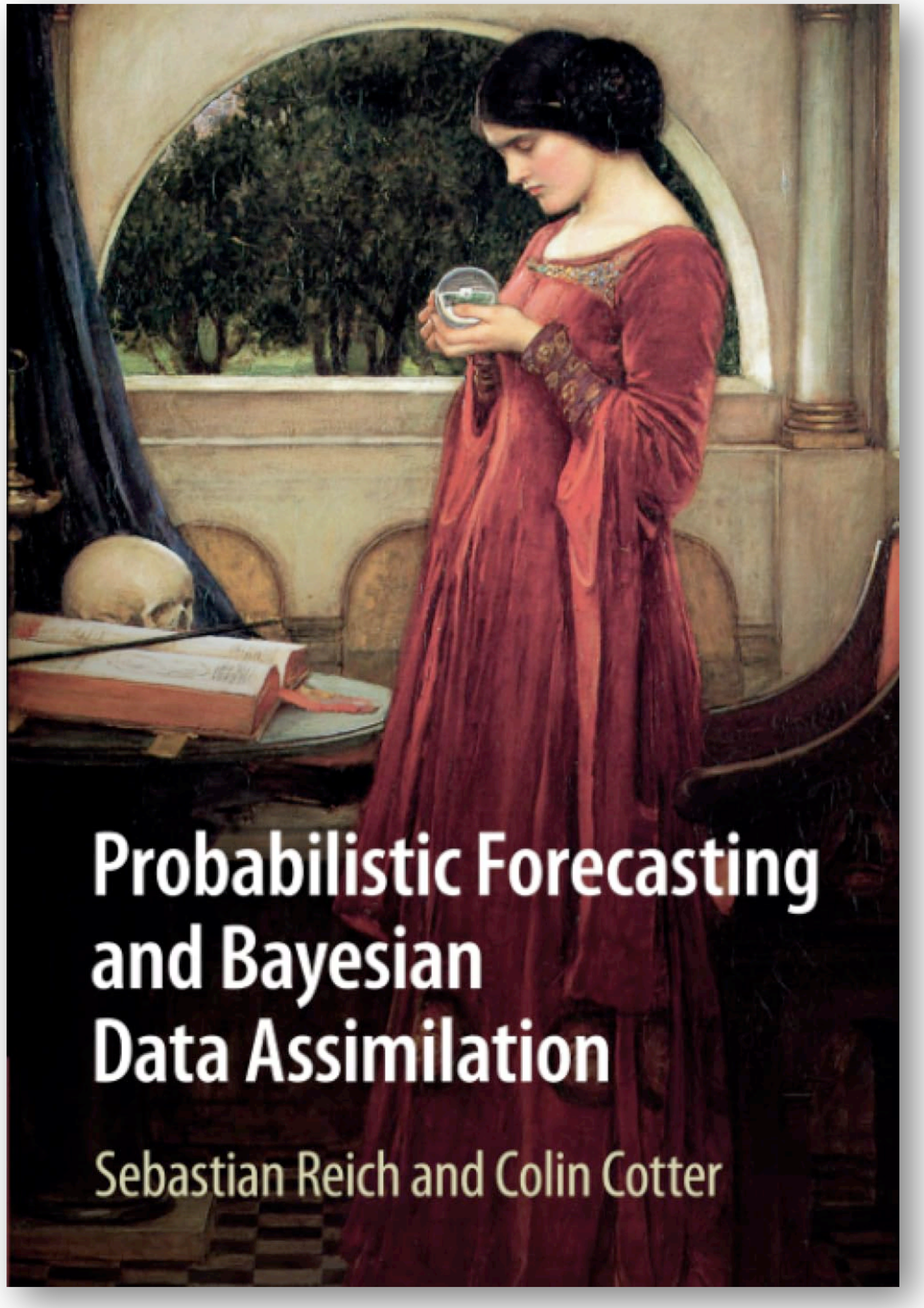

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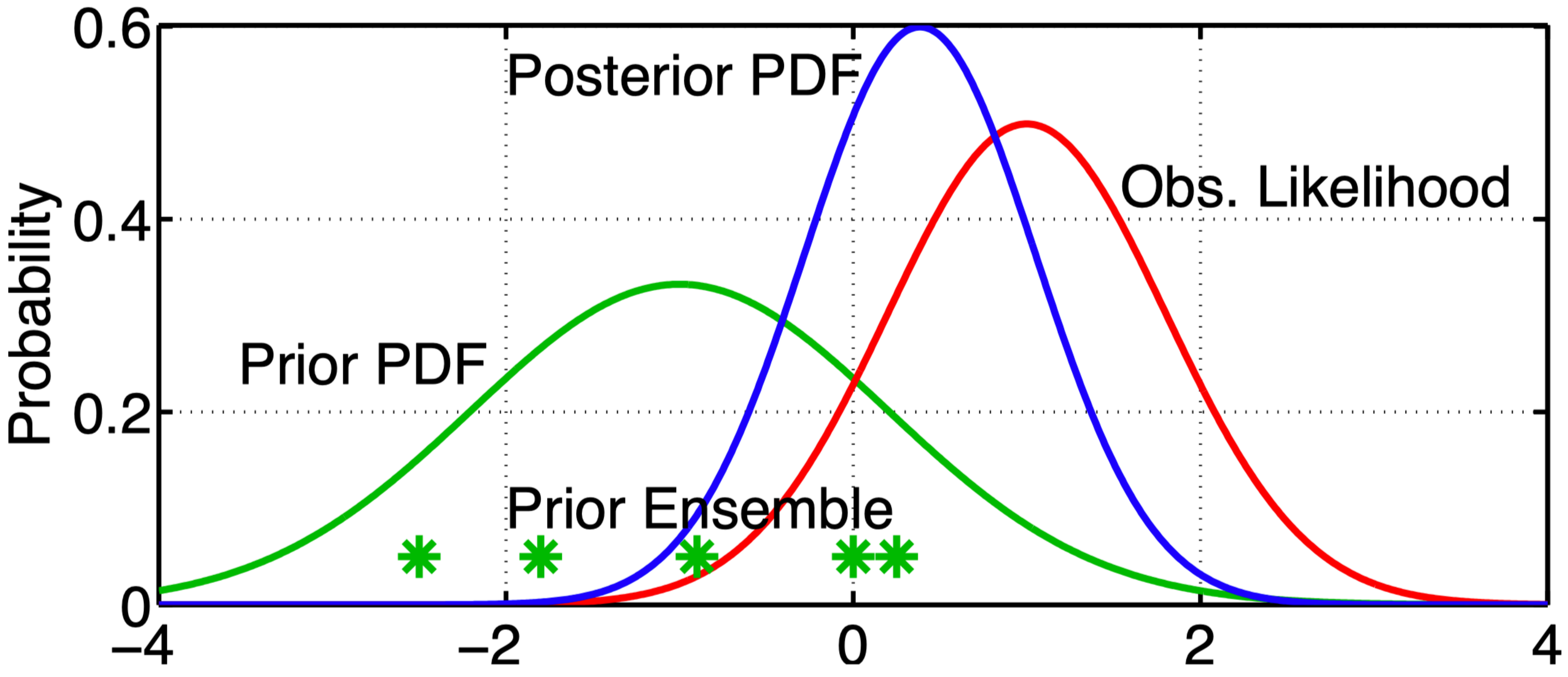
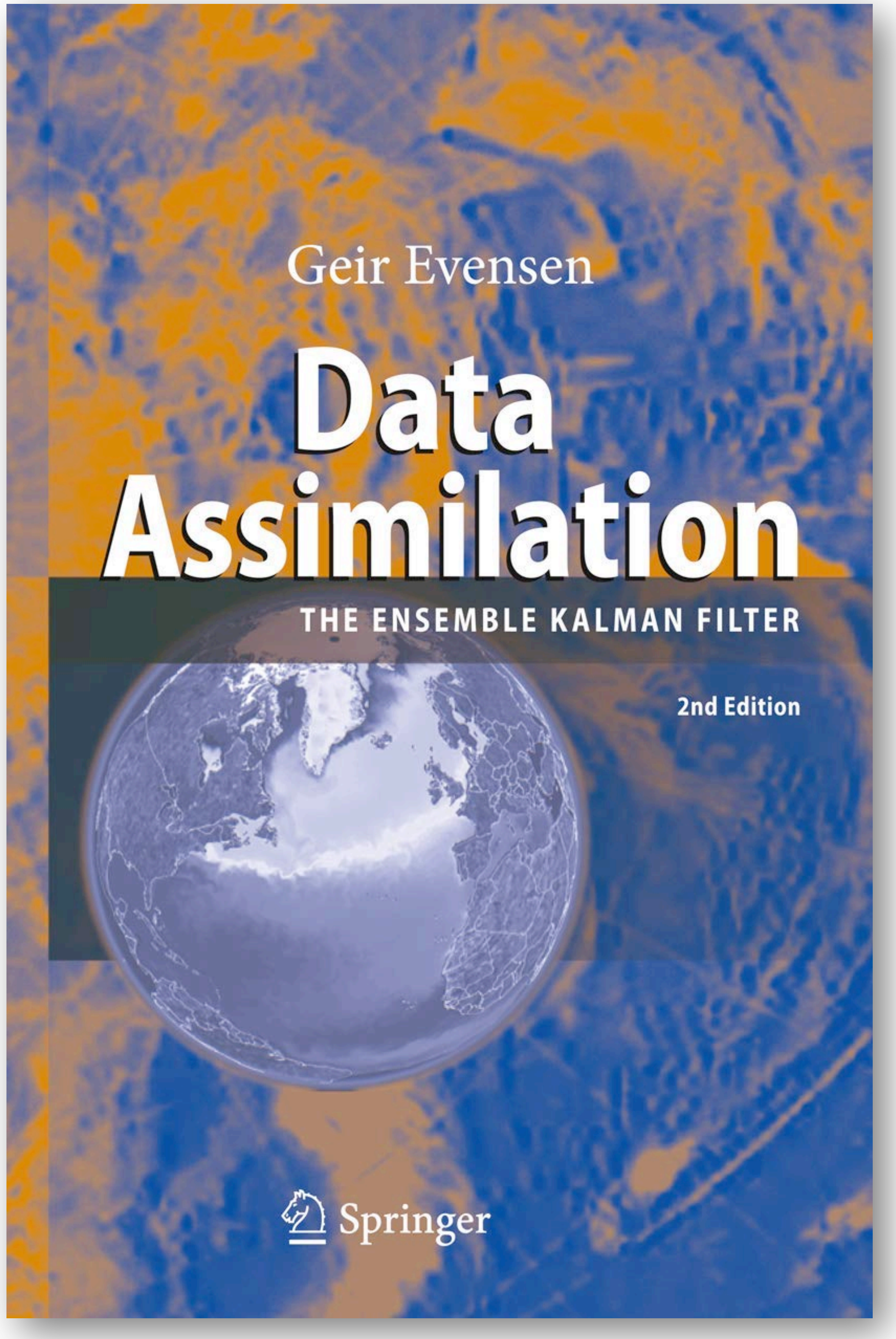


(DART Tutorial @NCAR)



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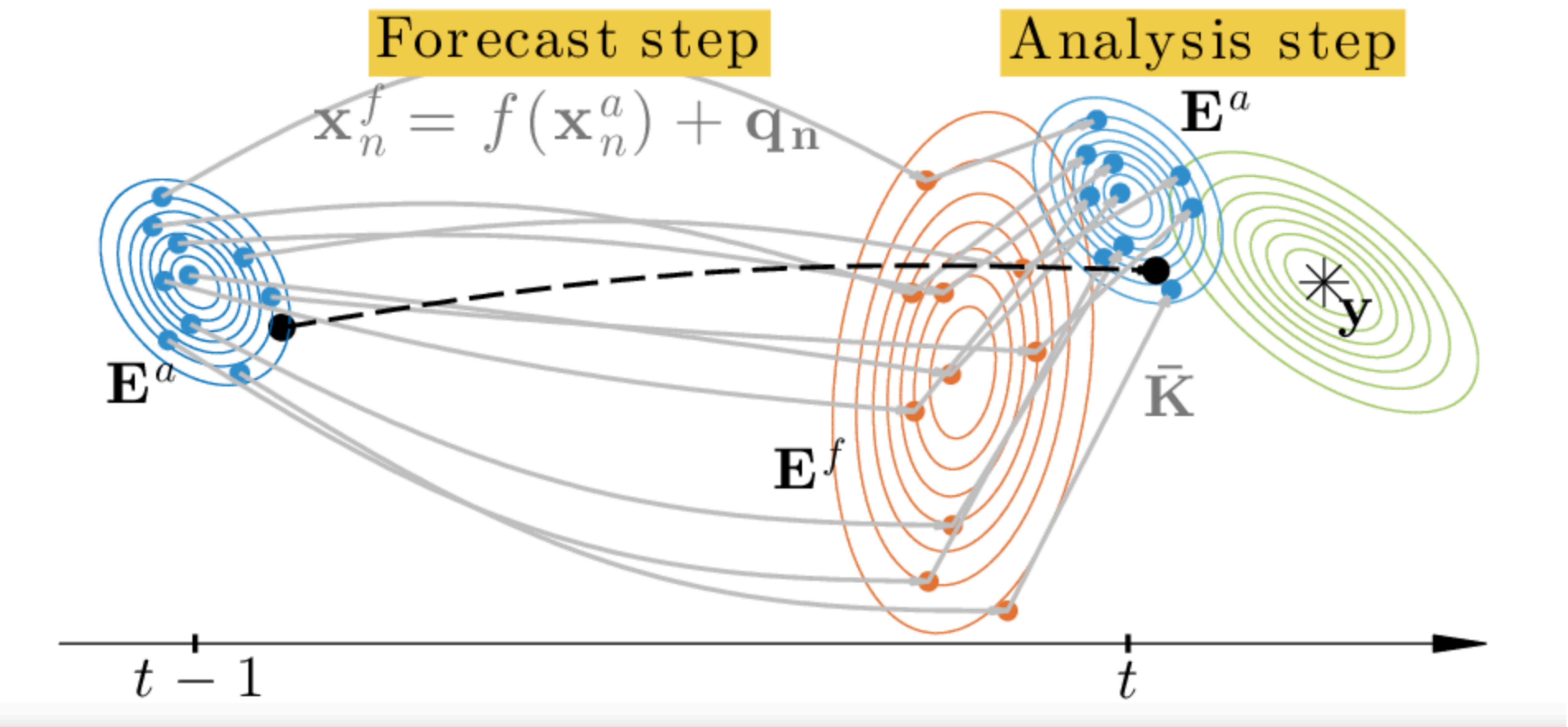

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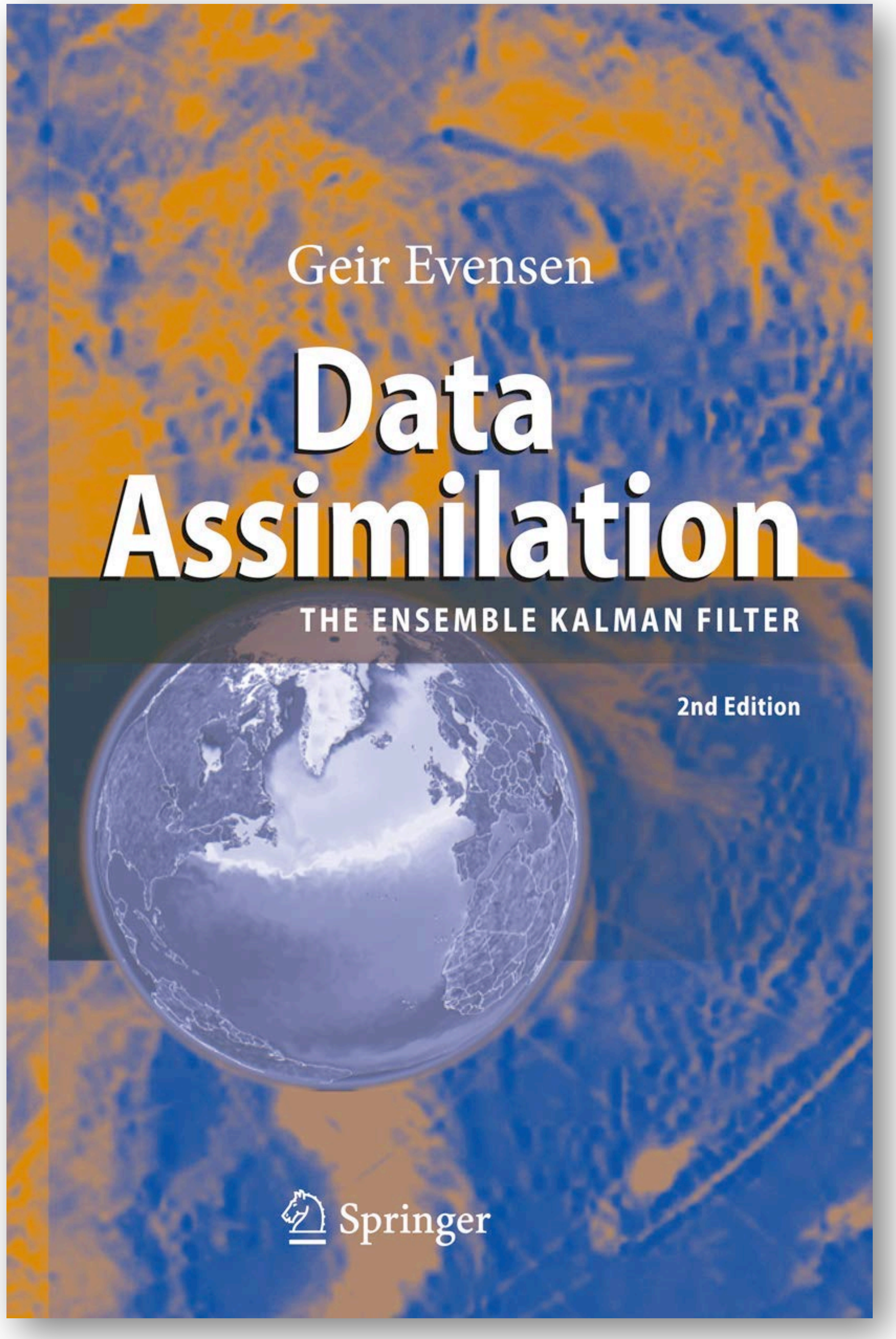

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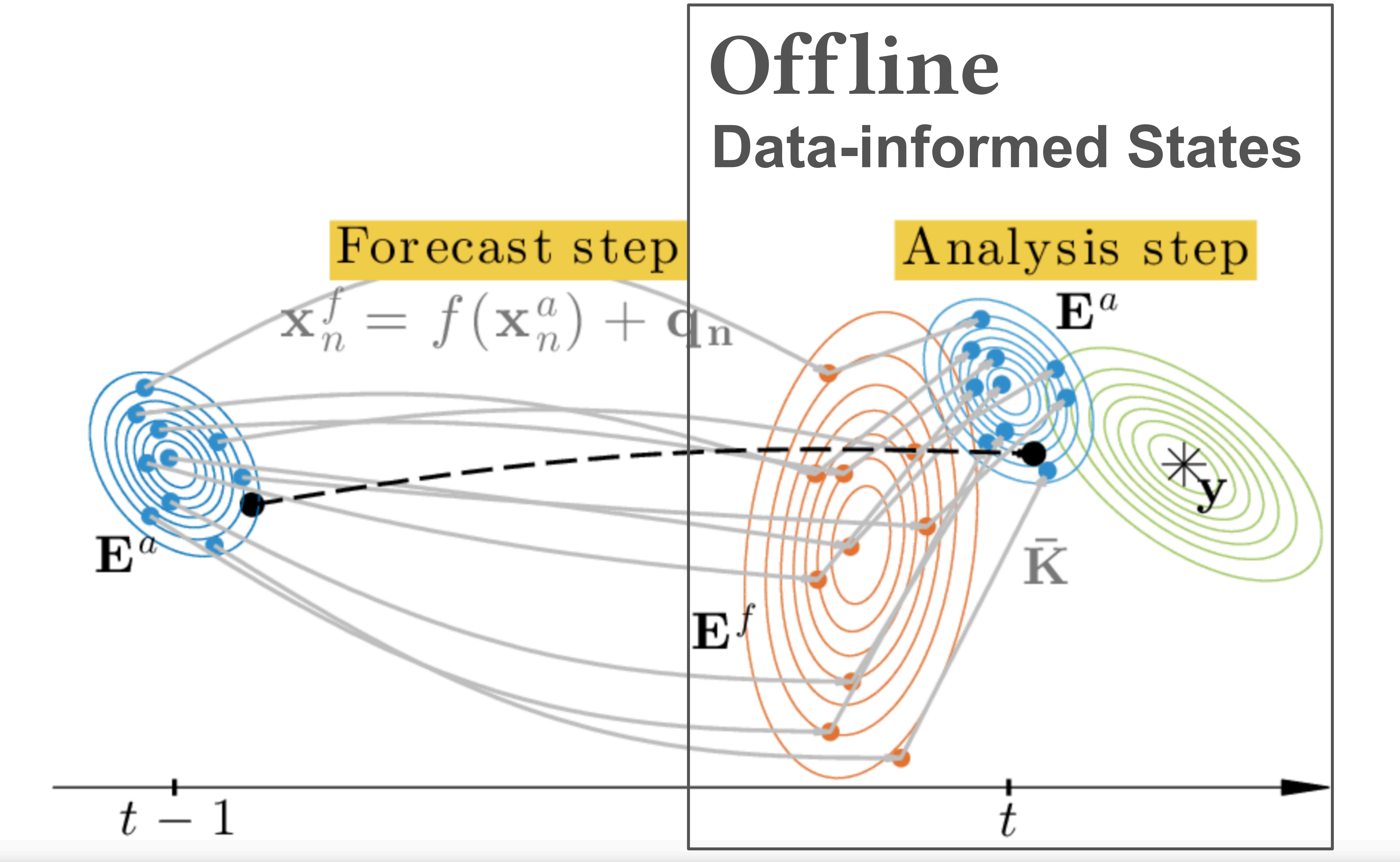

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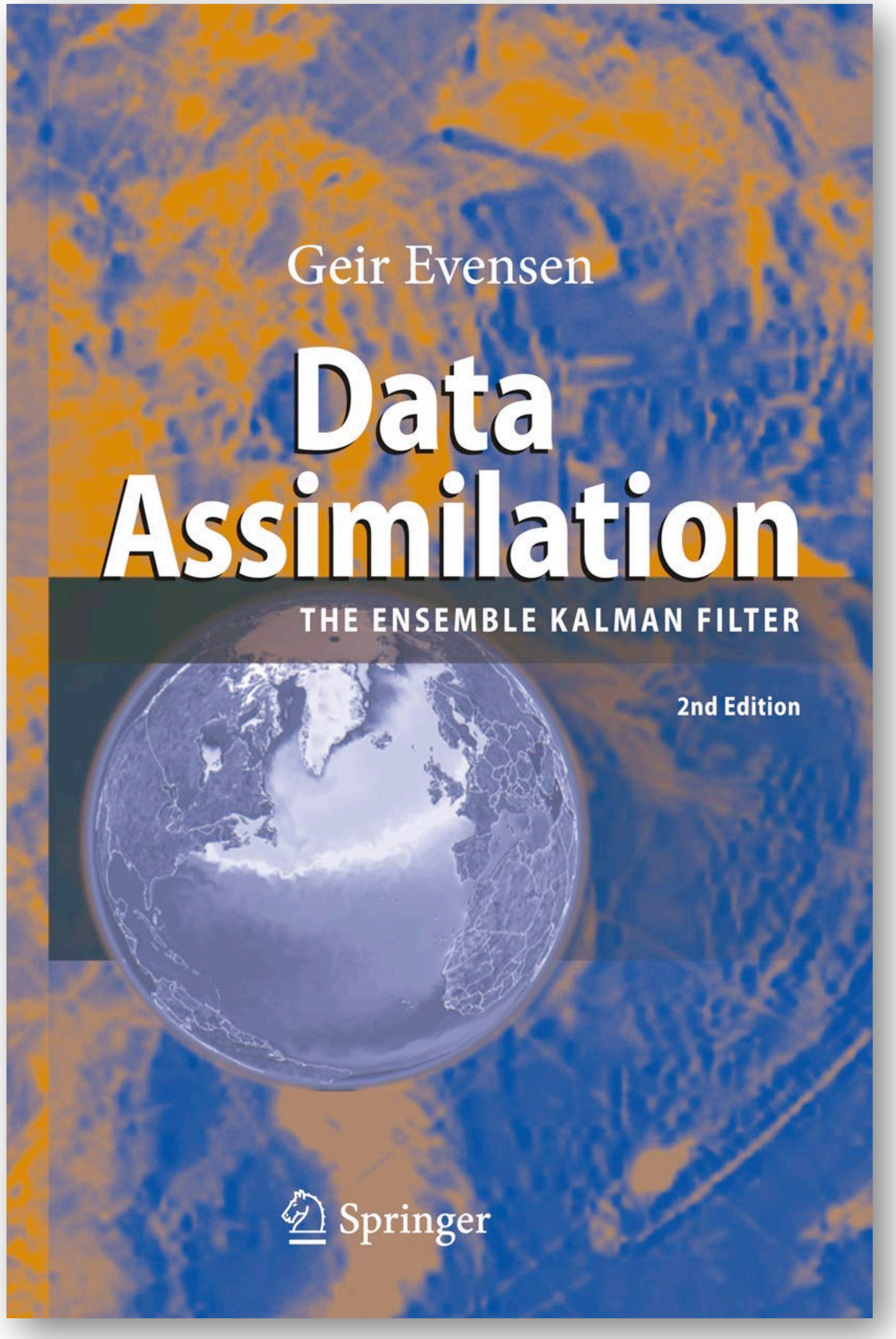

Assumption:
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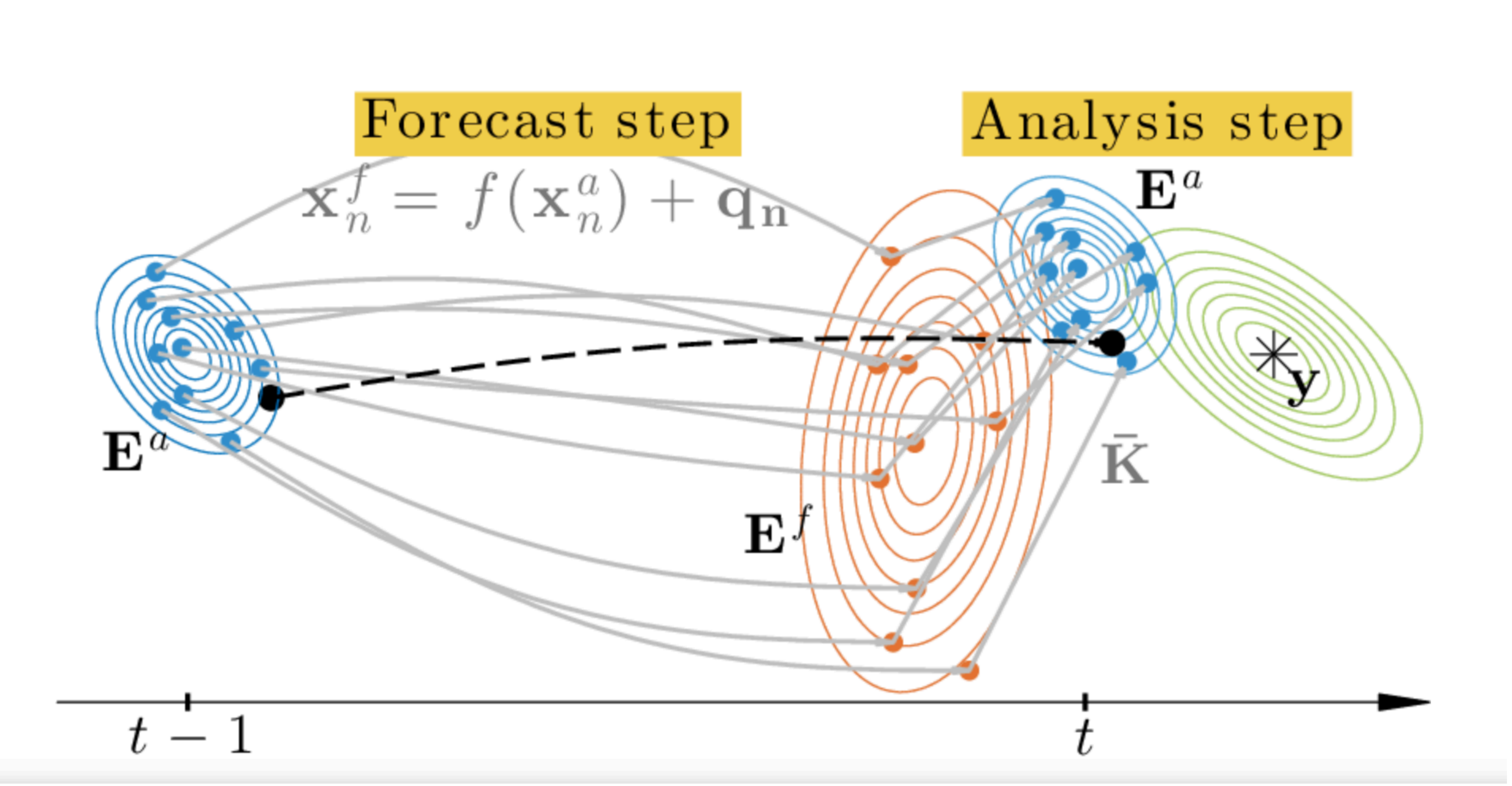

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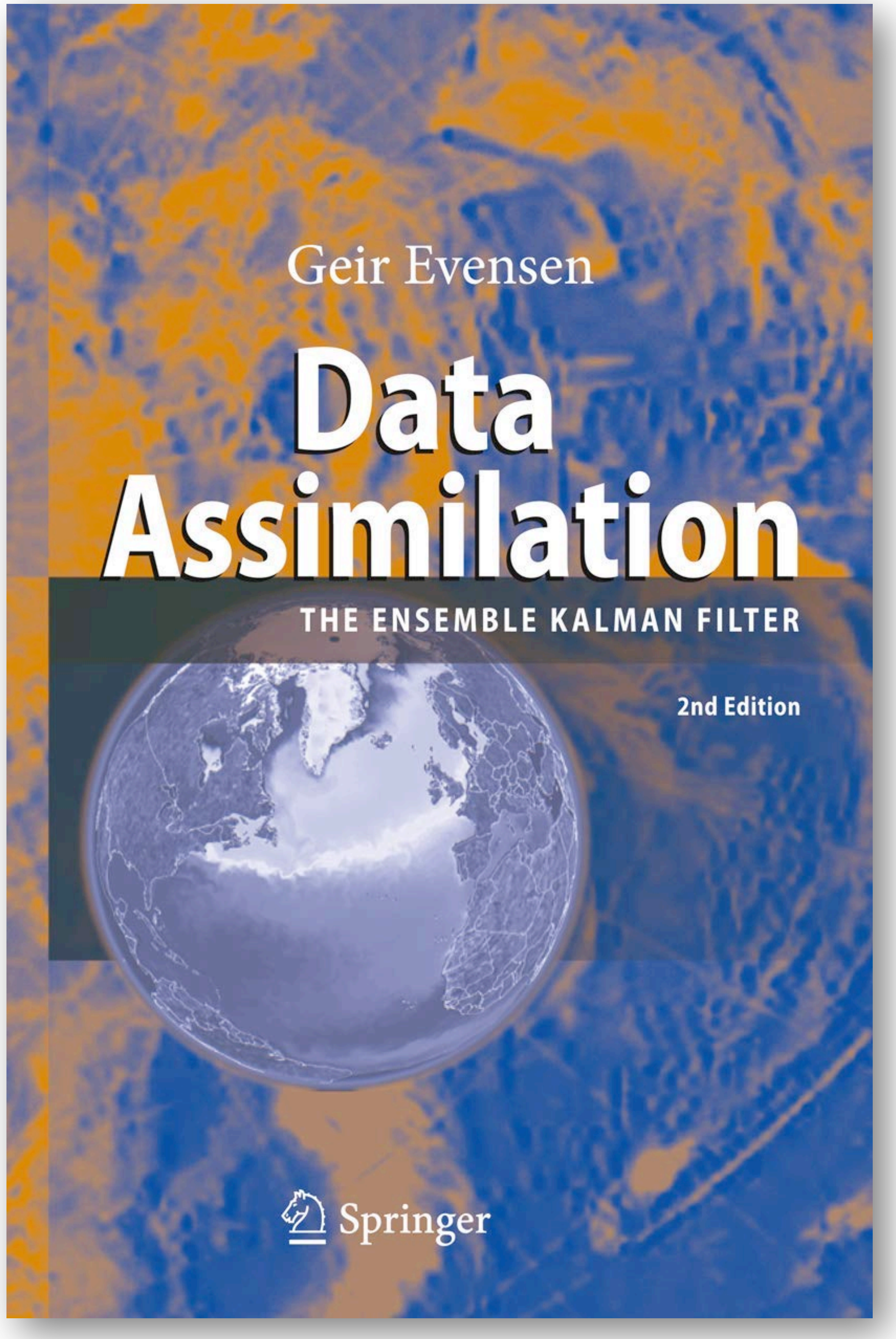
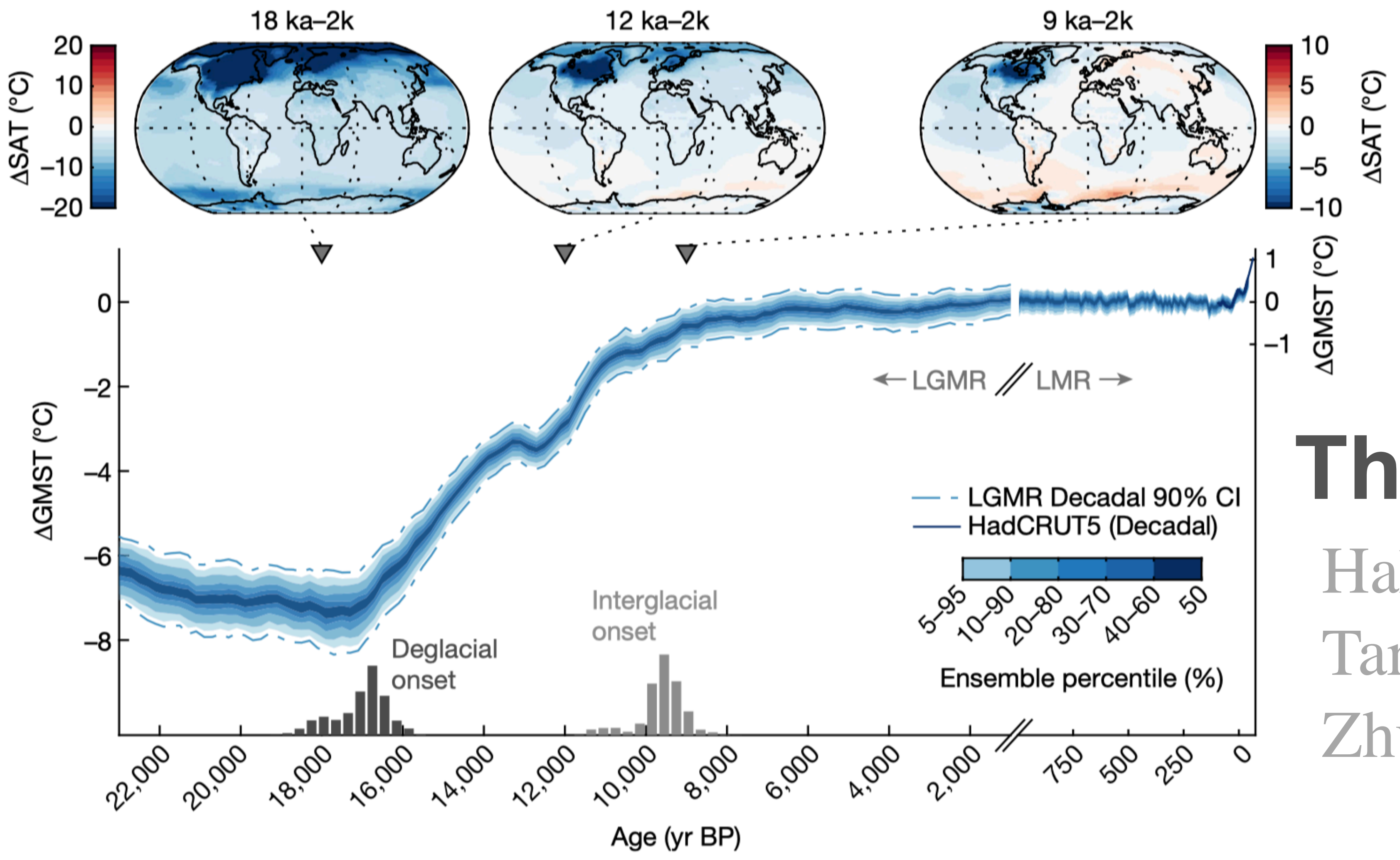


State-of-the-art: offline paleoDA

The Last Glacial Maximum

Osman et al. (2021, *Nature*)



The Last Millennium

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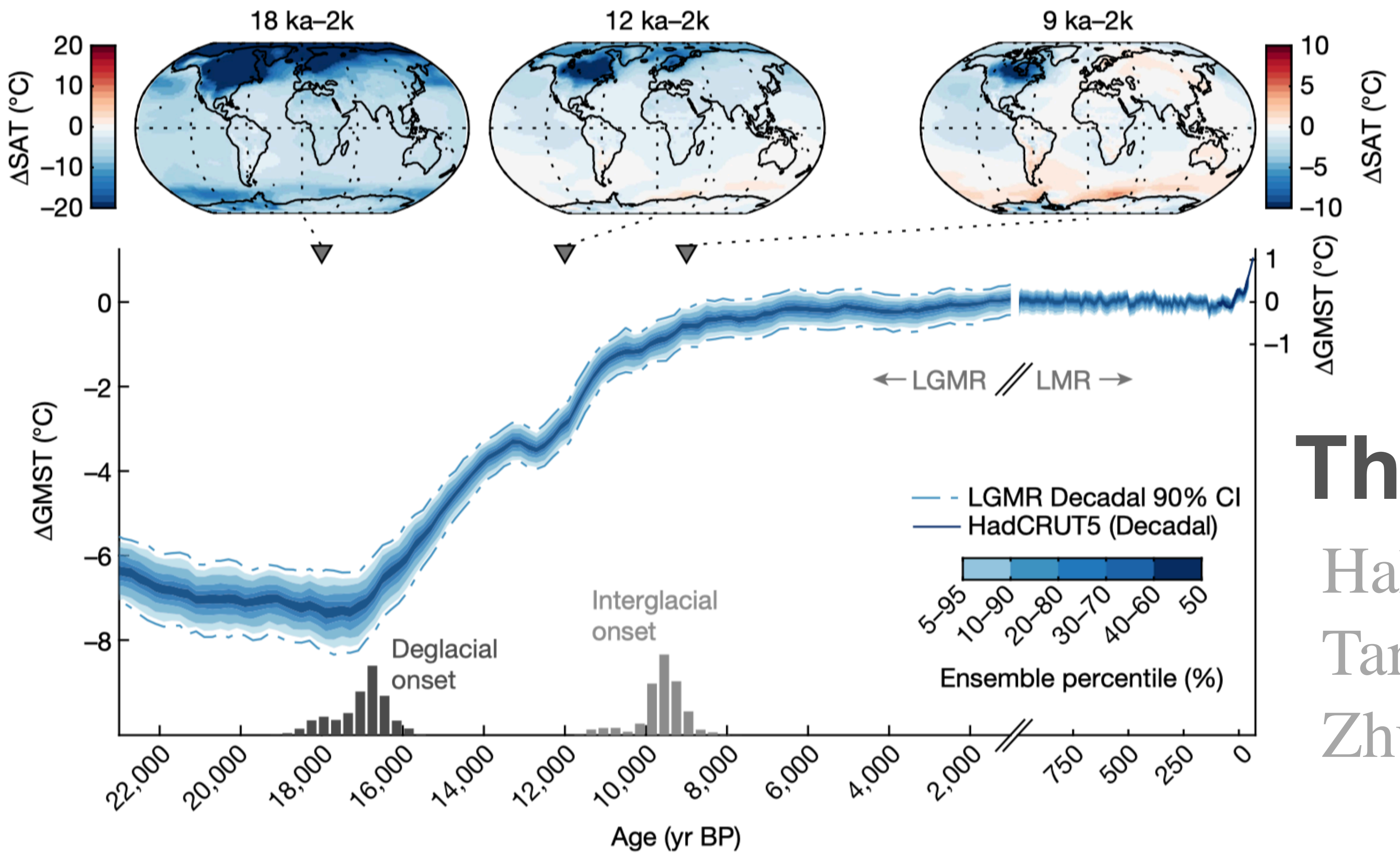

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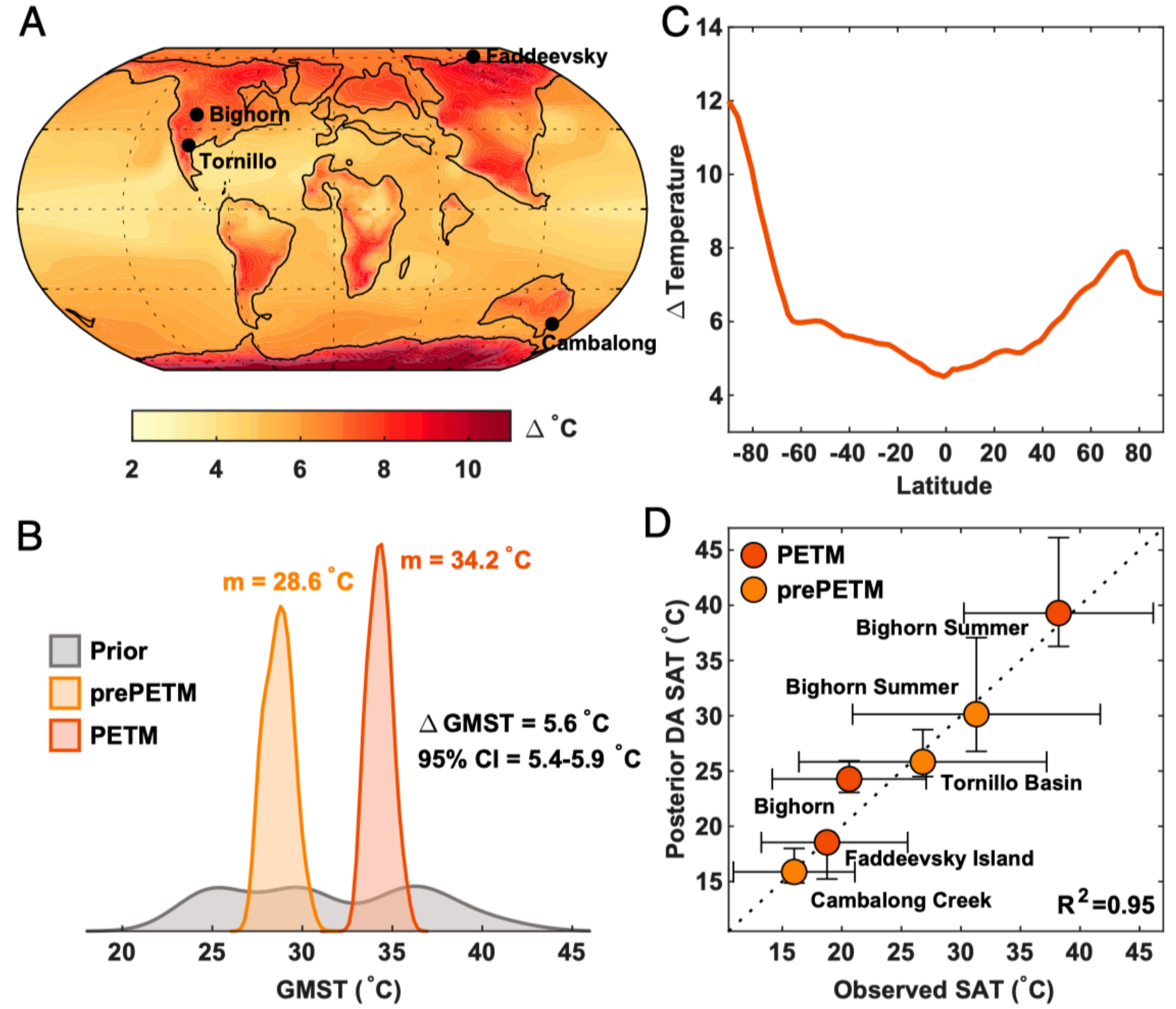
The Paleocene-Eocene Thermal Maximum



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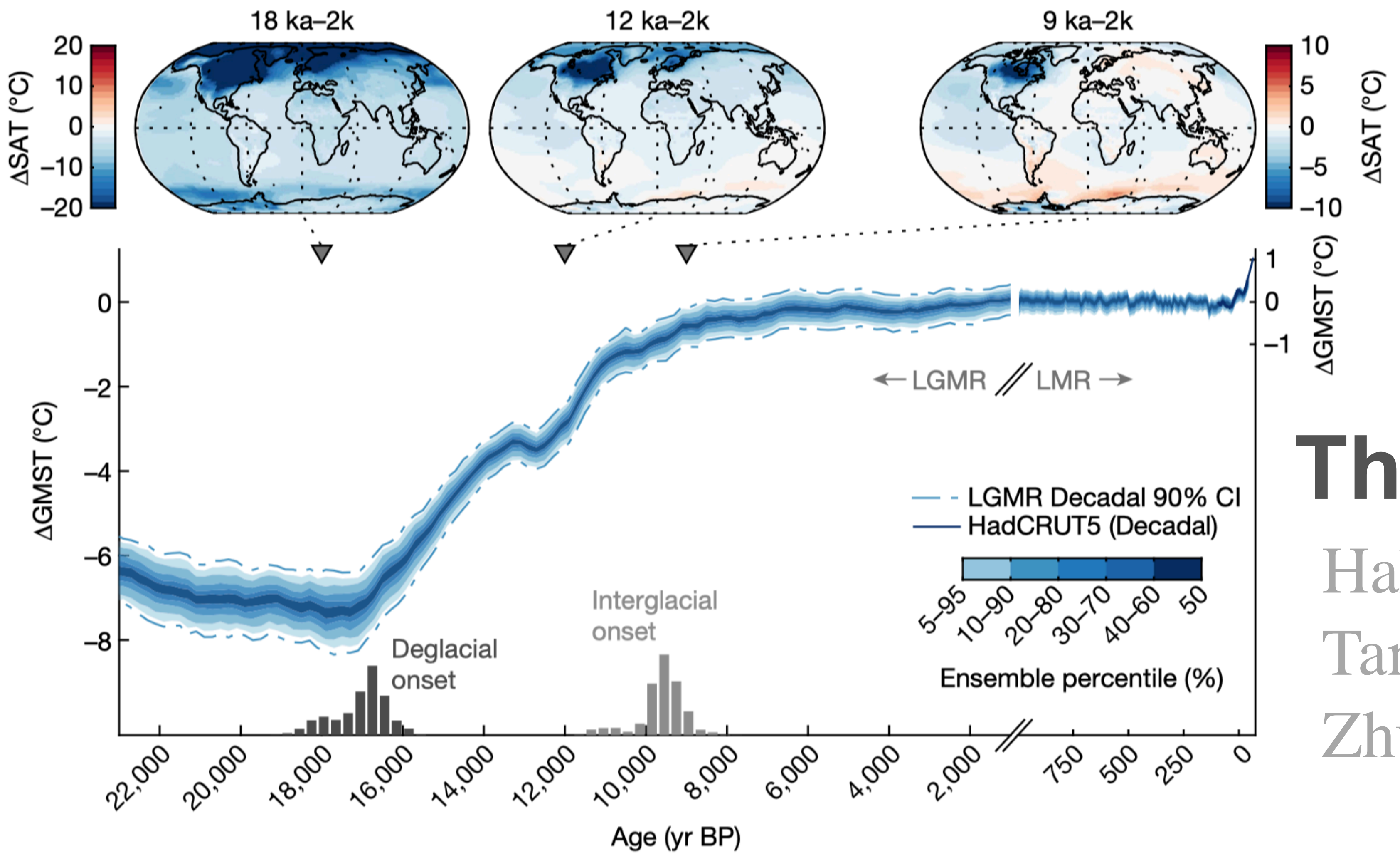

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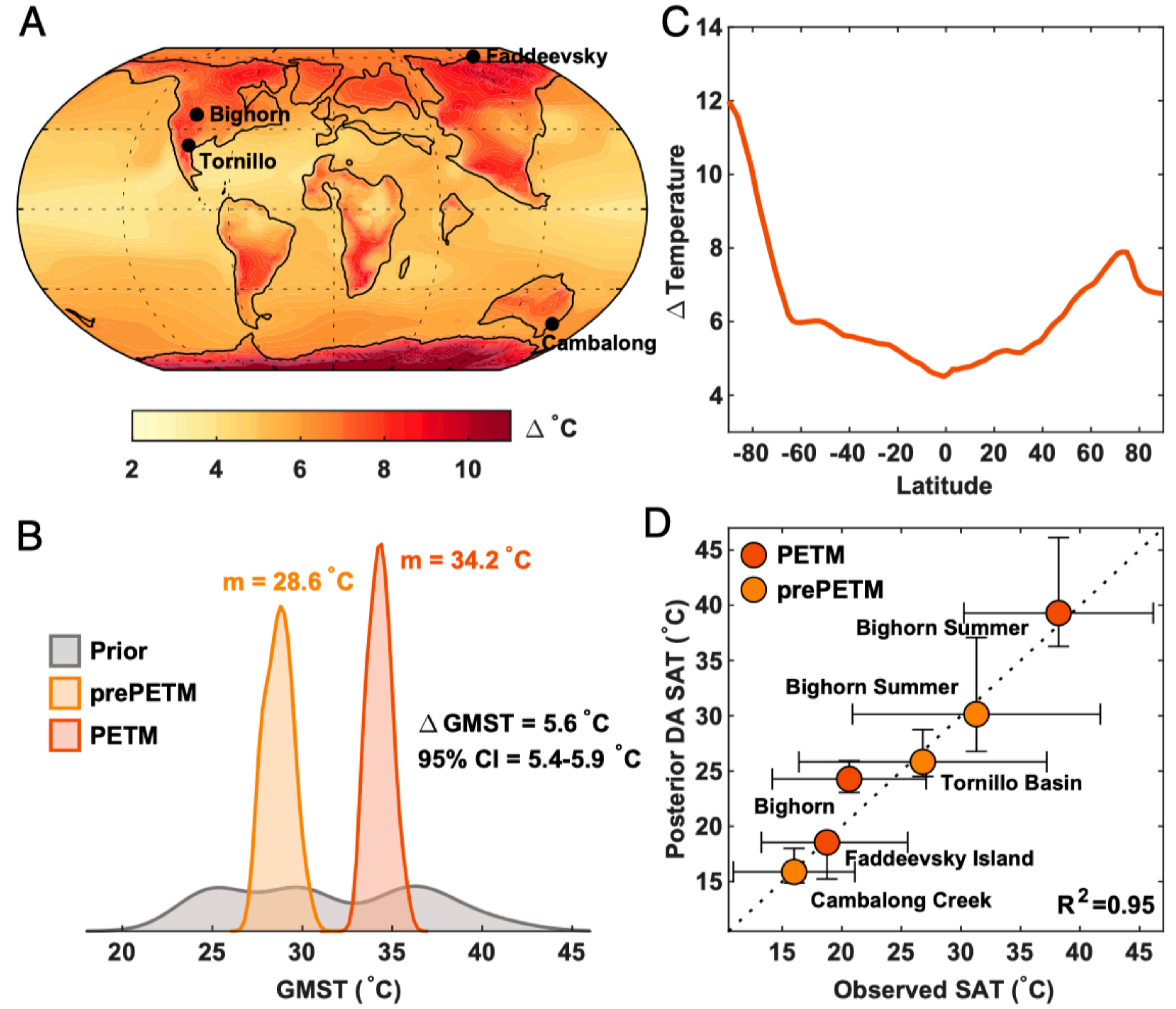

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A 485-million-year history

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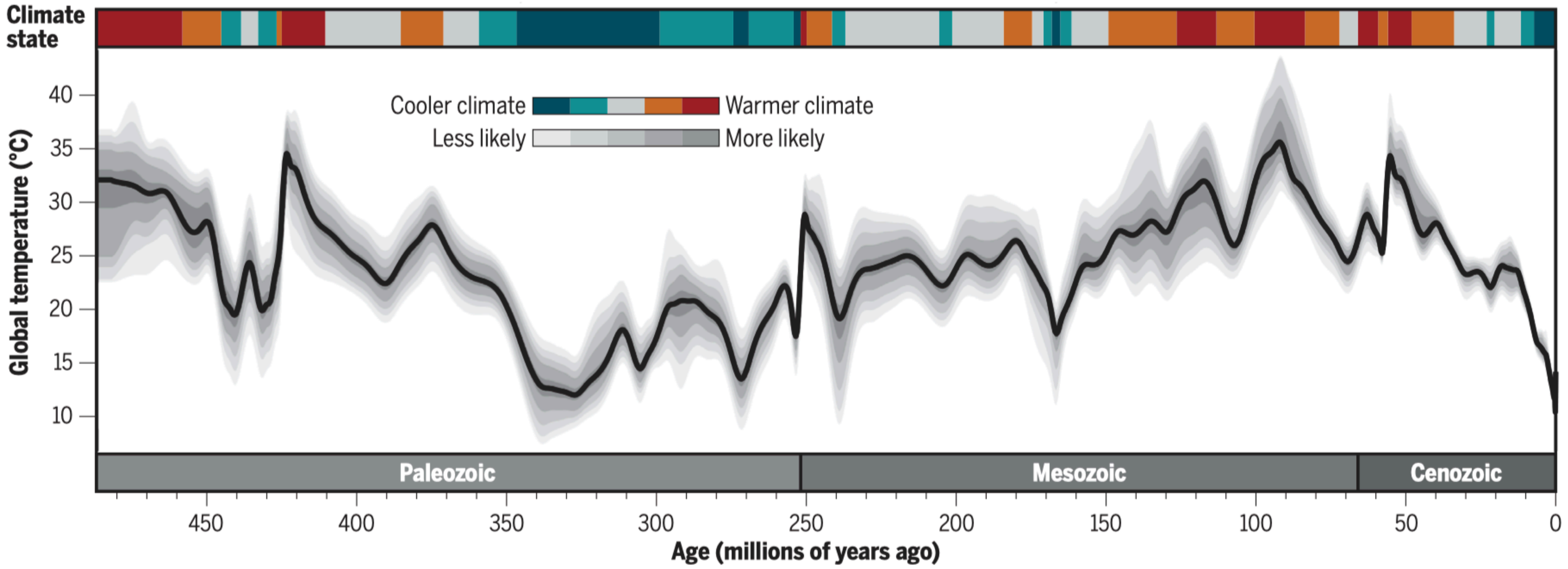

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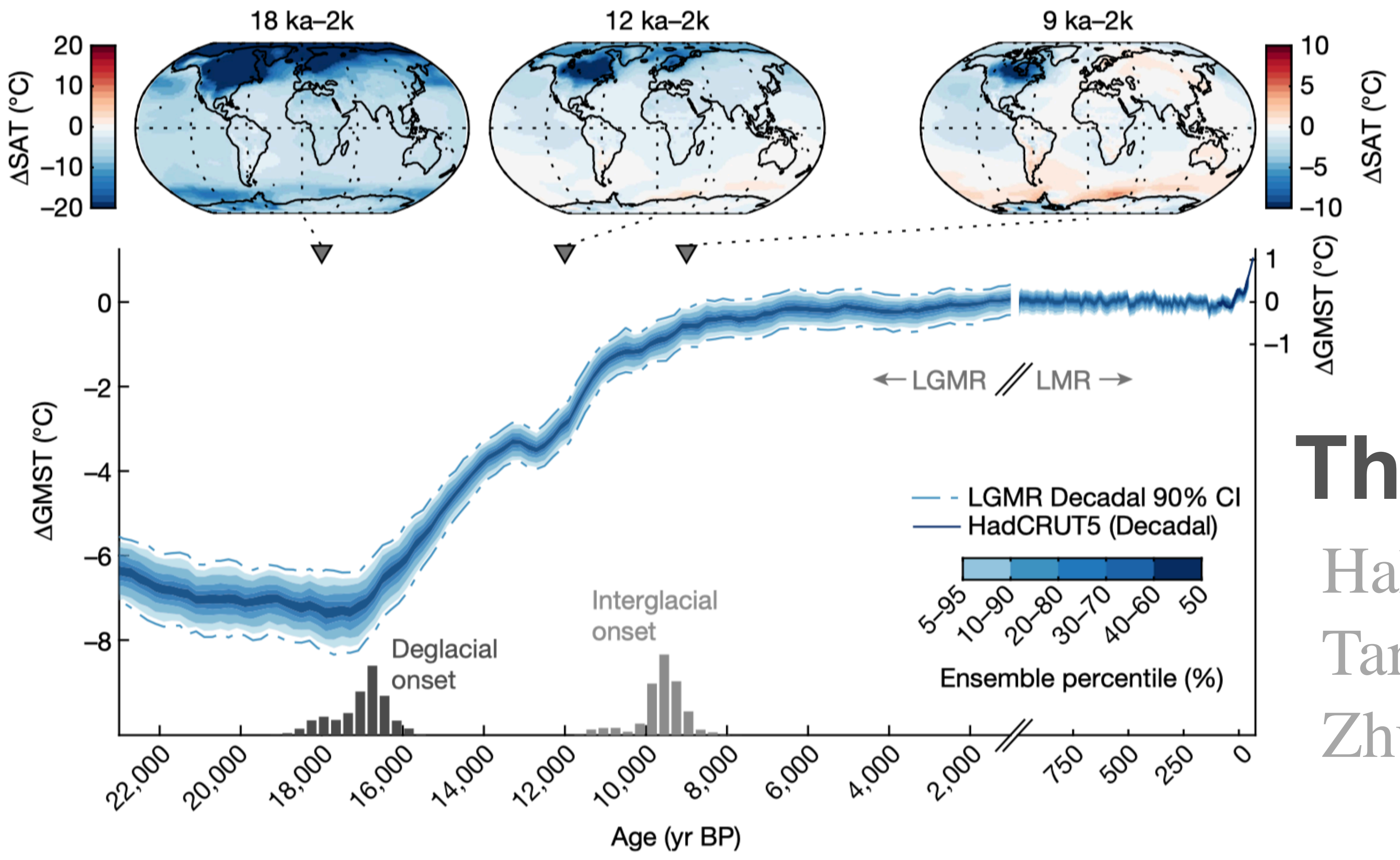

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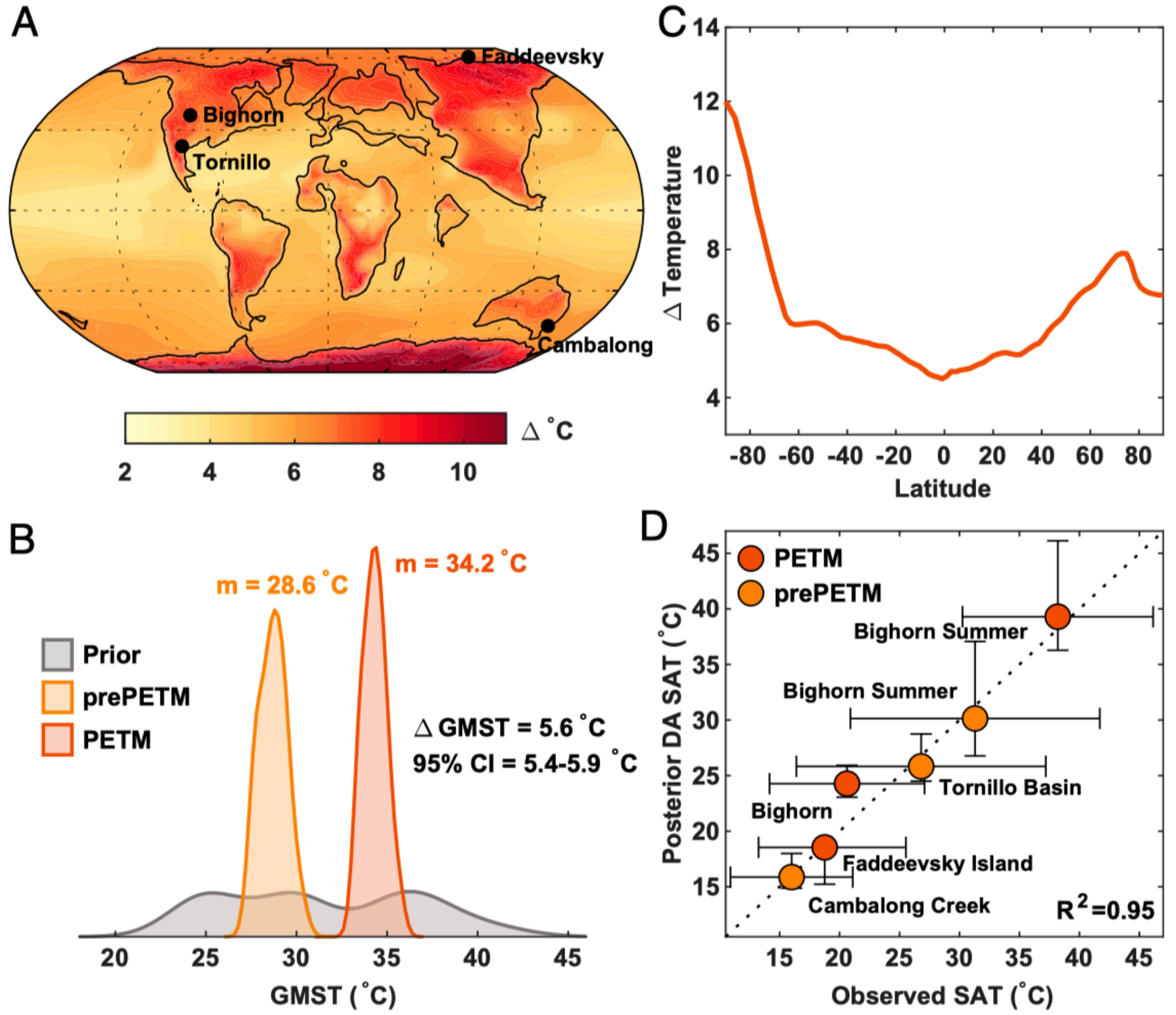

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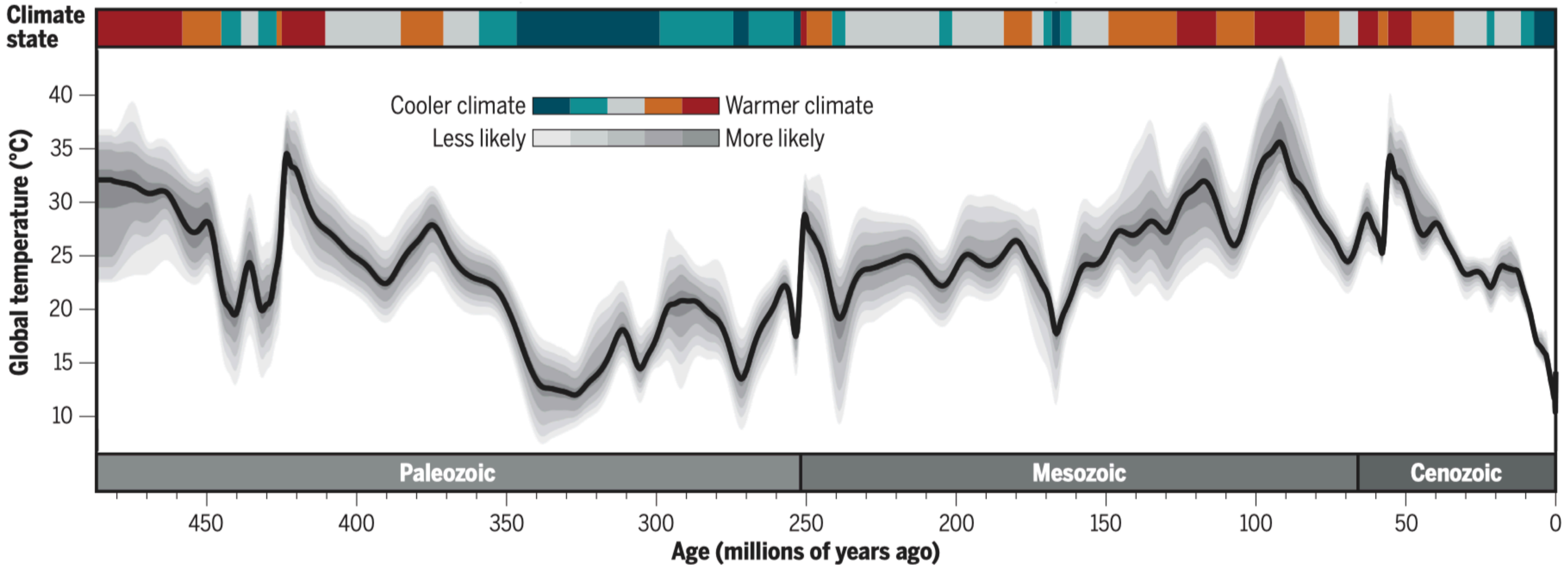
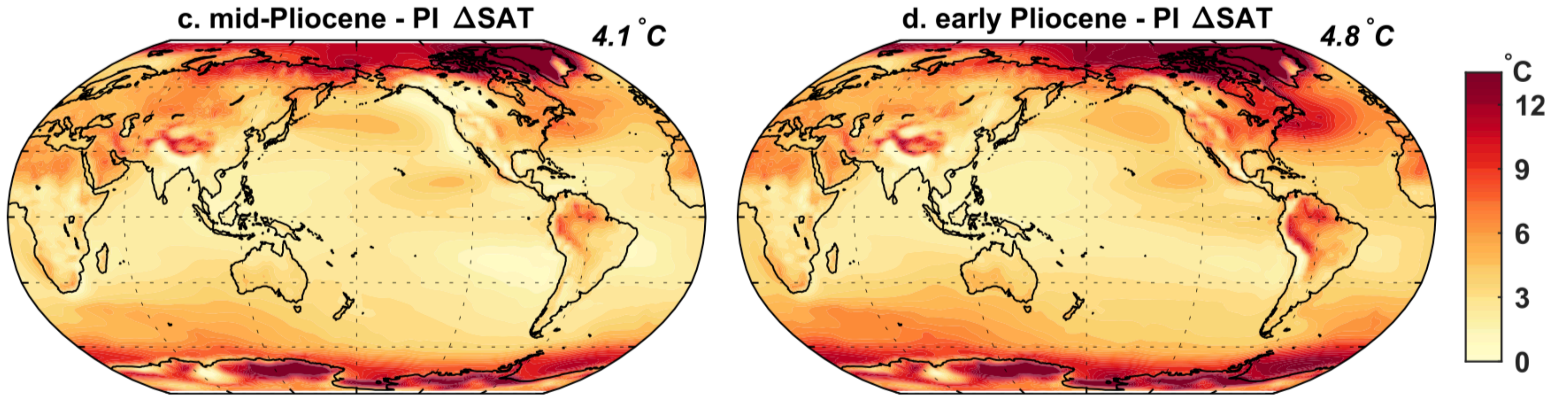
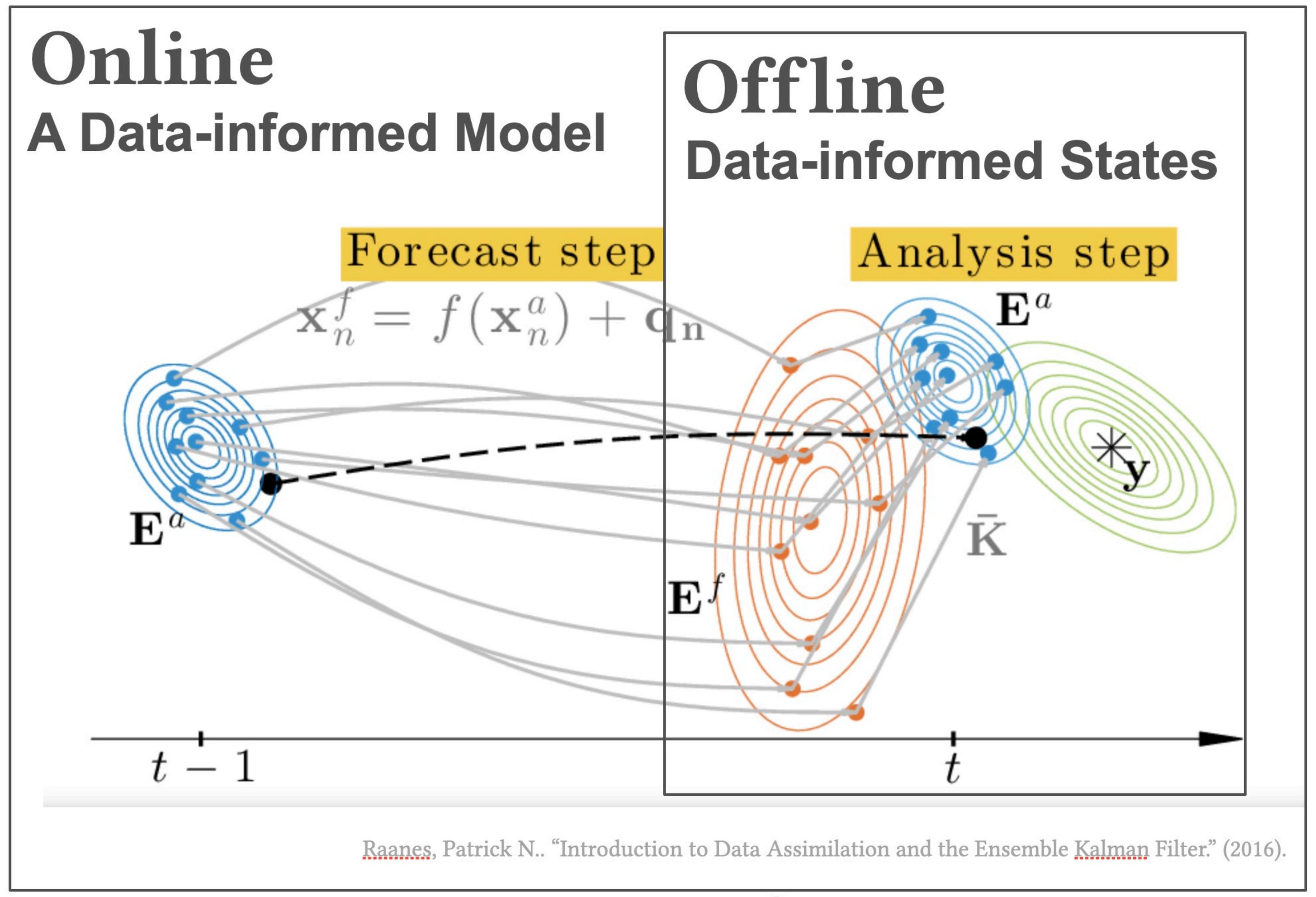


The Pliocene

Tierney et al. (2025, *AGU Adv.*)



Motivation for pursuing an online paleoDA solution



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Online paleoDA: combining model and data using nonlinear-nonGaussian dynamics.

→ **more physical** multivariate & spatial relationships

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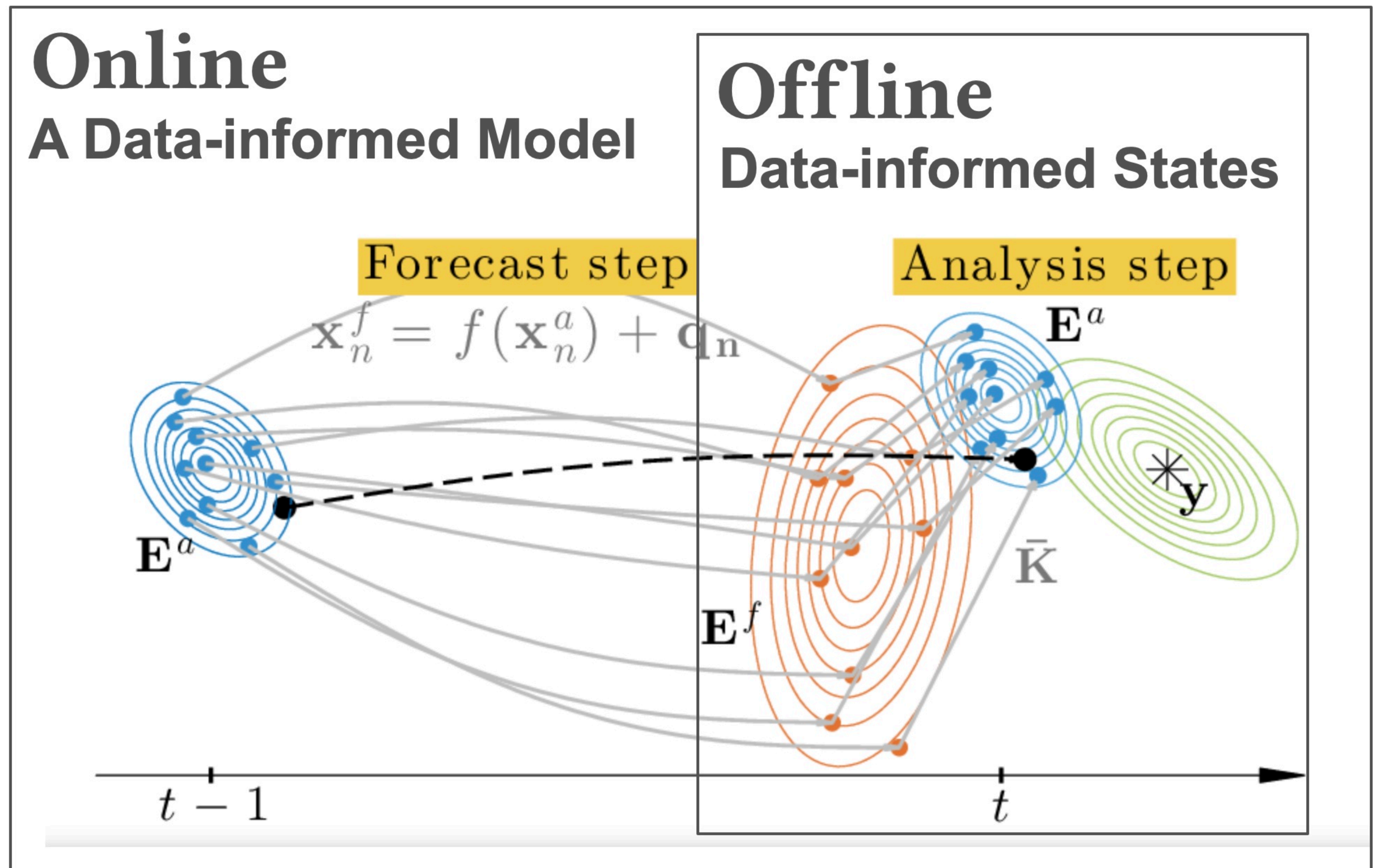

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Online paleoDA: combining model and data using nonlinear-nonGaussian dynamics.

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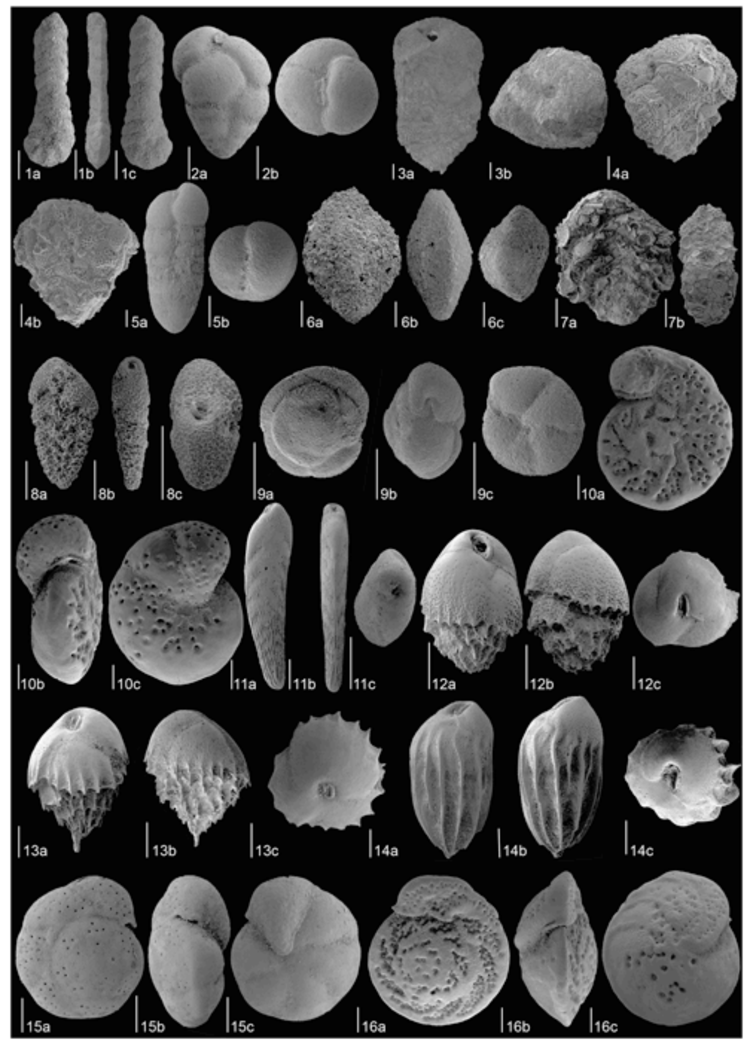
A bonus for deep-time climate: assessing **internal variability** under different climatological patterns.

For example, the ENSO variability.

(deep-time paleo records are proxies for long-term mean climatology)

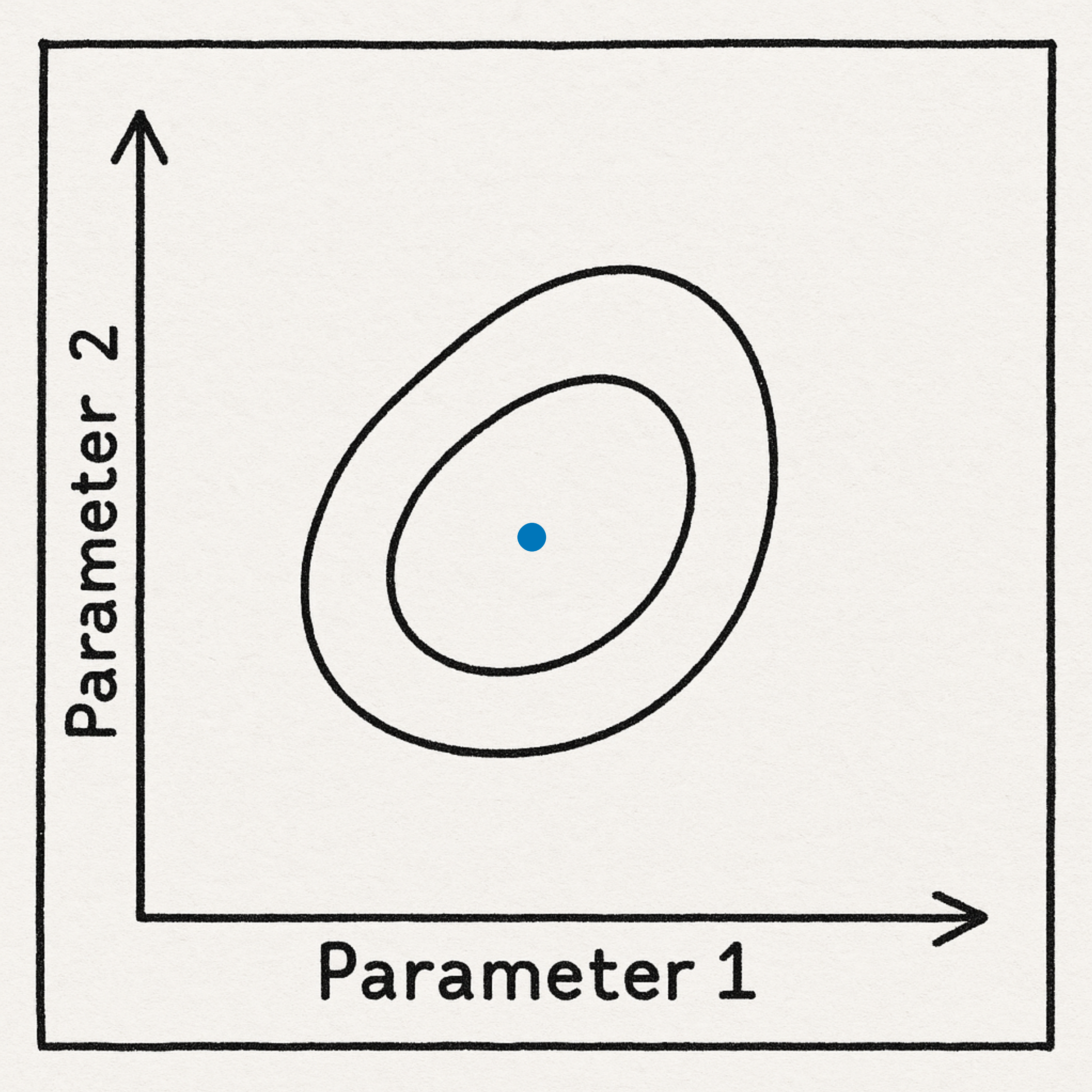


Gastaldello, M. E., Agnini, C., and Alegret, L (2024)

Deep-time climate: a boundary condition problem

An ideal approach:
Parameter Estimation

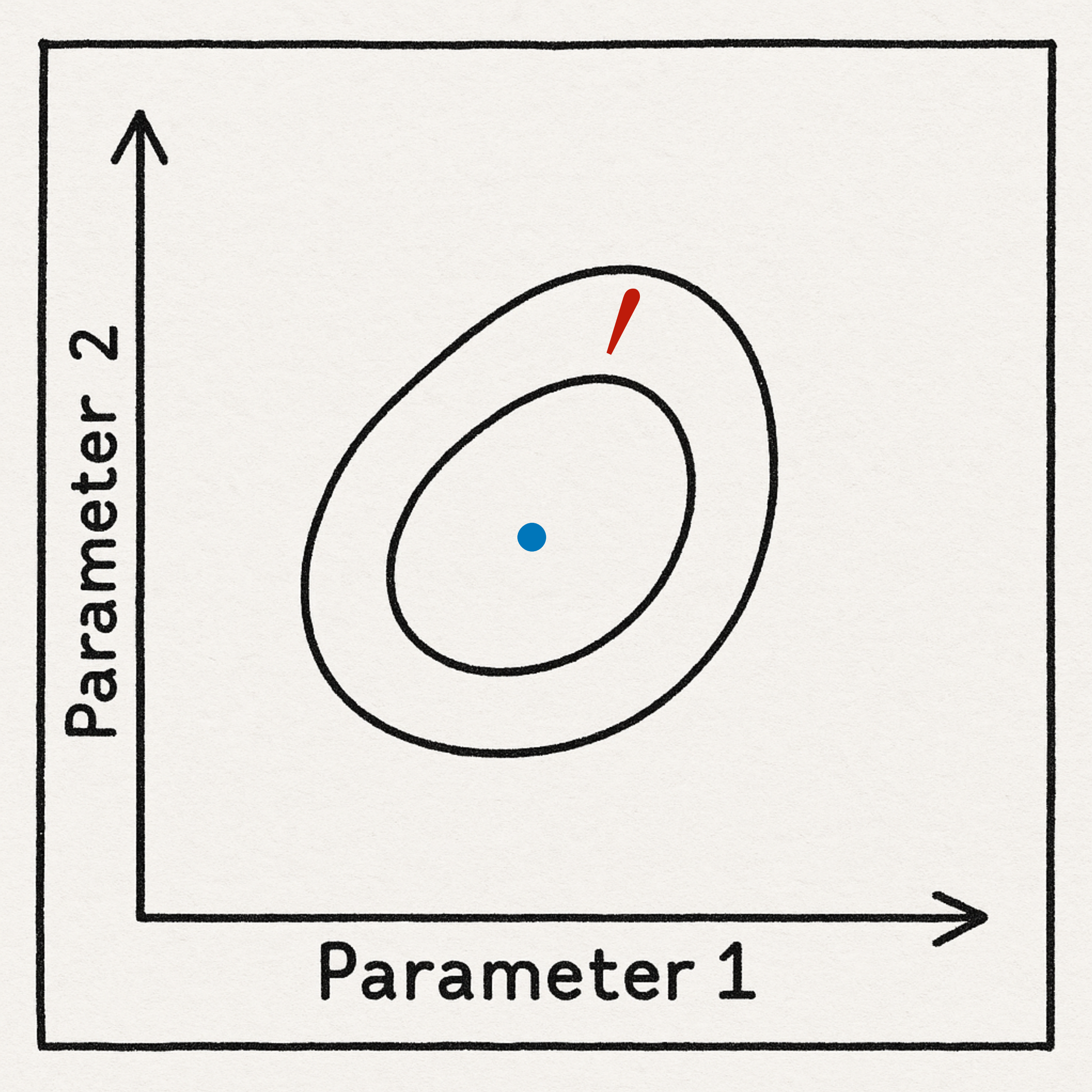
$$M(\theta) = X$$



Deep-time climate: a boundary condition problem

An ideal approach:
Parameter Estimation

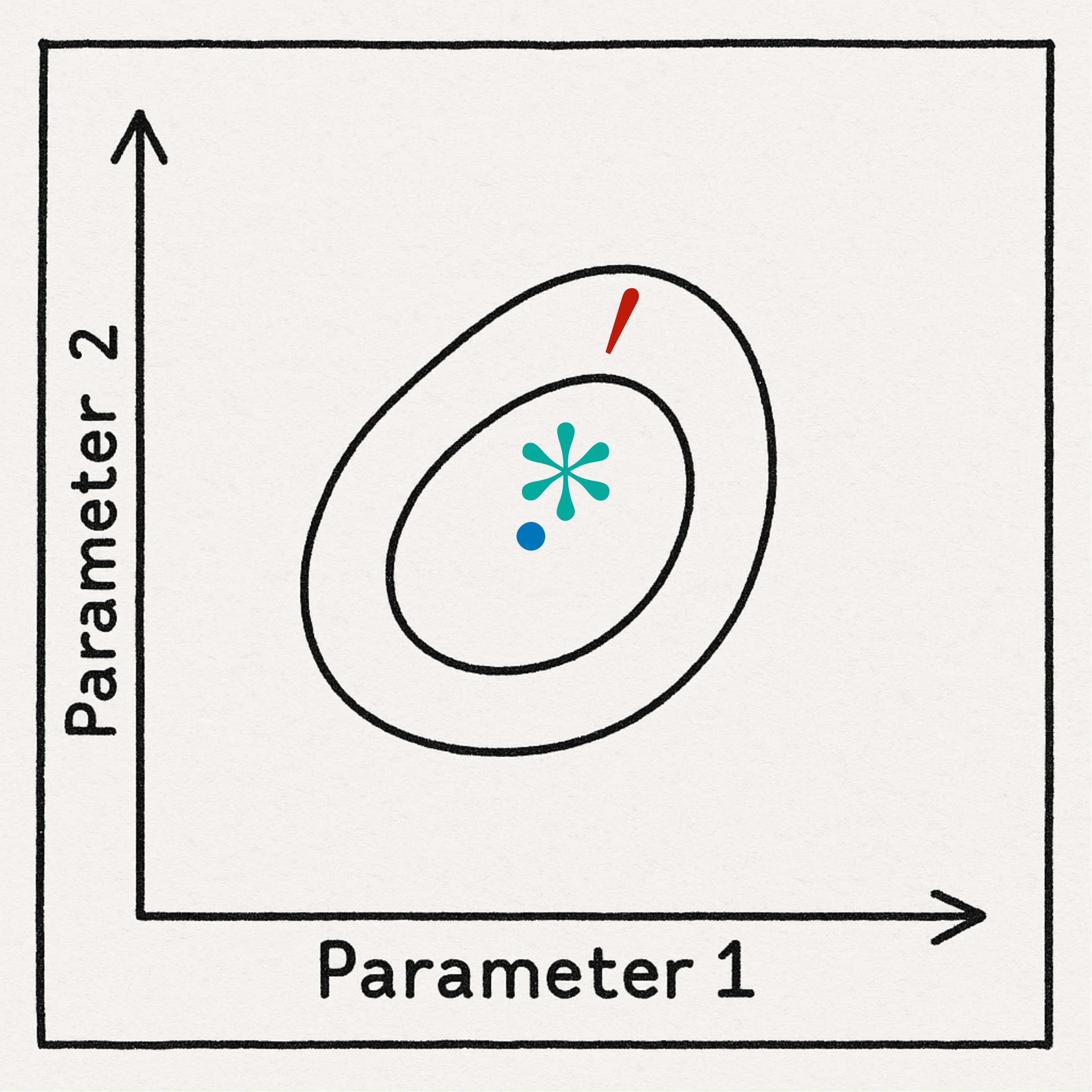
$$M(\theta) = X$$
$$M(\theta') = X'$$



Deep-time climate: a boundary condition problem

An ideal approach:
Parameter Estimation

$$M(\theta) = X$$
$$M(\theta') = X'$$
$$M(\theta^*) = X^*$$



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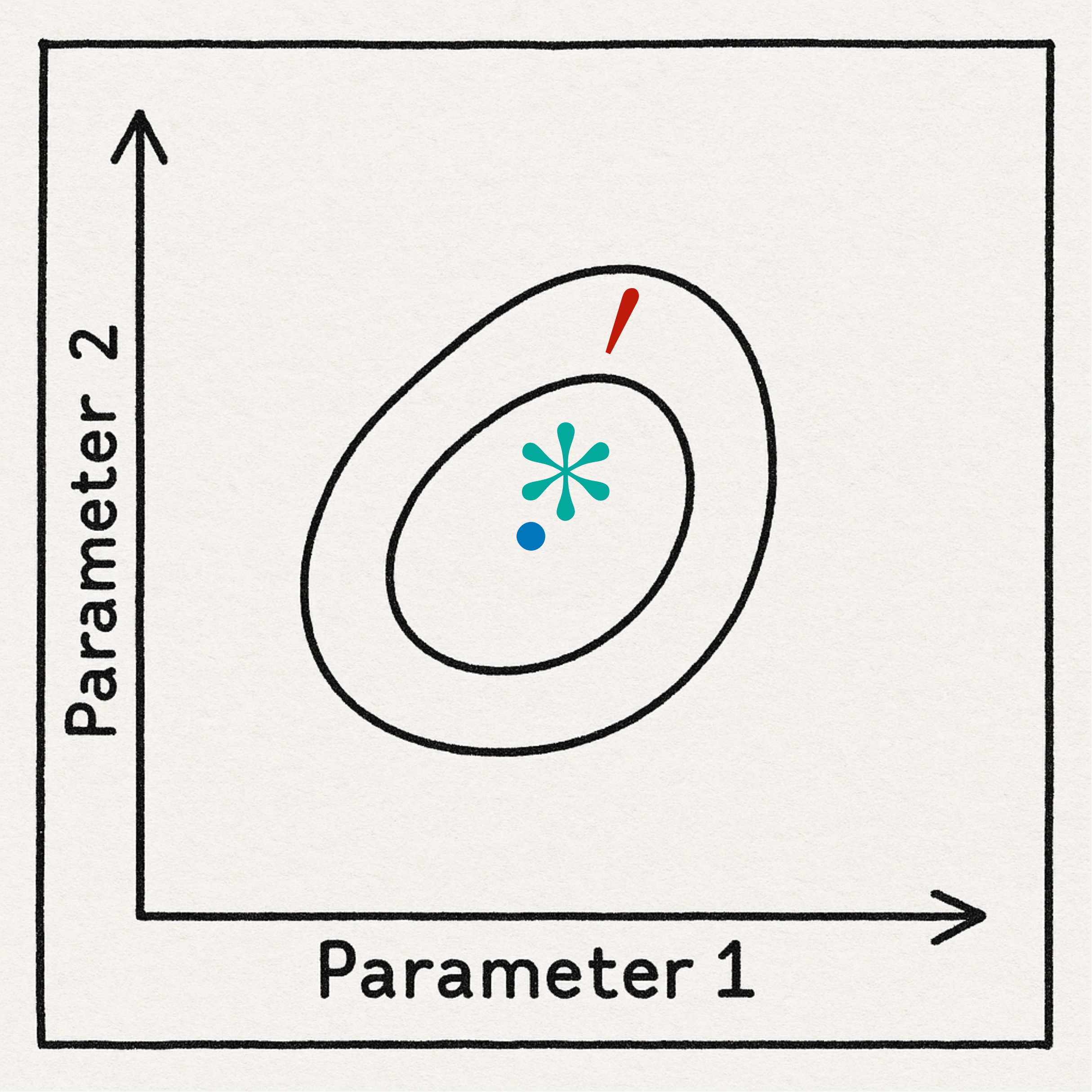
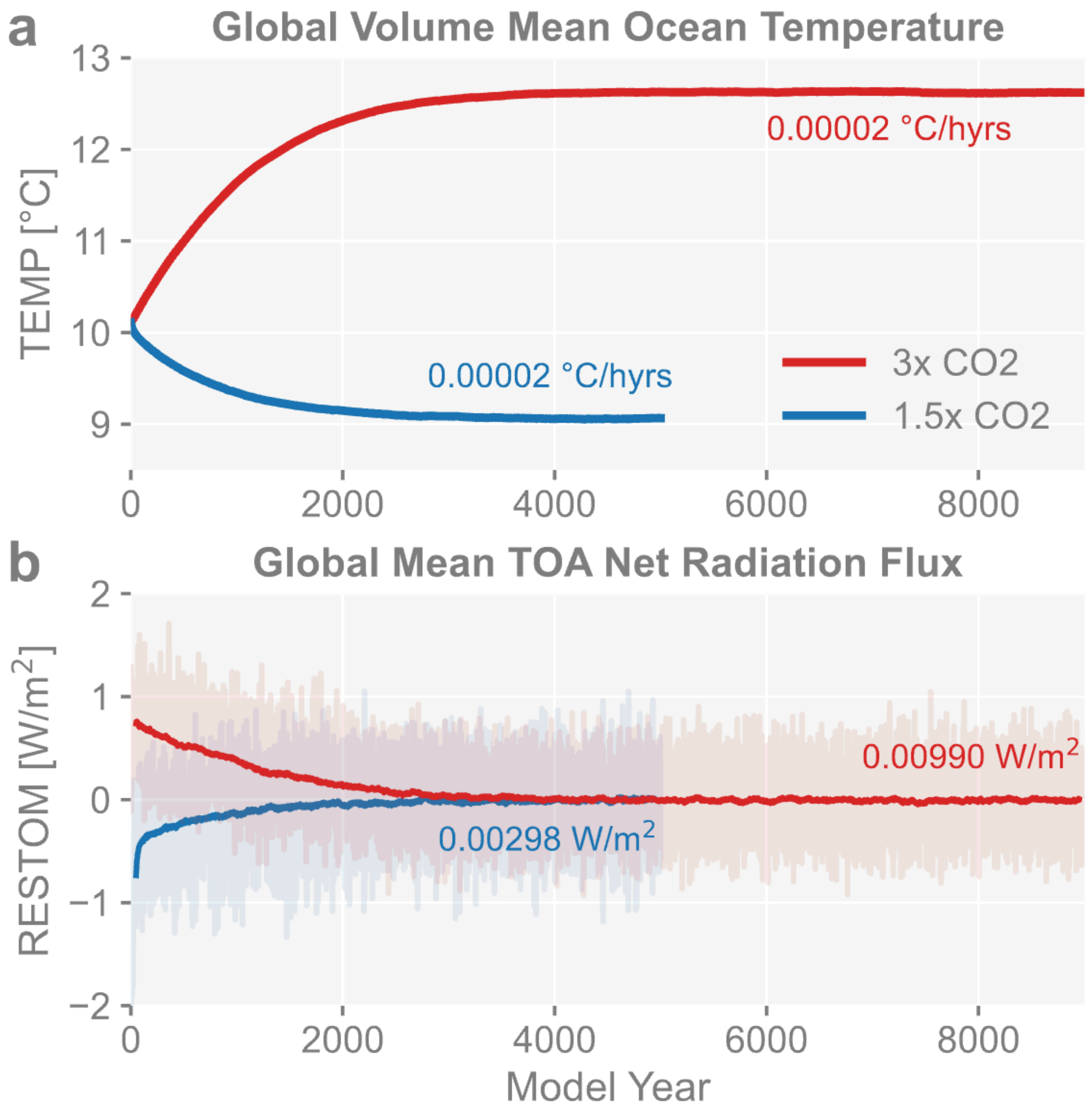


However, M is slow and expensive.



Zhu et al. (submitted to *Nat. Geosci.*)

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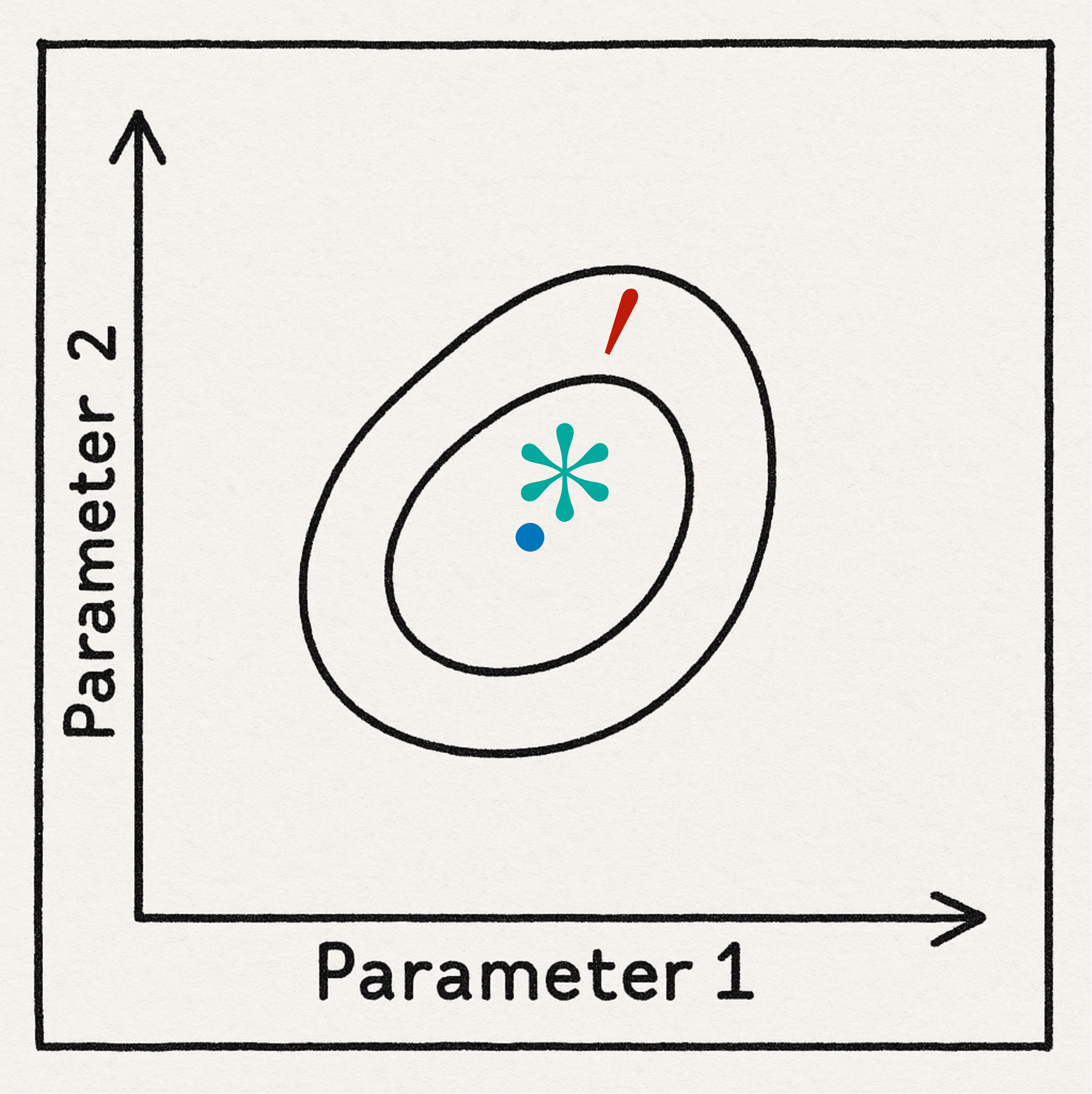
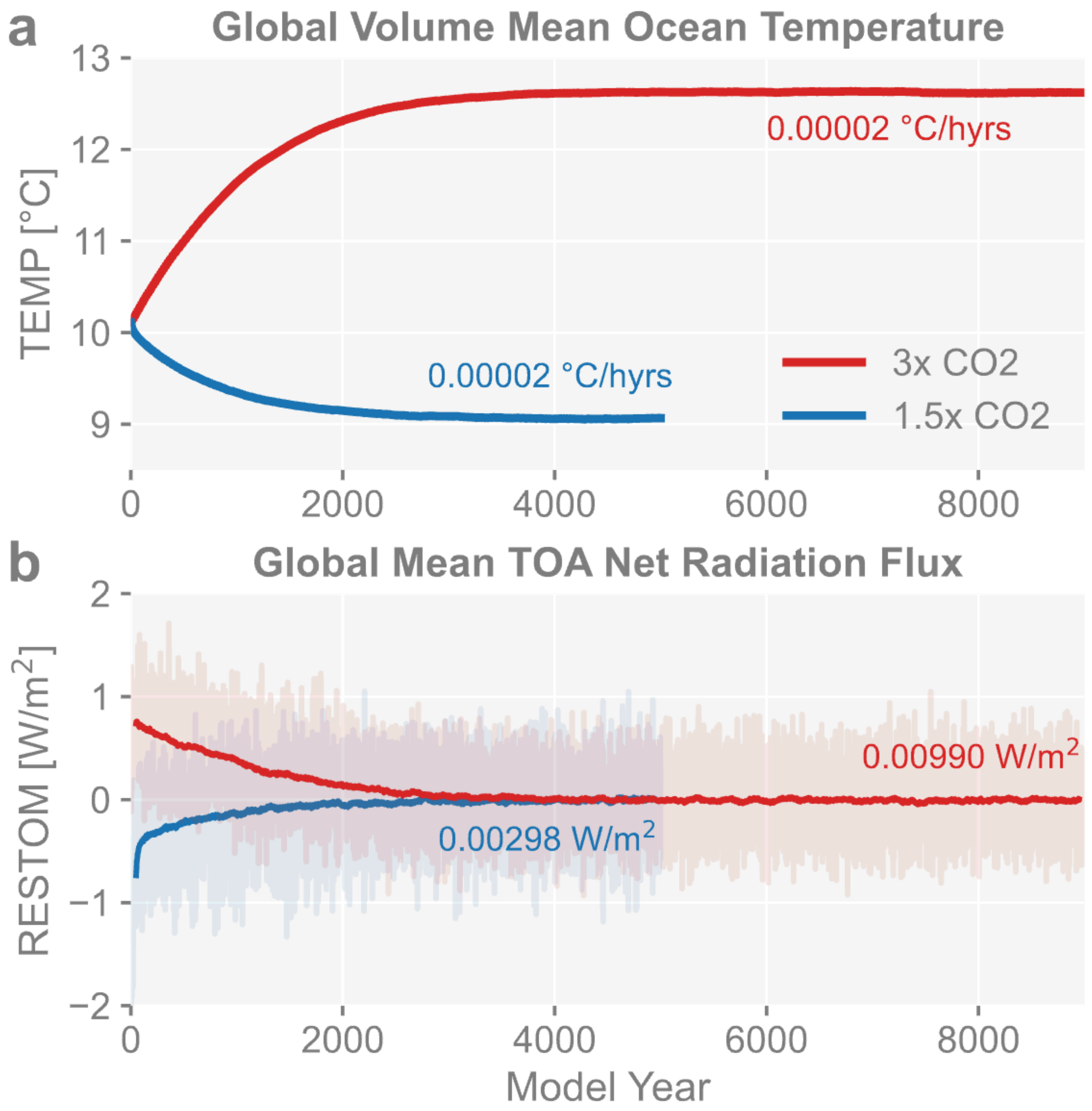


A more feasible approach:

$$M(\theta', f_X) = X^*$$

However, M is slow and expensive.



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A new online paleoDA approach in CESM

Goal:

- fit the SST proxy observations
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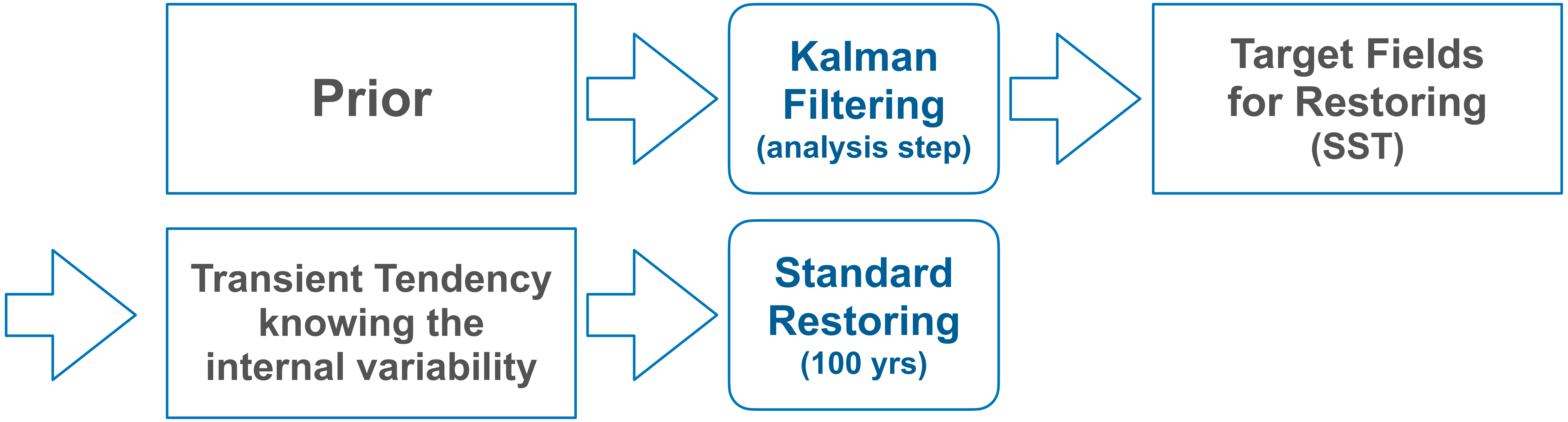


μ

$$\frac{dX(t)}{dt} = -\frac{1}{\tau}(X(t) - \mu)$$

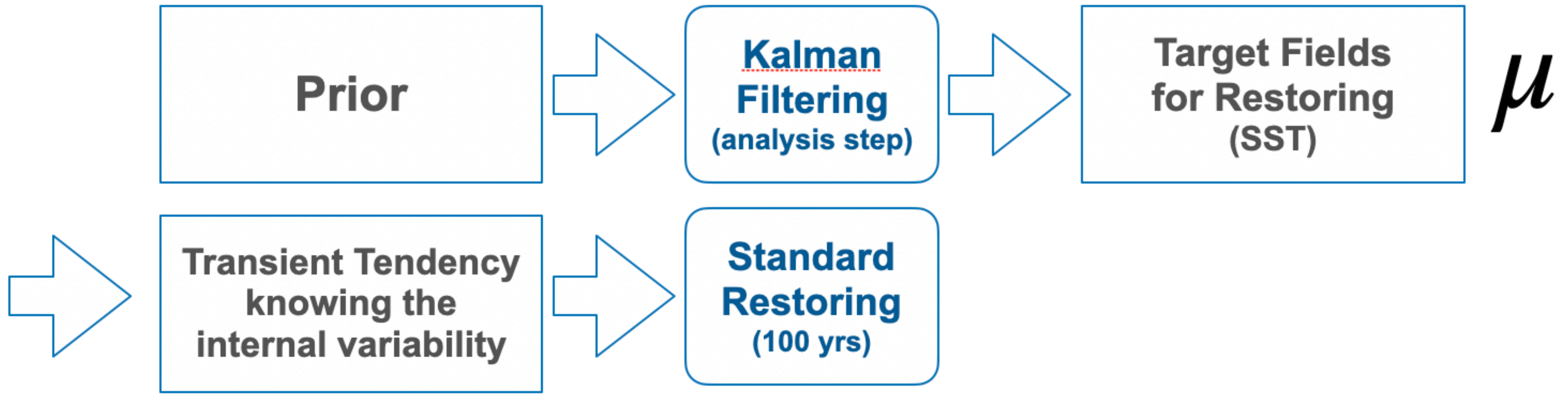
$$M(\theta', f_X) = X^*$$

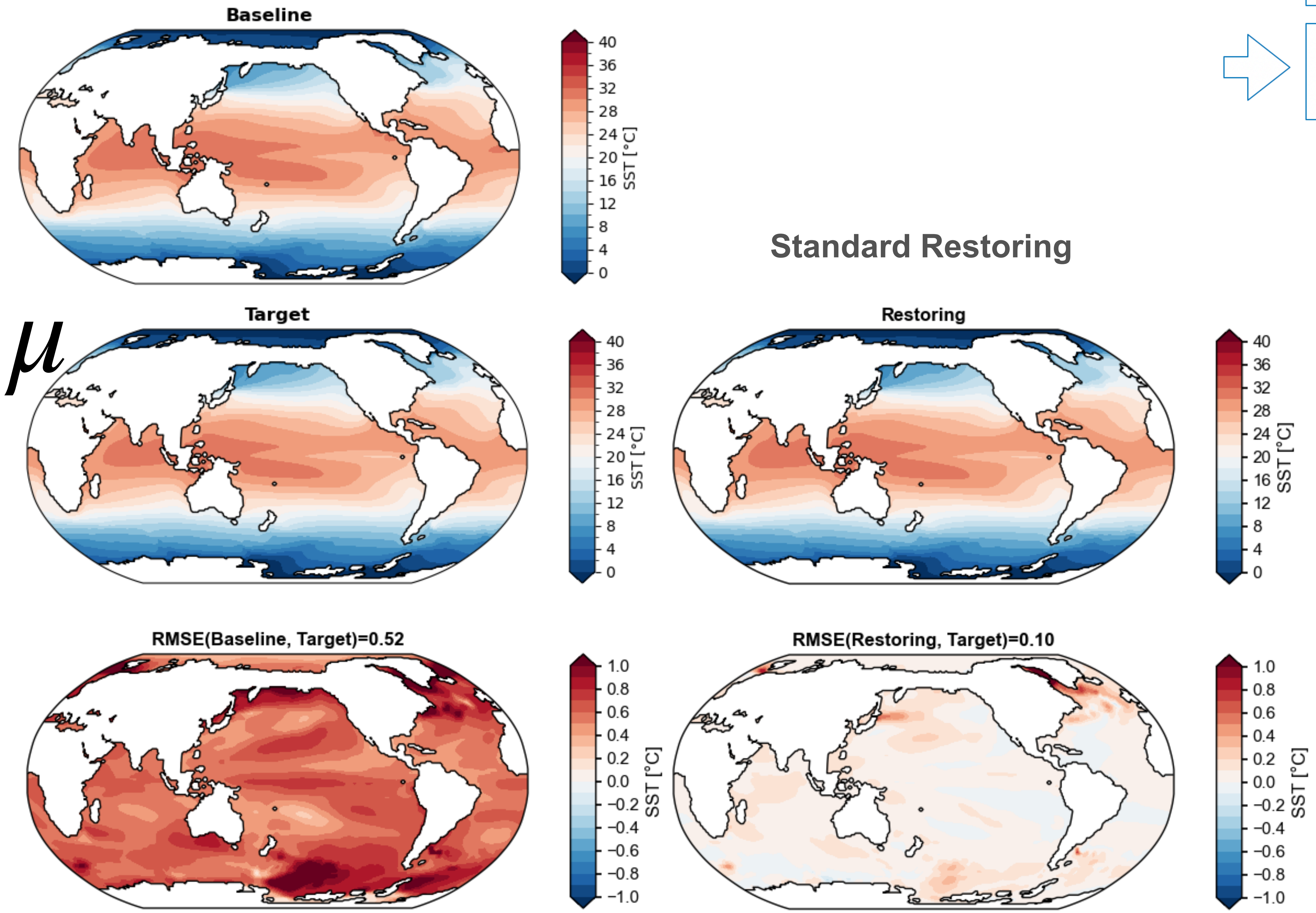
An ideal test on a Pliocene case

The Sea Surface Temperature Field

Baseline: 400ppm (Feng et al., 2020) **extended for another 800 yrs**

Target: 350ppm, branched from 400ppm (Feng et al., 2020) **and extended for another 400 yrs**





An ideal test on a Pliocene case

The Land Surface Temperature Field

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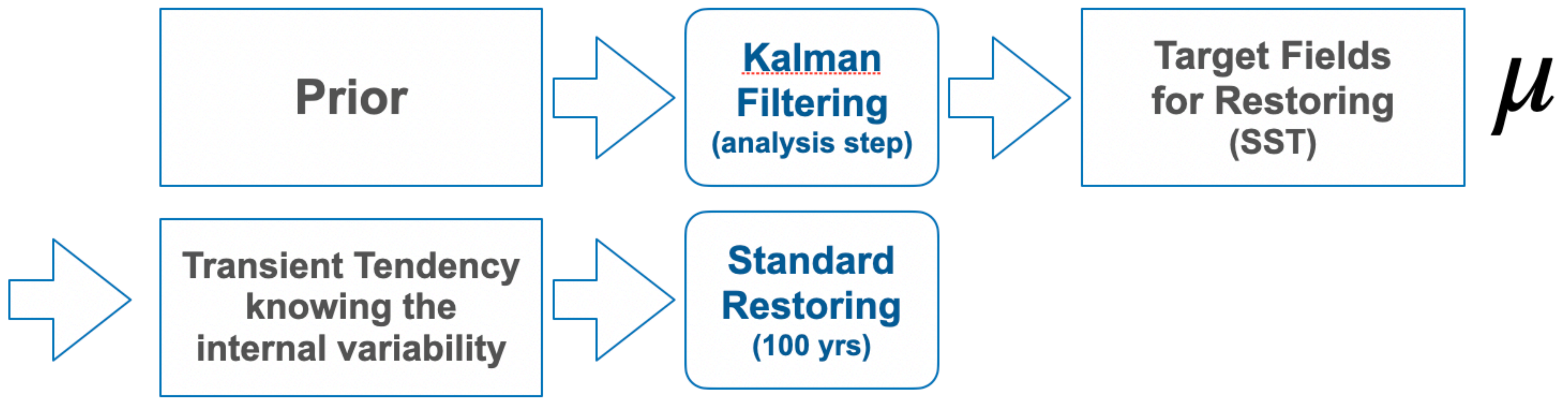
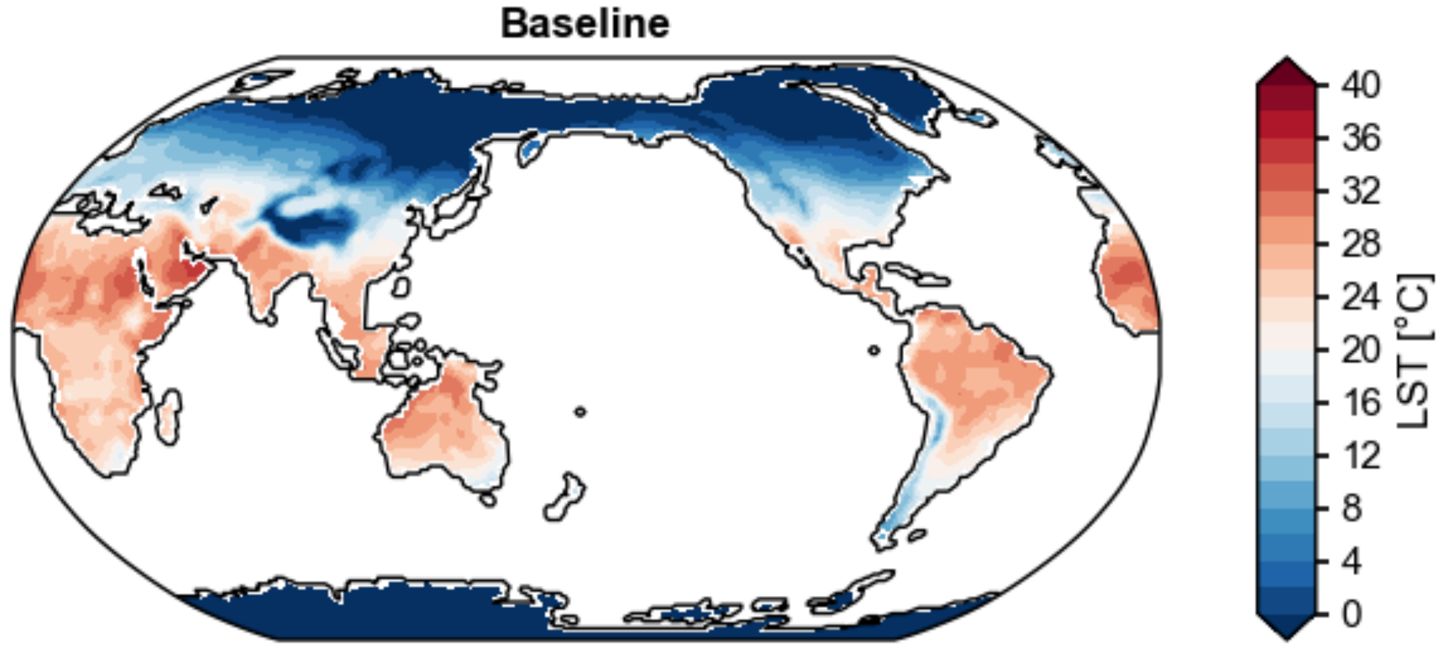
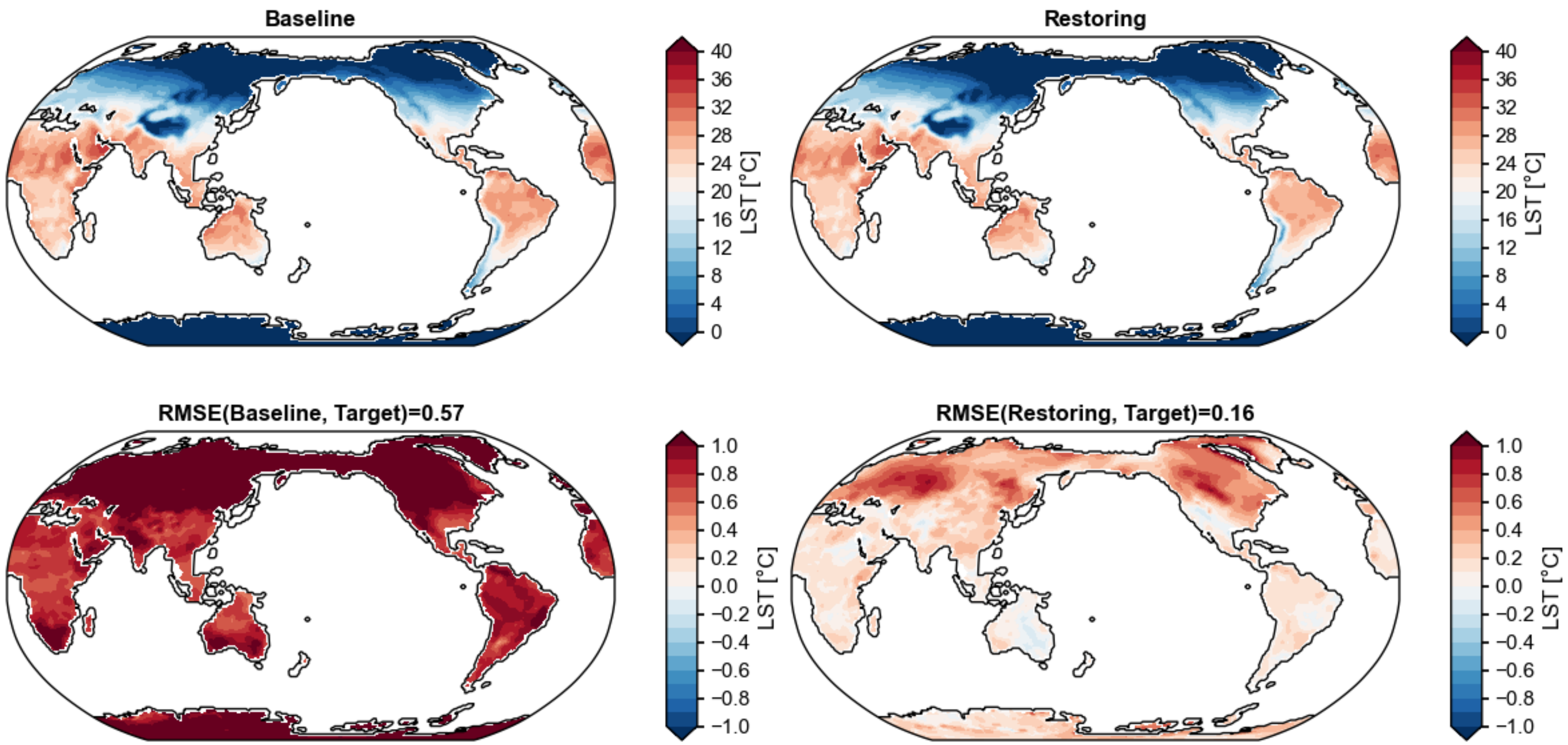




Standard Restoring



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The Sea Ice Area Field

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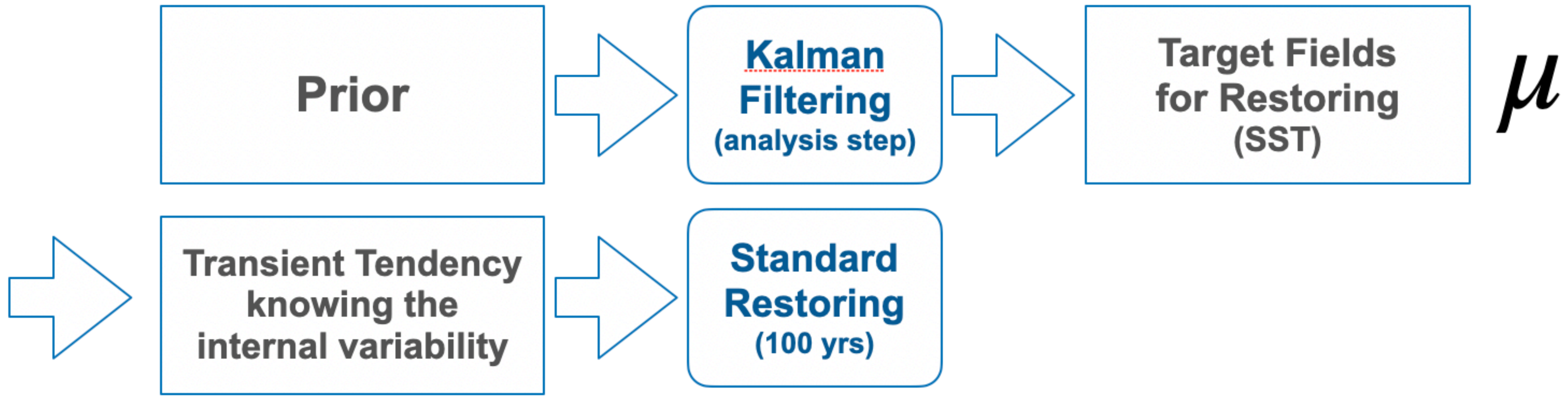
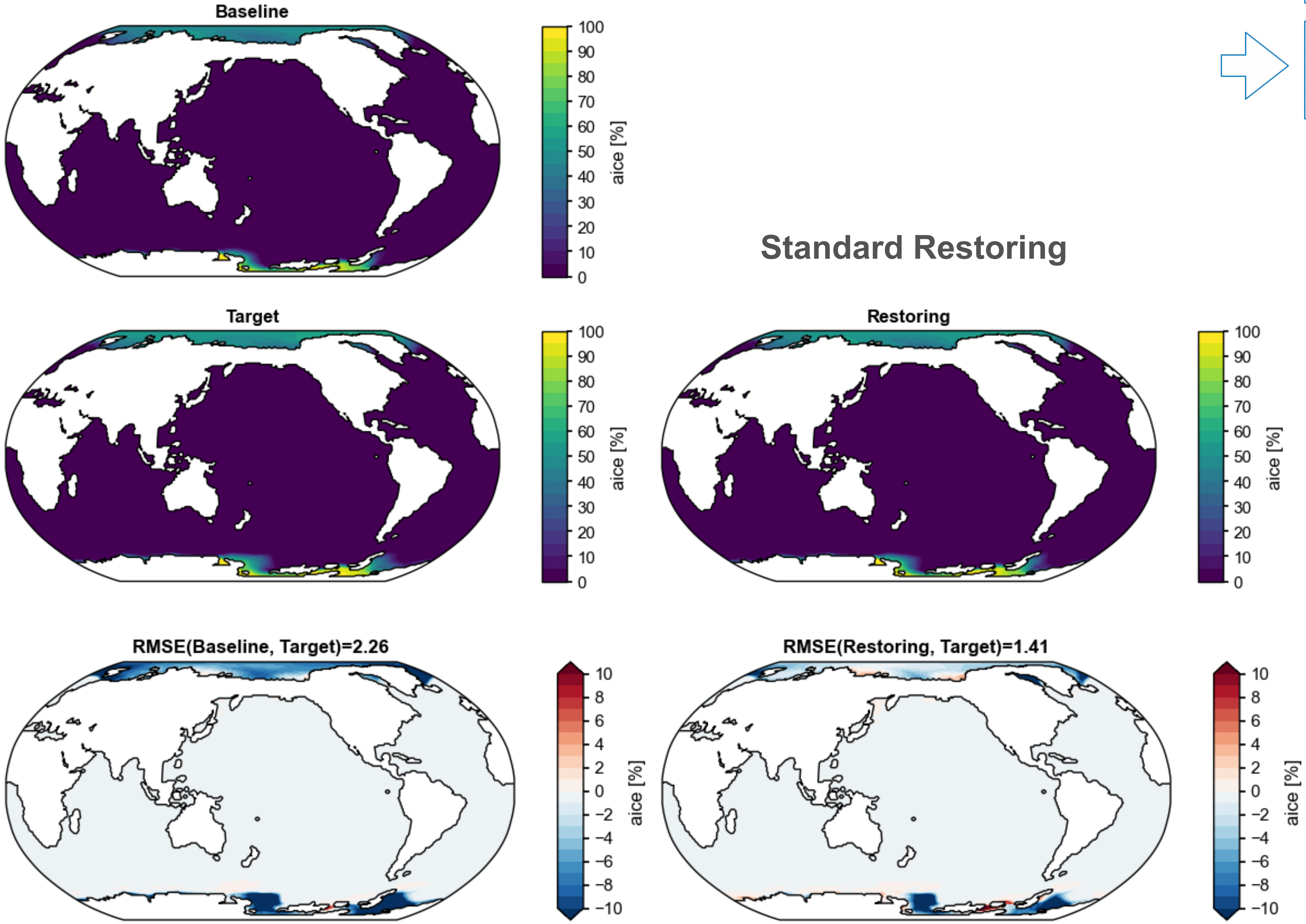
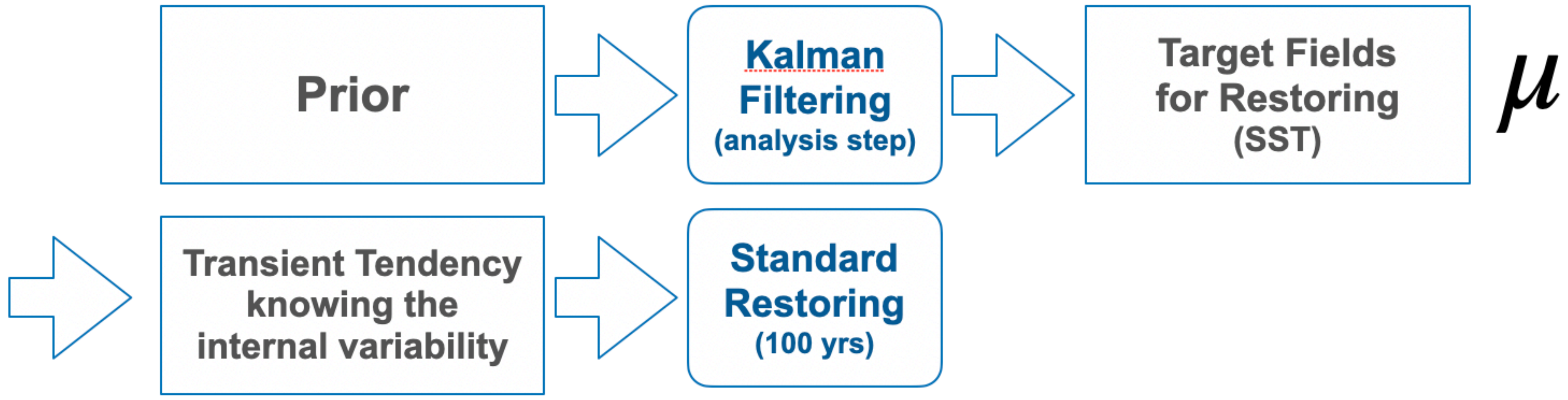




An ideal test on a Pliocene case

The Total Precipitation Rate Field



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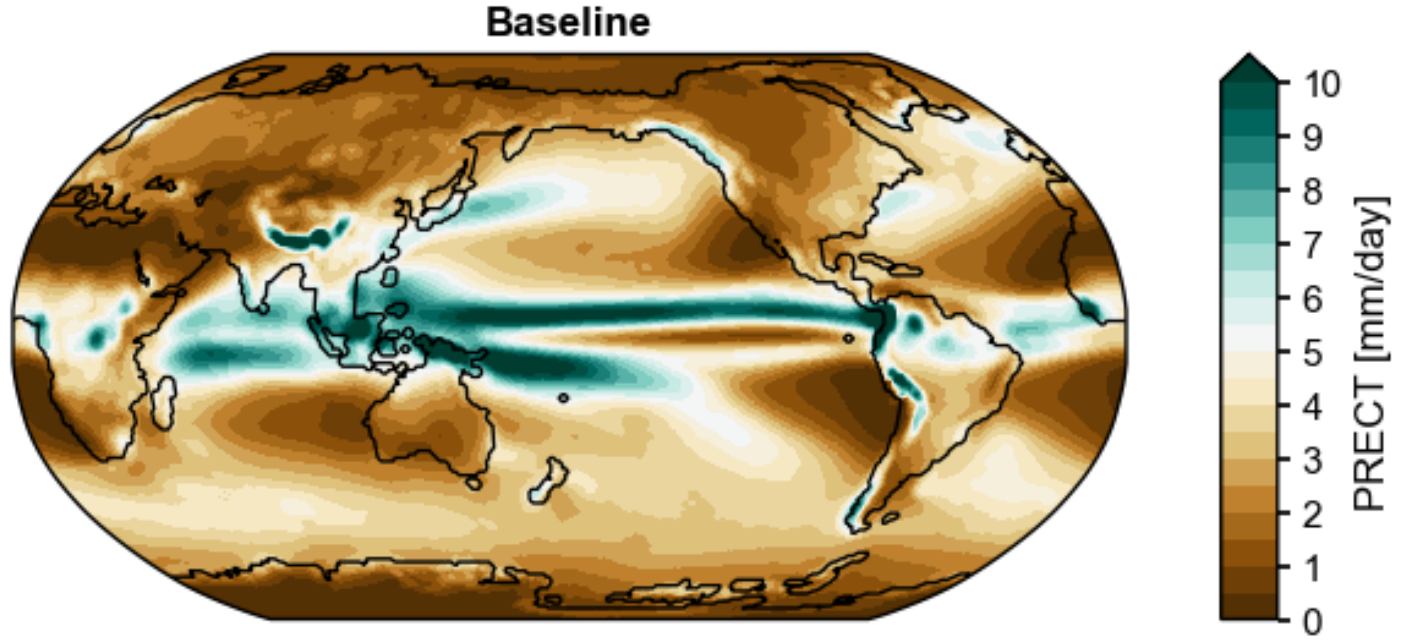

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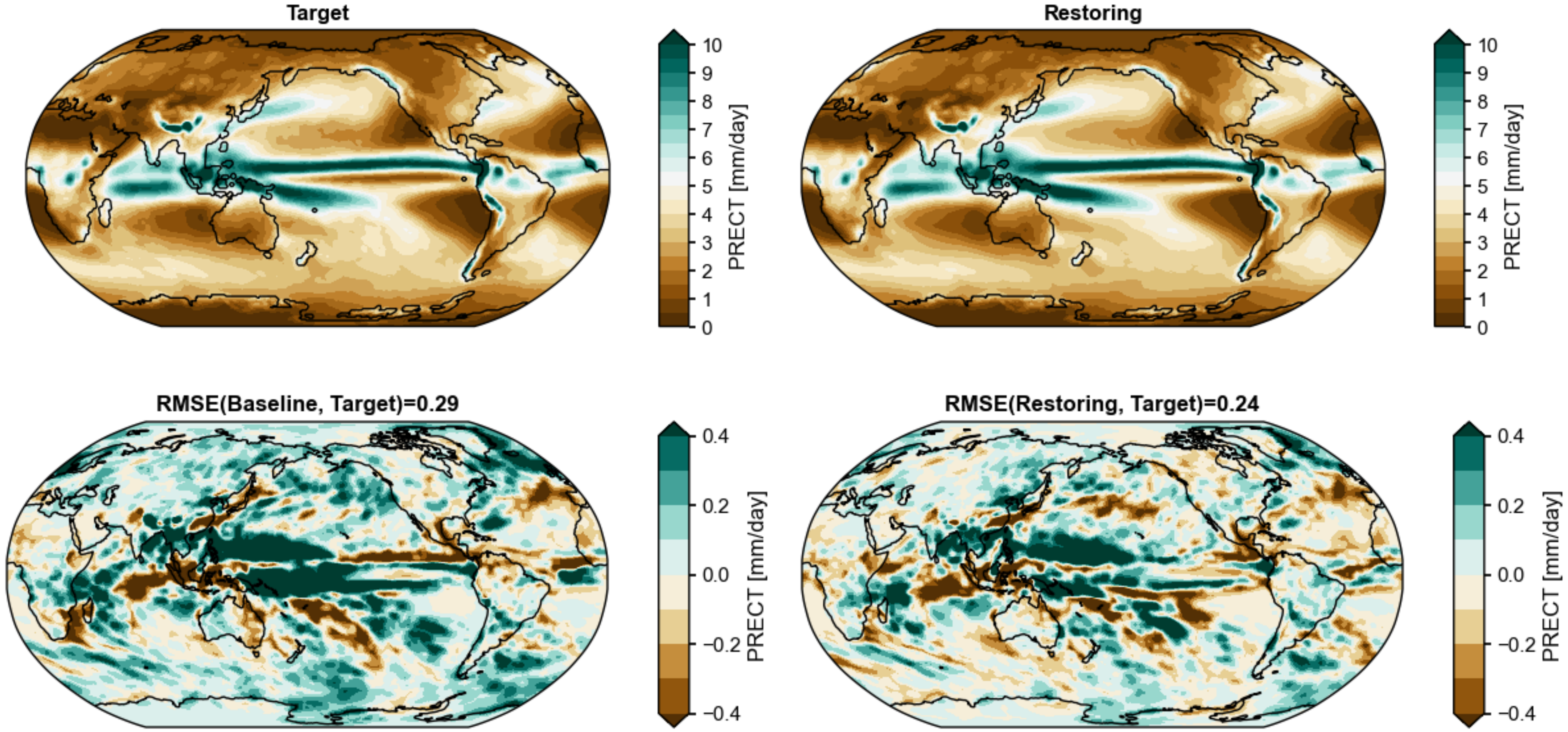

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The Sea Surface Salinity Field

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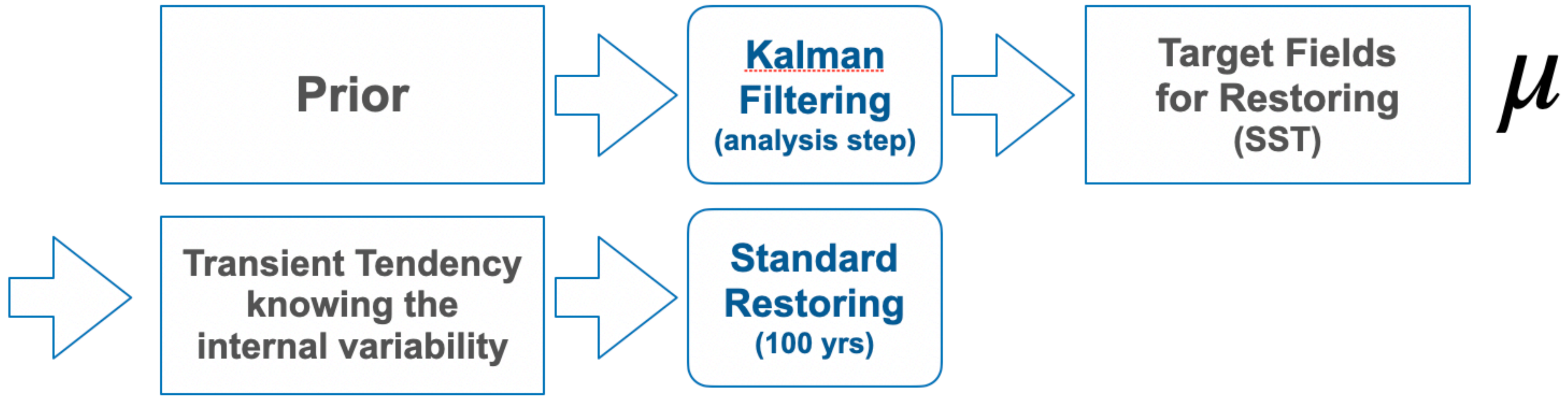

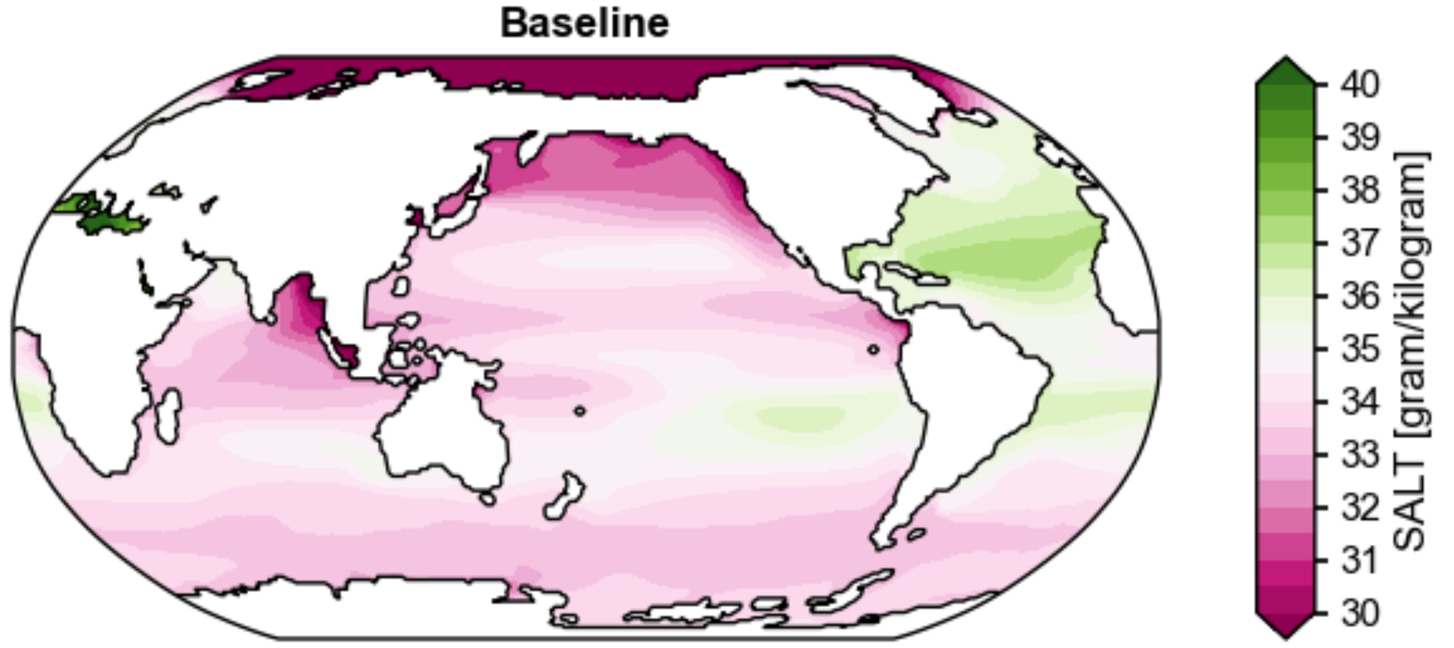

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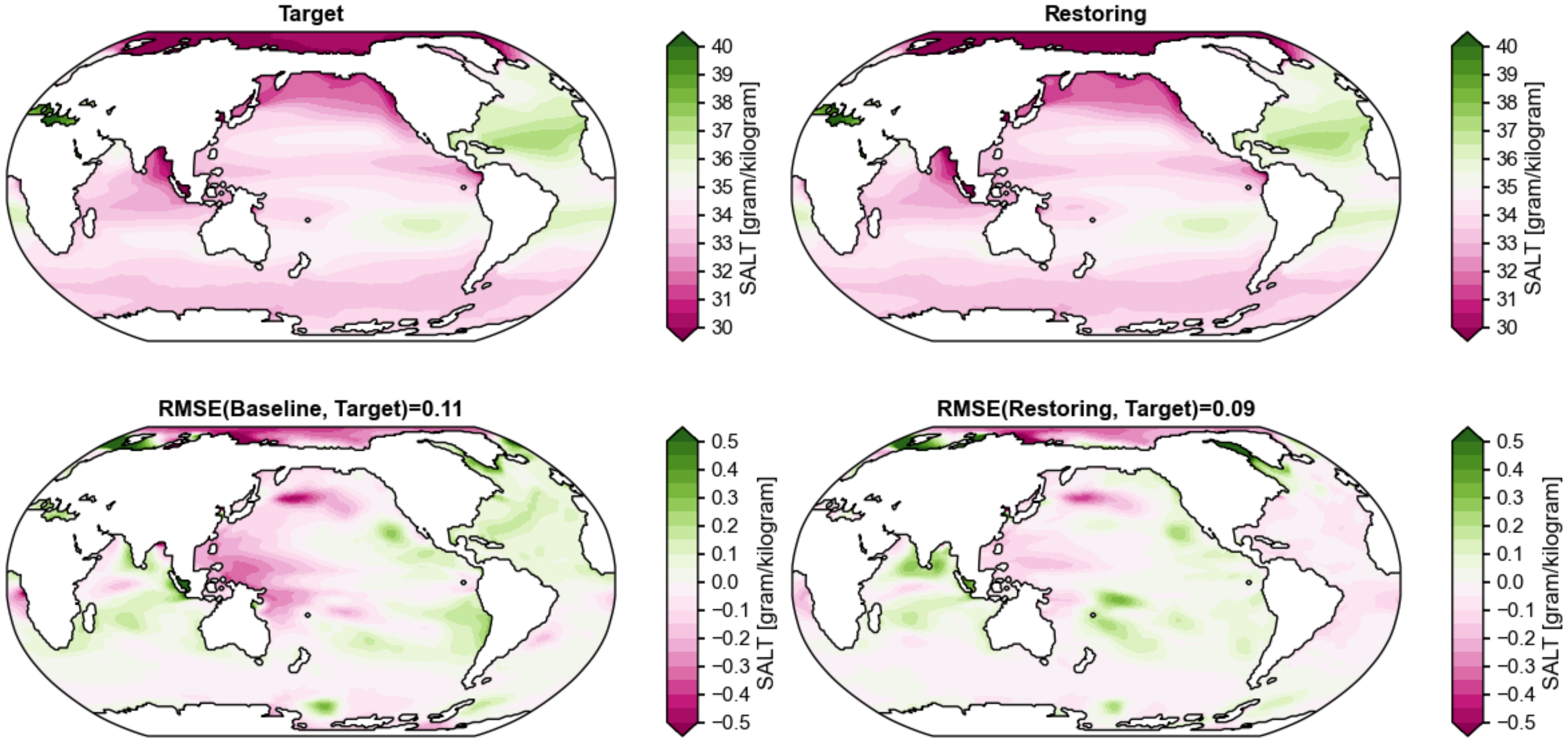

An ideal test on a Pliocene case

The Meridional Overturning Circulation (MOC)

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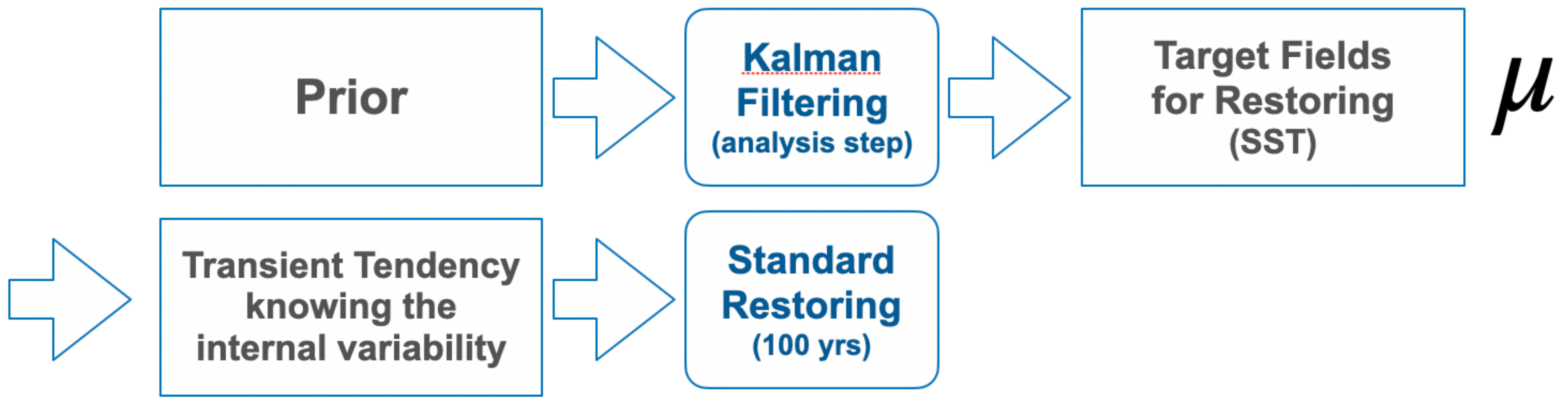

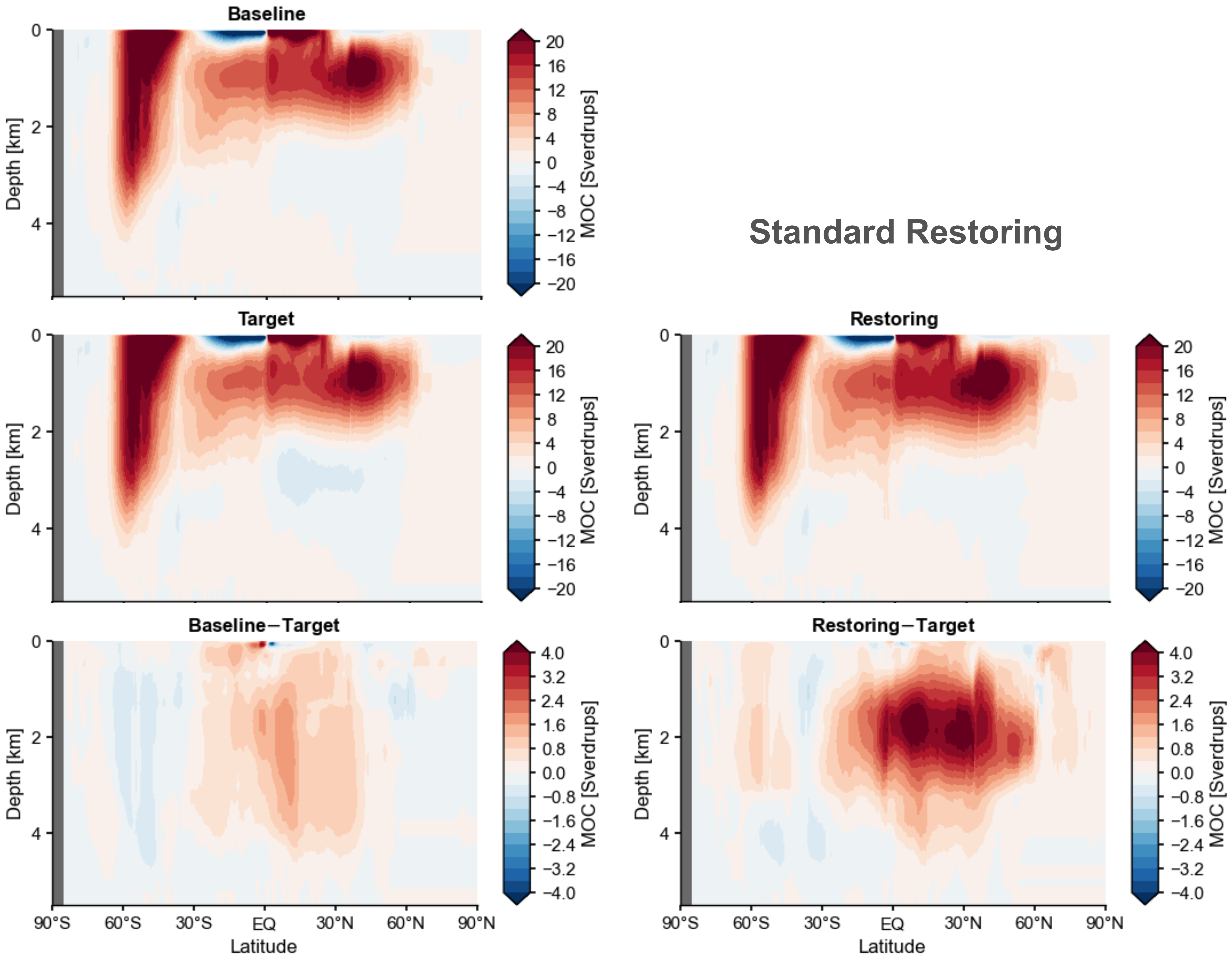

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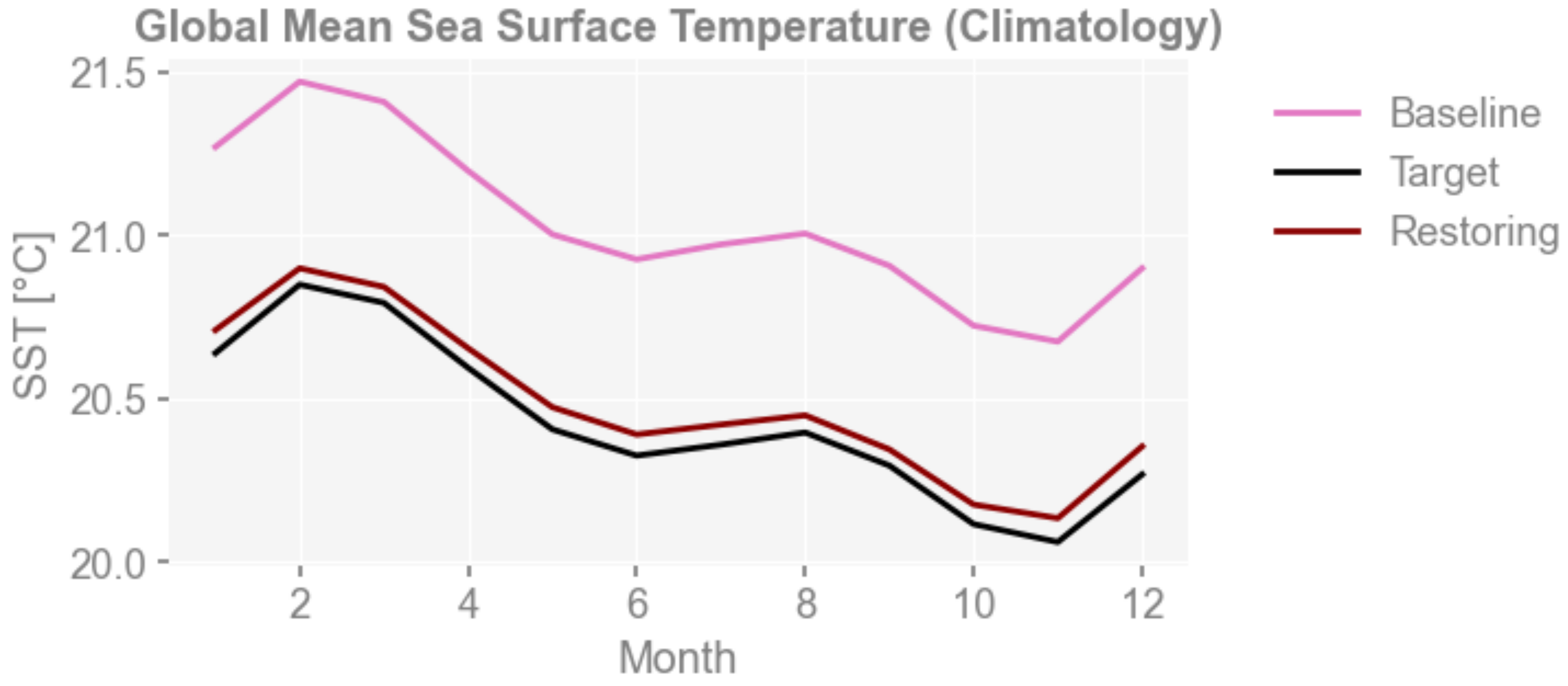
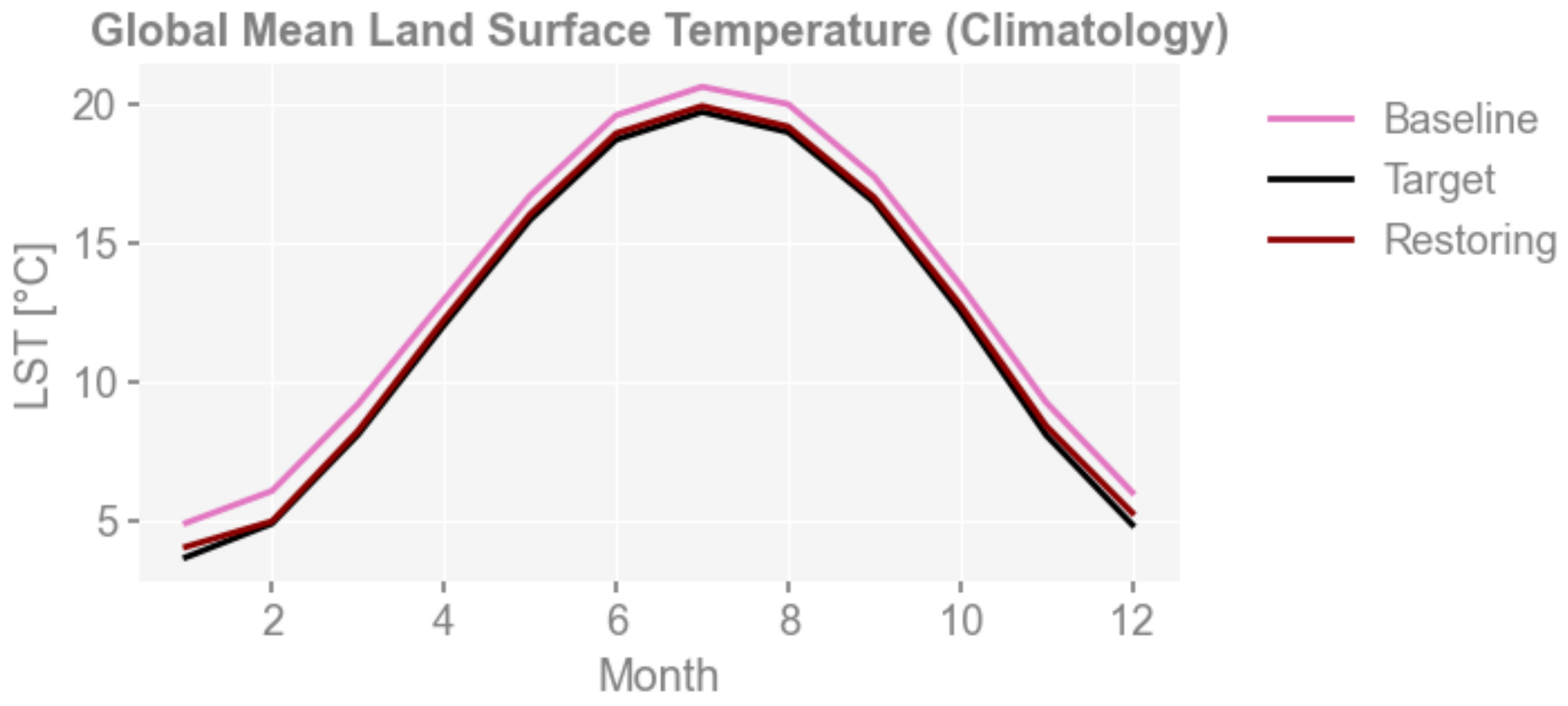
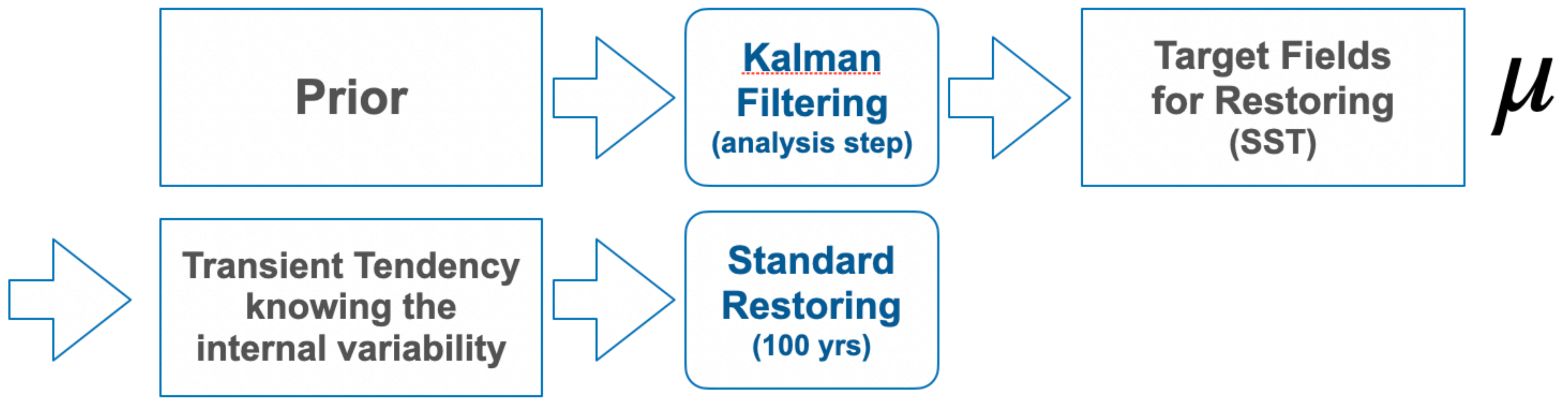
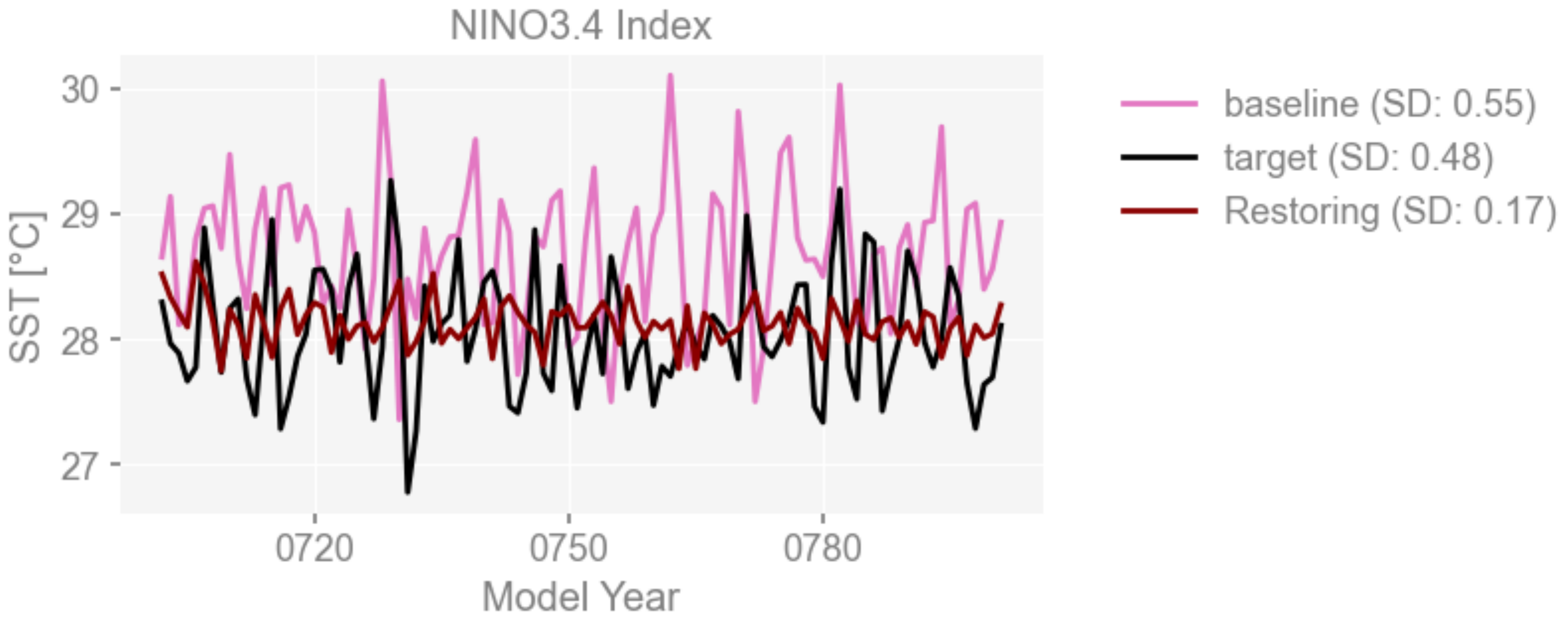




The Internal Variability





A new online paleoDA approach in CESM

Goal:

- fit the SST proxy observations
- a running data-informed model
- avoid unphysical disruptions (e.g., internal variability)

Prior → **Kalman Filtering** (analysis step) → Target Fields for Restoring (SST) μ

→ Transient Tendency knowing the internal variability → **Standard Restoring** (100 yrs) → Fixed Tendency *not* knowing the internal variability → **Fixed-Tendency Restoring** (100+ yrs)

$$\frac{dX(t)}{dt} = -\frac{1}{\tau}(X(t) - \mu)$$

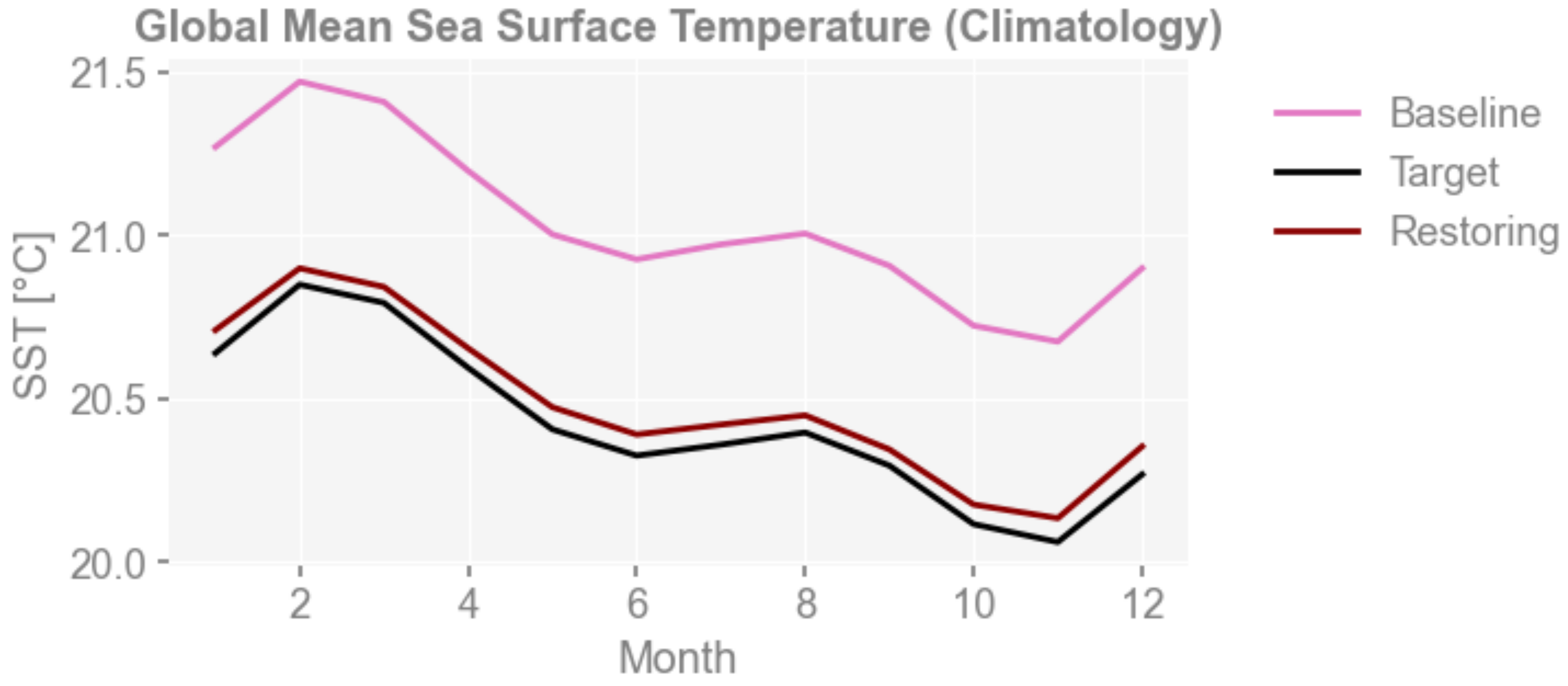
$$\frac{dX(t)}{dt} = -\frac{1}{\tau}(X_{eq} - \mu)$$

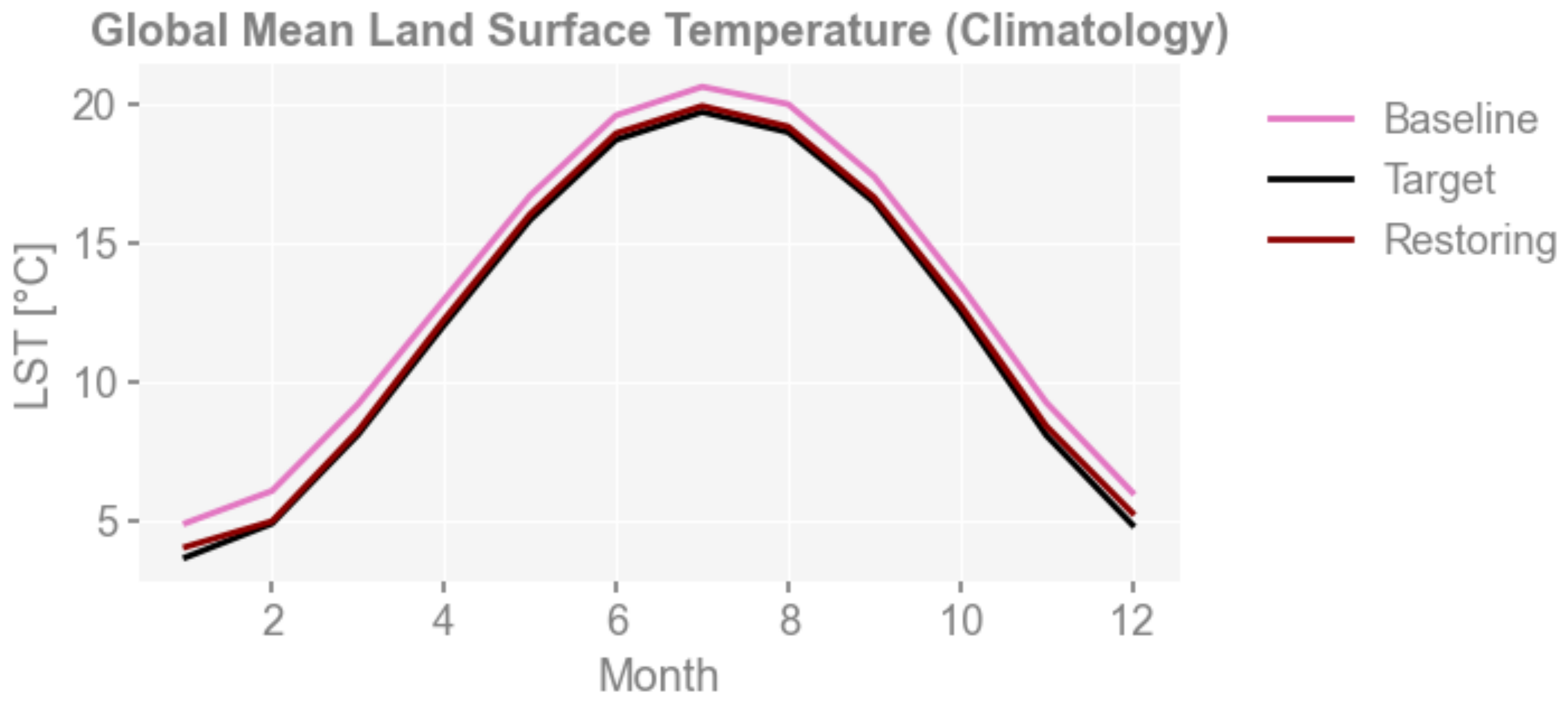
$$M(\theta', f_X) = X^*$$

An ideal test on a Pliocene case

Baseline: 400ppm (Feng et al., 2020) **extended for another 800 yrs**

Target: 350ppm, branched from 400ppm (Feng et al., 2020) **and extended for another 400 yrs**





The Internal Variability

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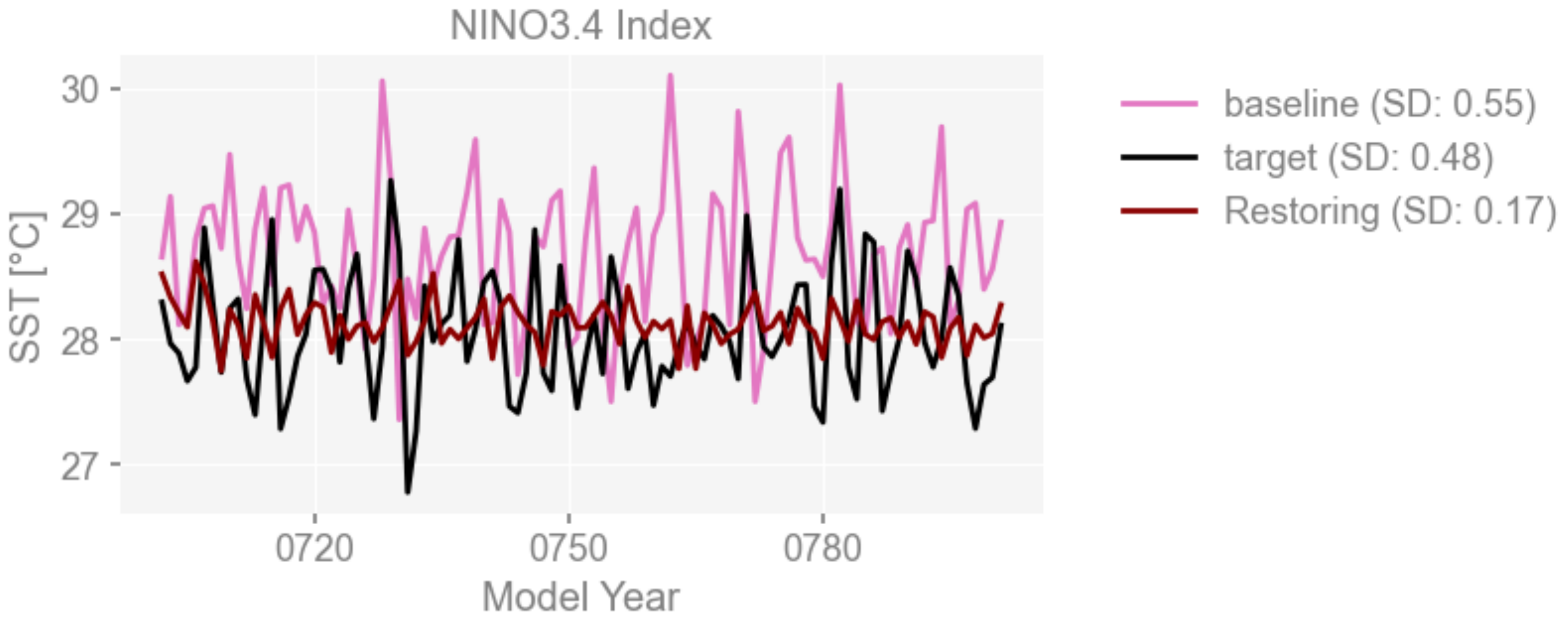
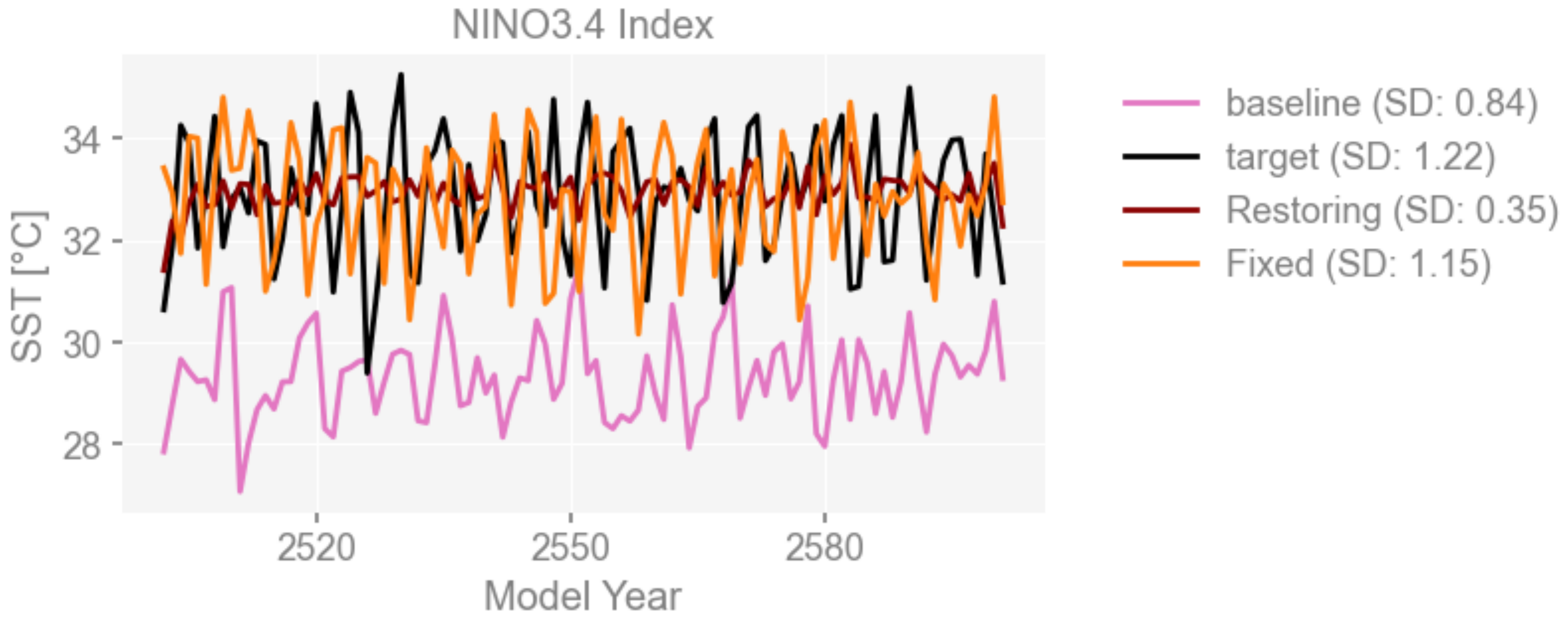


Another test case on Miocene Climatic Optimum



Summary

- We propose **a new online paleoDA approach in CESM** for deep-time climate reconstruction.
- We perform an ideal test on Pliocene climate reconstruction and get **a data-informed model** that:
  - fits the **SST proxy observations**,
  - yields **dynamically consistent multivariate & spatial relationships**,
  - allows assessing **internal variability** under different climatological patterns,
  - much more **expensive** to run compared to offline paleoDA (wall-time: days vs minutes).
- **Preliminary** results. Welcome comments & suggestions!

Advancing Deep-Time Climate Reconstruction with a New Online Paleoclimate Data Assimilation Approach in CESM

An Ongoing Research of the *paleoWeather* Project

Thank you!

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1. NSF NCAR 2. U Arizona 3. U Oregon 4. UC Irvine 5. U Connecticut

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