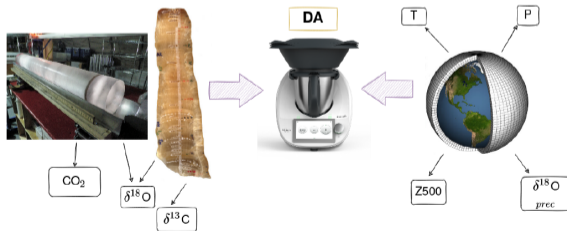


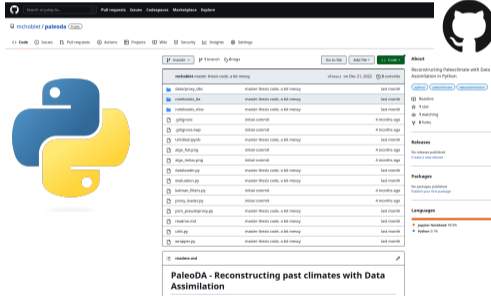
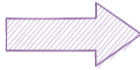
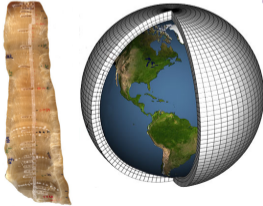
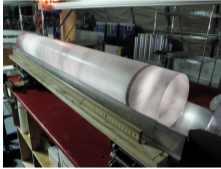
# Reconstructions of climate fields of the last millennium with Paleoclimate Data Assimilation

Mathurin Choblet  
mchoblet@iup.uni-heidelberg.de  
Climatology seminar  
February 6, 2023



## Central task

Implement a framework for PaleoDA with speleothem and ice core data



The screenshot shows the GitHub repository page for 'michoblet/paleoda'. The repository is titled 'Reconstructing Paleoclimate with Data Assimilation in Python'. It has 11 stars and 3 forks. The repository is a Python package. The main file is 'README.md', which contains the following text:

```
## paleoda

Reconstructing past climates with Data Assimilation
```

## Scientific questions

- What are the **characteristics** of reconstructed global and regional (hydro)climate for the last millennium?

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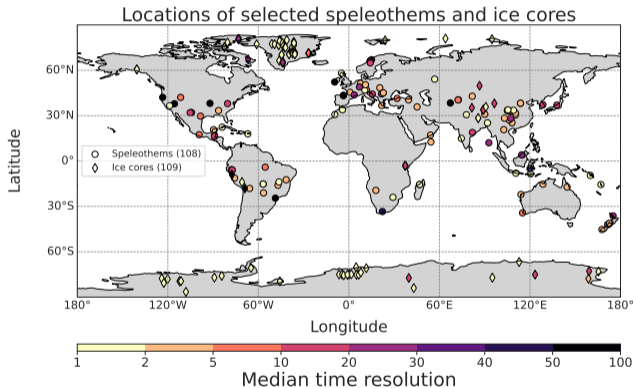
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## Scientific questions

- What are the **characteristics** of reconstructed global and regional (hydro)climate for the last millennium?
- How do the speleothem and ice core records **contribute** to the climate reconstructions?
- What is the **temporal variability** of the reconstructions?
- How do **model-biases** and **inter model-differences** affect the PaleoDA reconstructions?

## Proxy records ( $\delta^{18}\text{O}$ )

- Speleothems (SISAL v2)
- Ice cores (Iso2k)

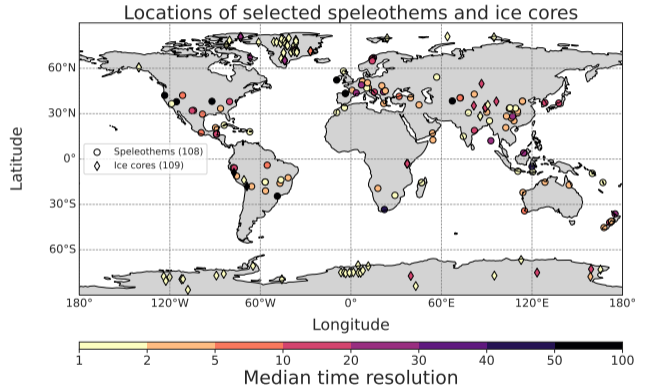


## Proxy records ( $\delta^{18}\text{O}$ )

- Speleothems (SISAL v2)
- Ice cores (Iso2k)

## Models (isotope-enabled)

- ECHAM5-wiso (96 x 48)
- iHadCM3 (96 x 73)
- GISS (140 x 90)
- iCESM (144 x 96)
- isoGSM (192 x 94)





$X^{prior}$  Prior state (Climate model)

$Y$  Observations (Proxy records)

$H$  Observation operator (PSM)

$HX^{prior}$  Observation estimates

$R$  Measurement error

## Update and Kalman Gain equation

$$X^{prior} + K(Y - HX^{prior}) = X^{post}$$

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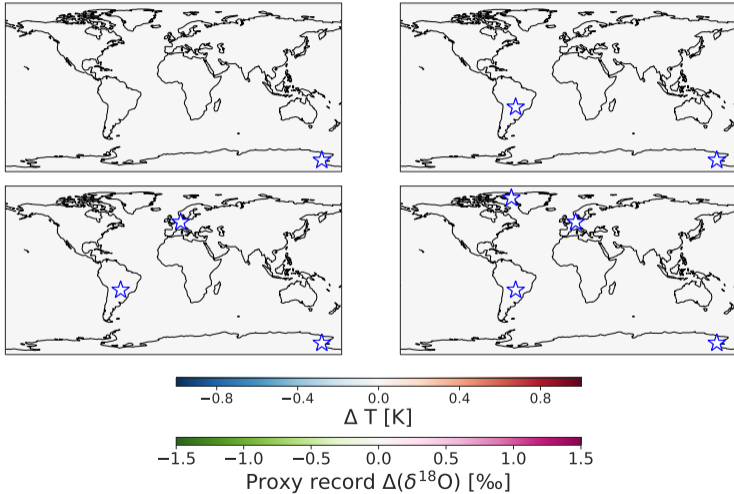
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- Covariance computation:
  - ⇒ **Ensemble** Kalman Filter
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- Ensemble Kalman Filter also computes posterior uncertainty (smaller)

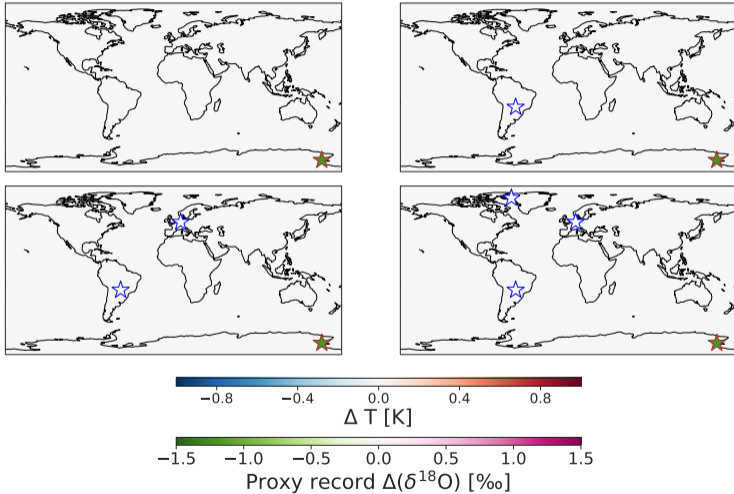
# The Method (example)

Assimilating 4  $\delta^{18}\text{O}$  measurements into a temperature field



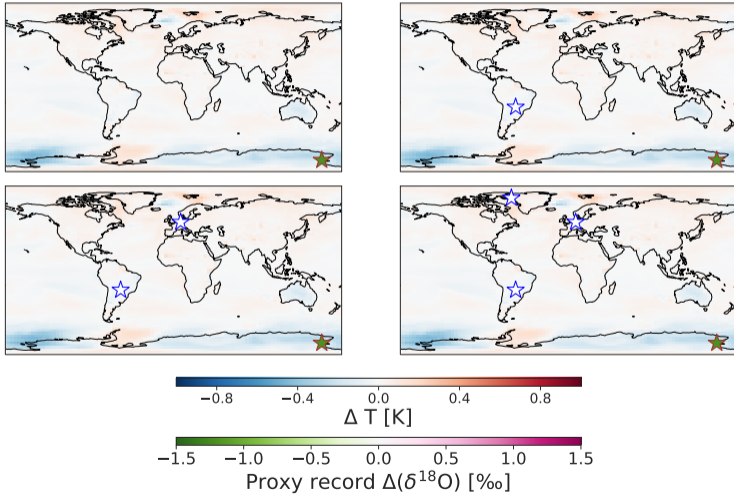
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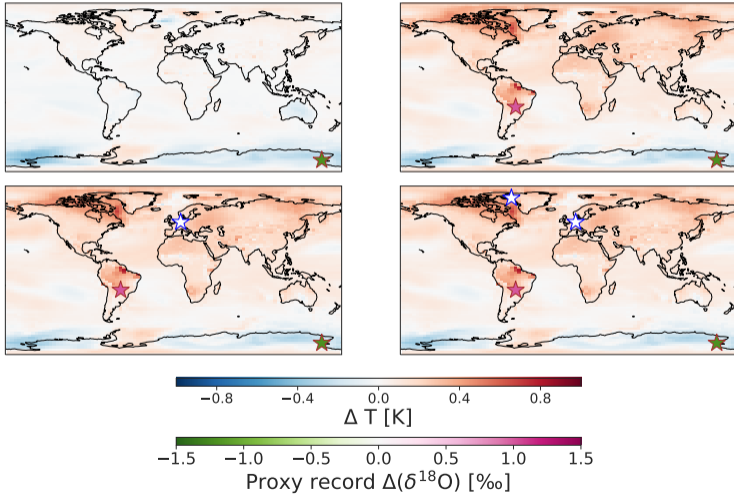
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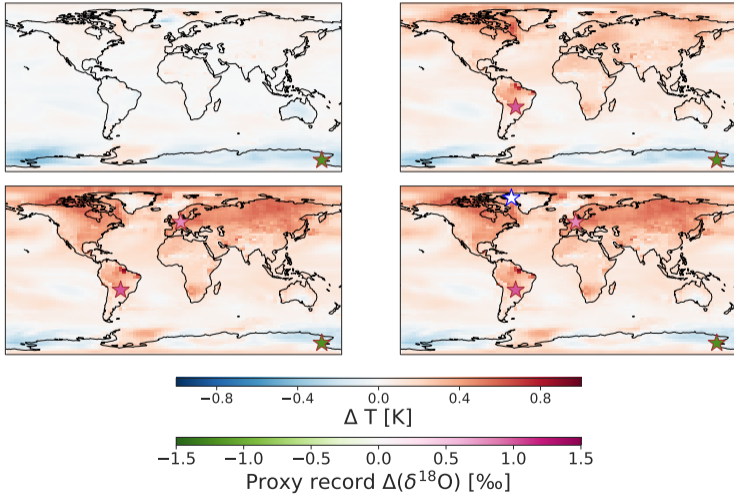
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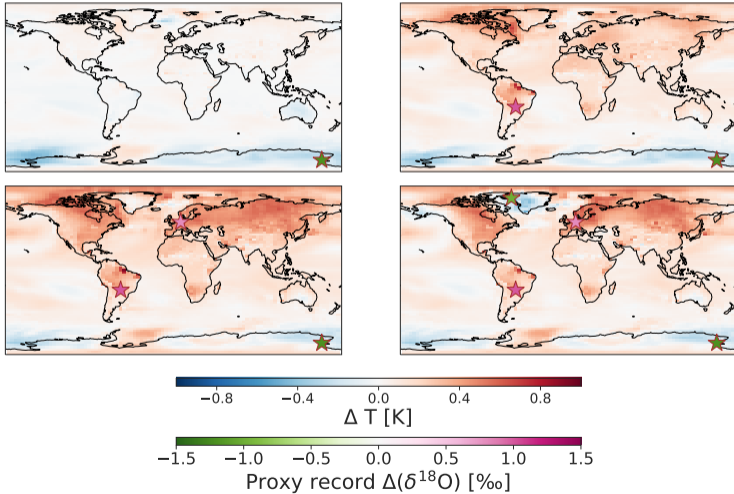
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Reconstruction method in short:

- Temporal information: Proxy records
- Spatial information: Simulation

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Two restrictions for the previous example

1. In practice: Simultaneous assimilation (computation speed is relevant)
2. Posterior uncertainties not shown in this example

- Large model-proxy  $\delta^{18}\text{O}$  offsets at individual locations
- Irregular time resolution of proxy records
- What is the right proxy record uncertainty?

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  - Question open because proxy-system-model not calibrated





PPE for temperature with  $\delta^{18}\text{O}$  from 217 proxy locations (SNR 0.5).

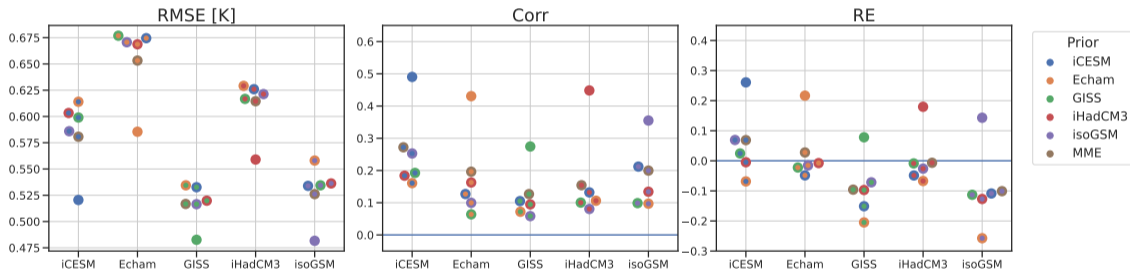
Using **different model for prior and target**. Global mean of error metrics.

# Validation of the framework with Pseudoproxy Experiments (PPE)



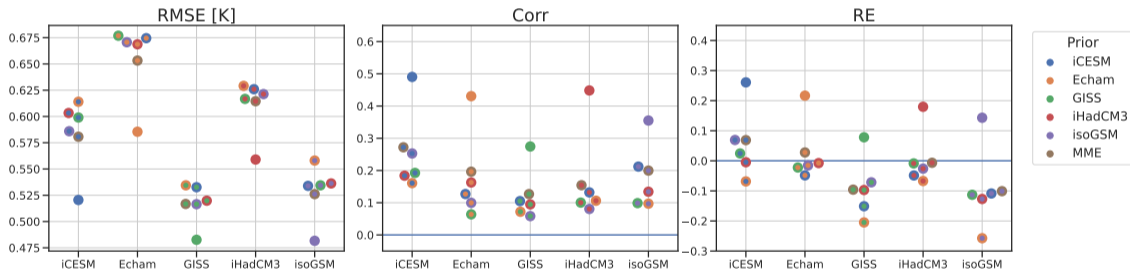
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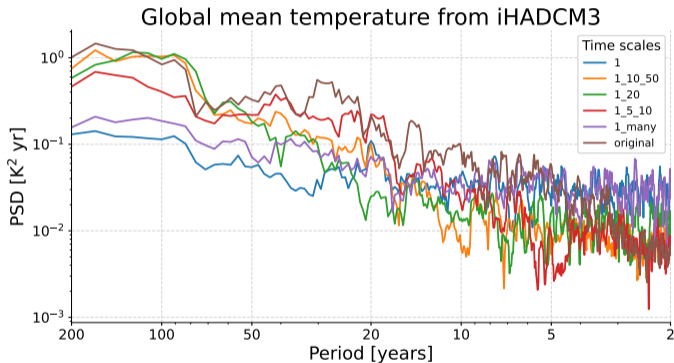
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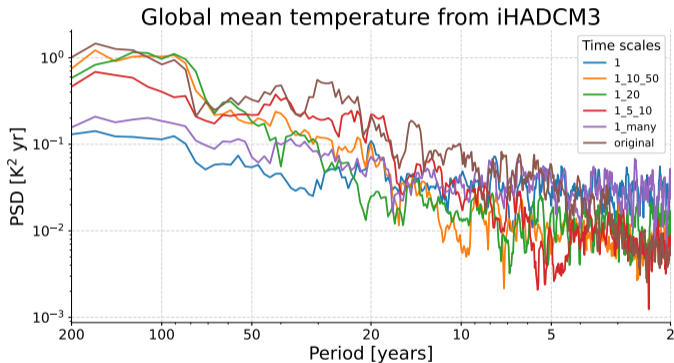
- Results are better for GMT
  - Multi model ensemble (MME) yields slightly better results
- ⇒ Biases in covariance even for anomaly reconstruction

PPE with  $\delta^{18}\text{O}$  from 100 locations (SNR 0.5).

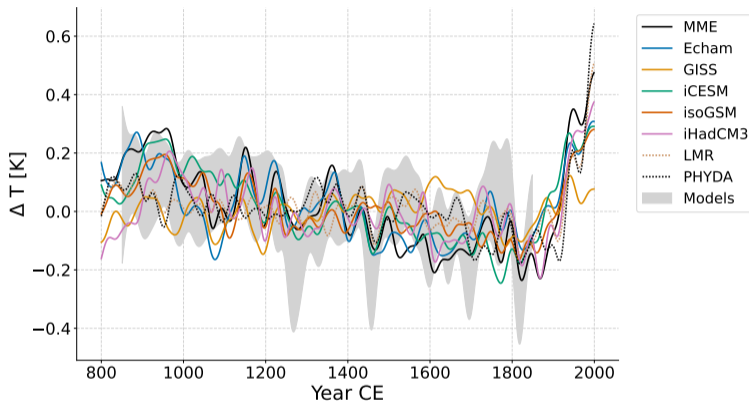




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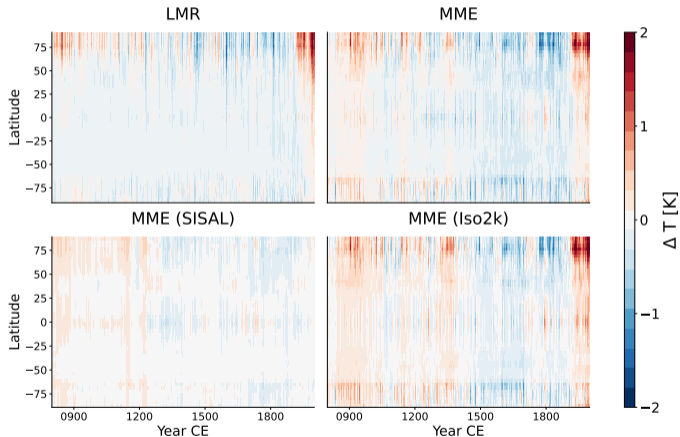


- ⇒ Hints at underestimation of multi-decadal variability
- Also real data experiments indicate better variability reconstruction
- ⇒ Requires more testing of experimental/pseudoproxy configurations



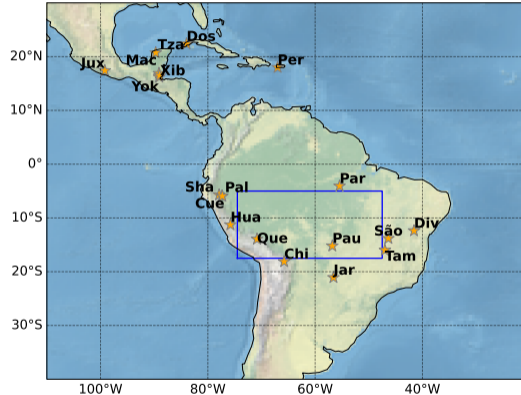
- Uncertainties in the range of 0.15K
- Prior dependency of amplitudes
- Fluctuations are comparable to LMR and PHYDA reconstruction

## Latitudinal mean temperature wrt 851-1849CE



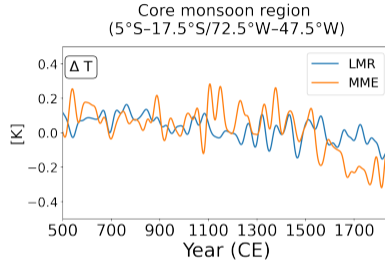
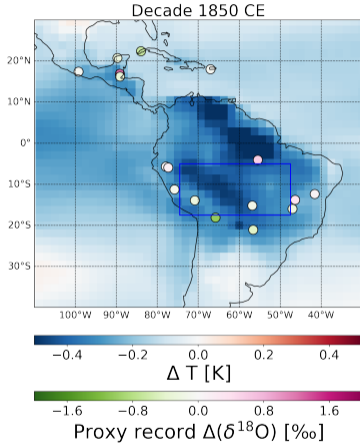
- Correlation analysis also underlines larger influence of the ice cores
- Smallest temperature changes in the mid latitudes

## Proxy record locations Tropical South America

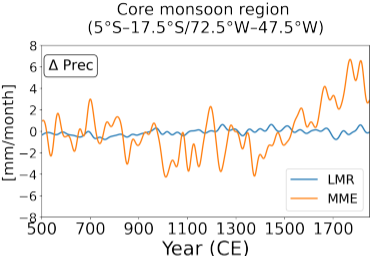
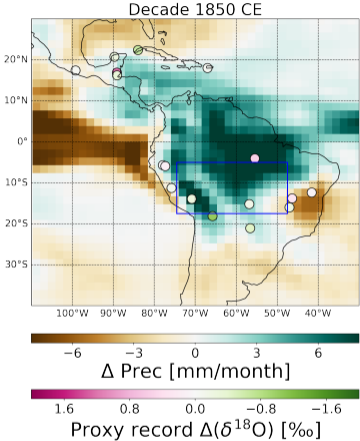


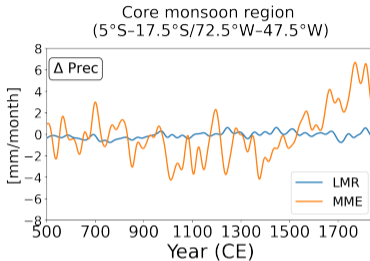
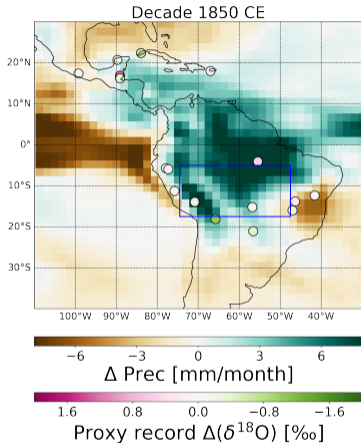
- Existing reconstructions use few proxy records from that region
- Blue box: Core South American summer monsoon region (Vuille 2012)

# Reconstruction of South American Hydroclimate



# Reconstruction of South American Hydroclimate





- "Little Ice Age" clearly visible in both temperature and precipitation
- Potential for more detailed reconstructions!

- First multi-time scale PaleoDA with isotope-enabled models, ice cores and speleothems
- Anomaly reconstructions yield realistic results



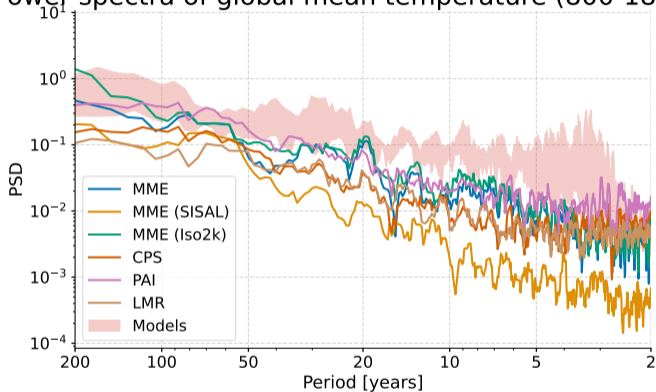
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  1. Realistic uncertainties
  2. Time scales of proxy records
  3. Quantifying the covariance structure and the influence of PSMs and observations
  4. Debiasing the model prior

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- Next months: Focus on South American Hydroclimate

Thank you!

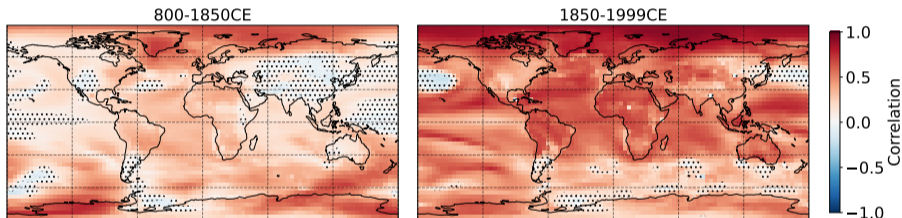
# Backup slides

Power spectra of global mean temperature (800-1850CE)



CPS and PAI are reconstructions from Pages2k 2019

## Local correlation of MME and LMR



No detrending.

Largest similarity over West Antarctica and Greenland.

- Developed for data-model comparison
- What proxy value does a simulated state represent?

$$X^{post} = X^{prior} + K(Y - HX^{prior})$$

→ **forward approach** (Evans 2013, Dee 2015)

- physics-based/statistical PSMs

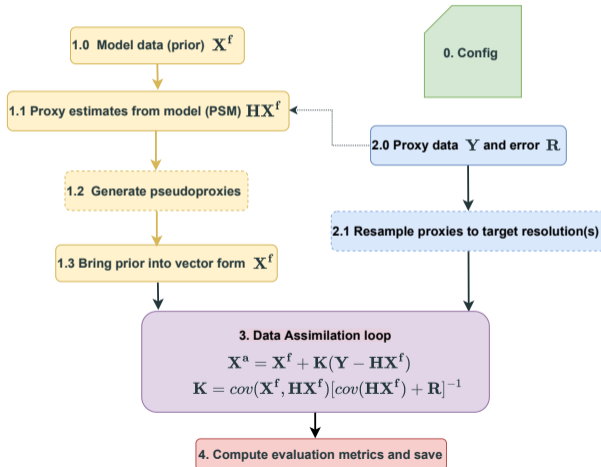
## Icecore $\delta^{18}\text{O}_{prec}$ -PSM

- Precipitation weighting for annual  $\delta^{18}\text{O}$
- Height correction (isotopic lapse rate)
- Diffusion

## Speleothem $\delta^{18}\text{O}_{prec}$ -PSM

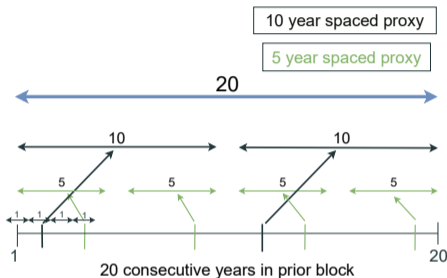
- Infiltration weighting for annual  $\delta^{18}\text{O}$
- Height correction (isotopic lapse rate)
- Fractionation
- Karst filter

## Algorithm sketch for Paleoclimate Data Assimilation





Idea:



- Reconstruct (sub-)blockwise instead of annually.

## Caveats

- assign proxies to (sub-)blocks  
→ resampling to median resolution
- additional calculations

## Advantages:

- Proxies representing mean state over several years can be used
- Use timescale appropriate covariances
- Get more reconstruction out of proxies

## Kalman Filter and posterior covariance $P^{post}$ (Kalman 1960)

$$X^{post} = X^{prior} + K(Y - HX^{prior}) \quad (1)$$

$$K = P^{prior} H^T (HP^{prior} H^T + R)^{-1} \quad (2)$$

$$P^{post} = (I - KH)P^{prior} \quad (3)$$

## Problem dimensions

$N_e$  Ensemble members in prior

$N_y$  Number of proxies

$N_x$  State vector length  
(grid  $\times$  vars)

- Nonlinear  $H$ , unknown prior covariance  $P^{prior}$ ?  $\rightarrow$  Ensemble Kalman Filter (Evensen 1994)
- Original EnKF gets  $P^{post}$  too small  $\rightarrow$  EnKF in square root form

$$P^{post} = \frac{X^{post} (X^{post})^T}{N_e - 1} \quad (4)$$

$$= X^{prior} T (X^{prior} T)^T \quad (5)$$

$$= X^{prior} (TT^T) X^{prior T} \quad (6)$$

## Find the matrix $T$

- not uniquely defined, use Lin Alg tools: SVD, EVD ...
- Best solution depends on problem dimensions

## References

- S. Dee, J. Emile-Geay, M. N. Evans, A. Allam, E. J. Steig, and D. Thompson. PRYSM: An open-source framework for PRoxY System Modeling, with applications to oxygen-isotope systems. *Journal of Advances in Modeling Earth Systems*, 7(3): 1220–1247, 2015. ISSN 1942-2466. doi: 10.1002/2015MS000447. URL <https://onlinelibrary.wiley.com/doi/abs/10.1002/2015MS000447>. eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1002/2015MS000447>.
- M. N. Evans, S. E. Tolwinski-Ward, D. M. Thompson, and K. J. Anchukaitis. Applications of proxy system modeling in high resolution paleoclimatology. *Quaternary science reviews*, 76:16–28, 2013.

- G. Evensen. Sequential data assimilation with a nonlinear quasi-geostrophic model using monte carlo methods to forecast error statistics. *Journal of Geophysical Research: Oceans*, 99(C5):10143–10162, 1994.
- R. E. Kalman. A new approach to linear filtering and prediction problems. 1960.
- Pages2k. Consistent multidecadal variability in global temperature reconstructions and simulations over the common era. *Nature geoscience*, 12(8):643–649, 2019.
- N. Steiger and G. Hakim. Multi-timescale data assimilation for atmosphere–ocean state estimates. *Climate of the Past*, 12(6):1375–1388, June 2016. ISSN 1814-9332. doi: 10.5194/cp-12-1375-2016. URL <https://cp.copernicus.org/articles/12/1375/2016/>.

- N. J. Steiger, J. E. Smerdon, E. R. Cook, and B. I. Cook. A reconstruction of global hydroclimate and dynamical variables over the common era. *Scientific data*, 5(1): 1–15, 2018.
- R. Tardif, G. J. Hakim, W. A. Perkins, K. A. Horlick, M. P. Erb, J. Emile-Geay, D. M. Anderson, E. J. Steig, and D. Noone. Last millennium reanalysis with an expanded proxy database and seasonal proxy modeling. *Climate of the Past*, 15(4):1251–1273, 2019.
- M. Vuille, S. J. Burns, B. L. Taylor, F. W. Cruz, B. W. Bird, M. B. Abbott, L. C. Kanner, H. Cheng, and V. F. Novello. A review of the south american monsoon history as recorded in stable isotopic proxies over the past two millennia. *Climate of the Past*, 8(4):1309–1321, 2012.