Narrowing Uncertainties of Climate Projections using Data-driven Methods: the AMOC Case Study

Pierre Tandeo, Pierre Le Bras, Florian Sévellec, Pierre Ailliot, Juan Ruiz

Narrowing Uncertainties of Climate Projections using Data-driven Methods

The AMOC case study

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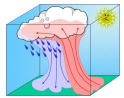
The 6th International Workshop on Nonhydrostatic Models (NHM-WS 2023)



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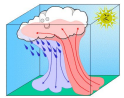


Hokkaido University Conference Hall, Sapporo, Japan

Context: Atlantic Meridional Overturning Circulation (AMOC)

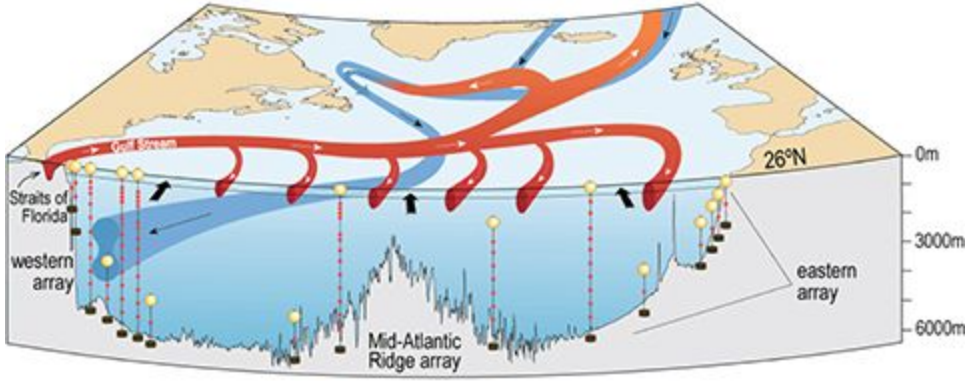


Fig.1: Schematic of AMOC [Source: *http://www.noc.soton.ac.uk/rapidmoc/*]

AMOC

→ **Circulation in the Atlantic ocean**

Shallow warm water northward

Deep cold water southward

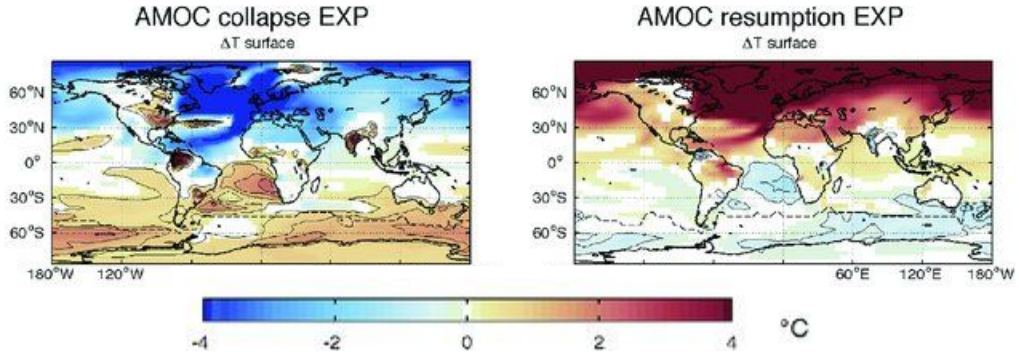


Fig.2: Experiences of AMOC collapse/resumption and influence on surface temperature anomalies
[Source: *Pedro et al., 2018*]

→ **Influence on climate of Atlantic regions**

→ **Essential to monitor its evolution**

Context: AMOC observations and AMOC projections in climate models

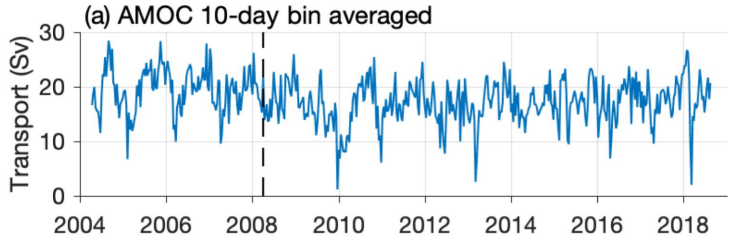


Fig.1: AMOC observations from RAPID/MOCHA system
[Source: Moat et al., 2020]

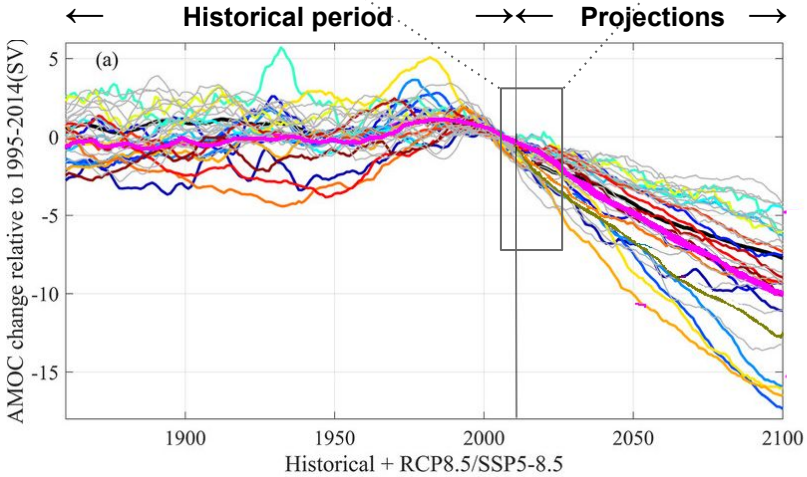


Fig.2: AMOC anomalies from different models (SSP5-8.5 in CMIP5-6)
[Source: *Lyu and Church, 2020*]

Observations:

→ Seasonal and interannual variability
→ Hard to measure, lot of noise

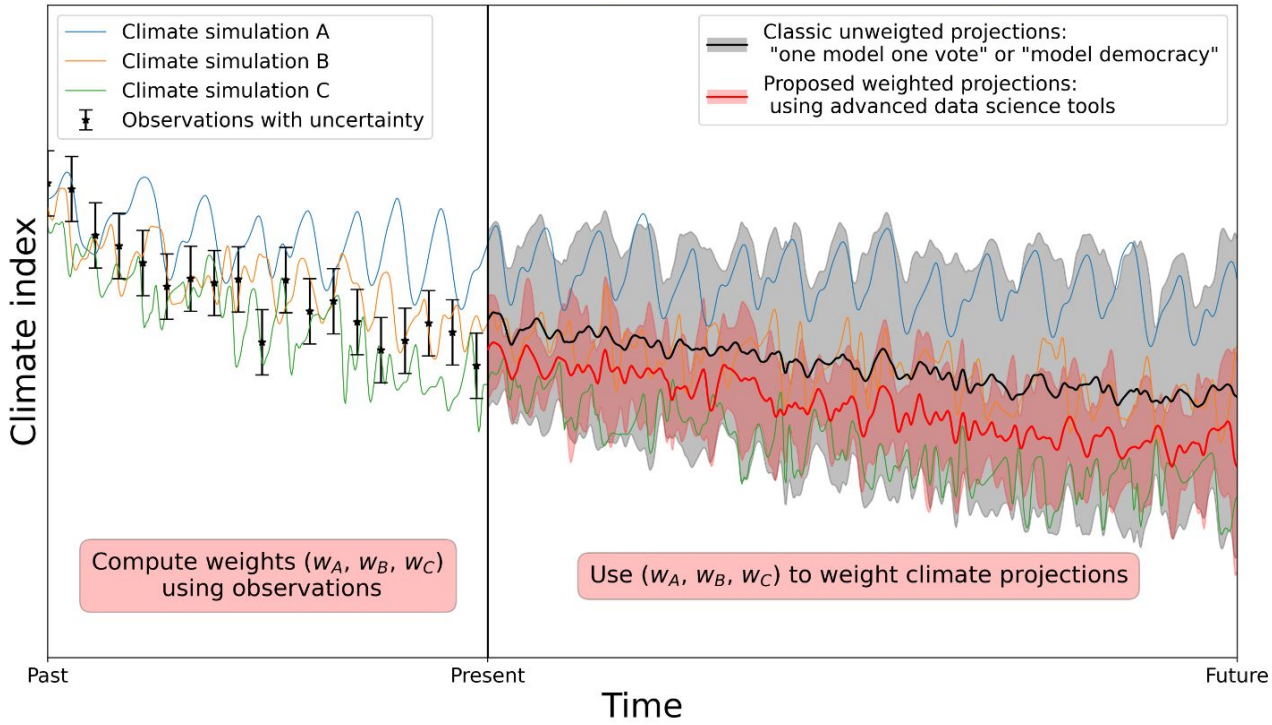
CMIP Model projections:

→ **Models predict severe decrease of the AMOC**

→ **Wide spread** (model uncertainty)

How to improve accuracy and reliability of AMOC projections?

Aim of this study: compute weights to constraint climate projections



State of the art → Model democracy (same weights)

→ Questionable (e.g., *Knutti et al., 2019*)

Our goal → Weight the projections

→ <u>Using available simulations and observations</u>

→ Reduce the uncertainty

Proposed methodology: combination of data assimilation and machine learning

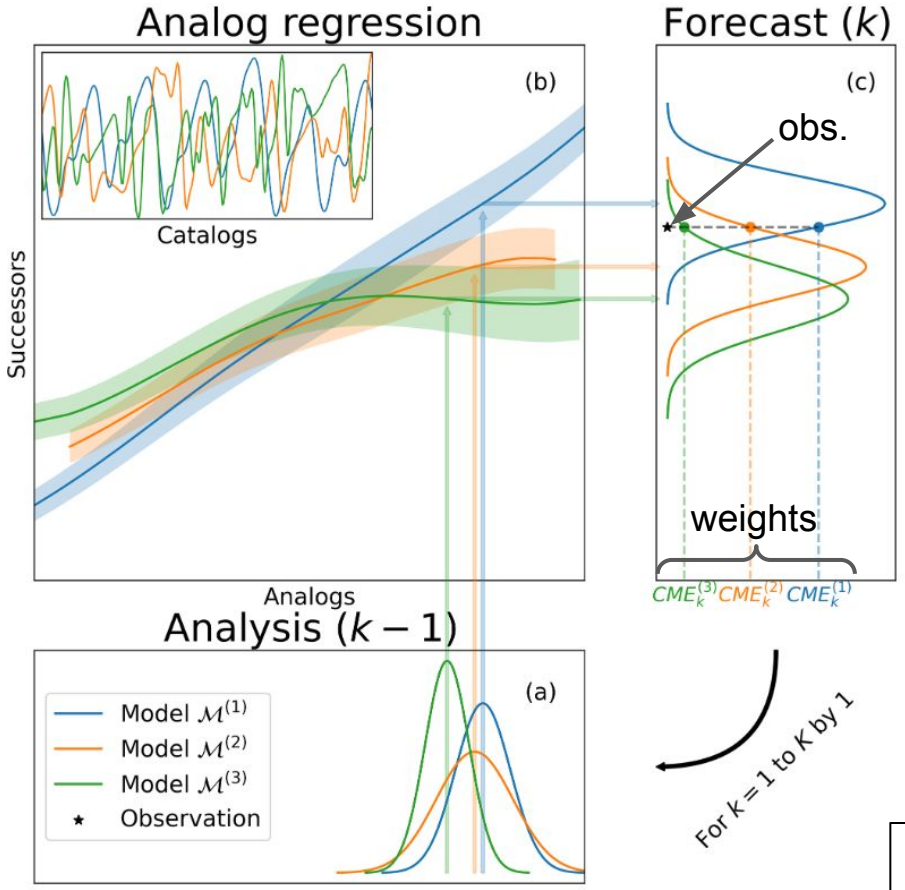


Fig.1: Scheme of the methodology
[Source: Ruiz et al., 2022]

Step (a): Data assimilation

→ start from an accurate initial condition
→ Ensemble Kalman filter (EnKF)

Step (b): Data-driven forecast

→ make forecasts without equations
→ analog method

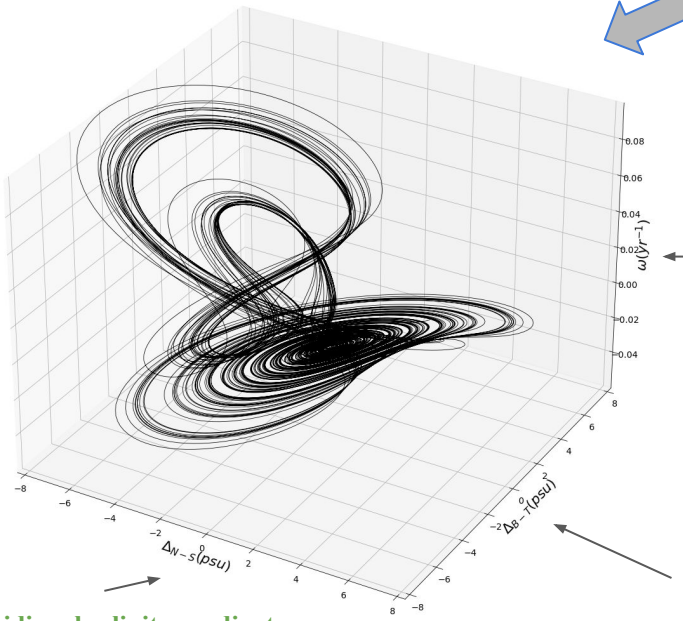
Step (c): Weighting procedure

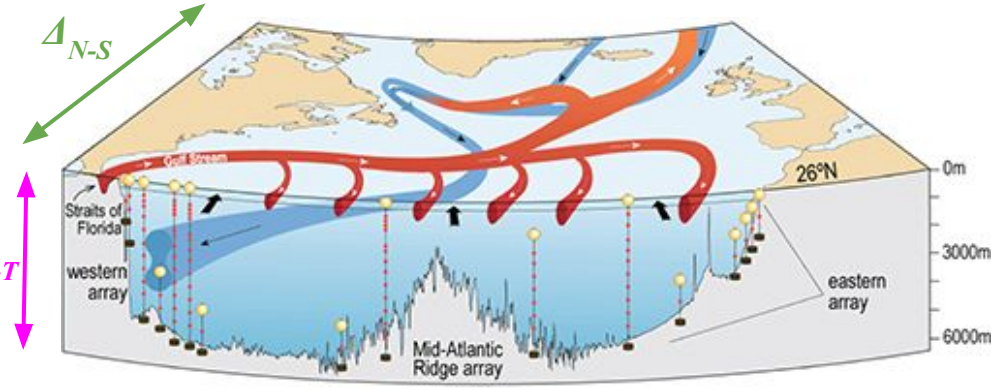
→ compute observation-forecast distance
→ contextual model evidence (CME)

Ruiz, J., Ailliot, P., Chau, T. T. T., Le Bras, P., Monbet, V., Sévellec, F., & Tandeo, P. (2022). Analog data assimilation for the selection of suitable general circulation models. *Geoscientific Model Development*, *15*(18), 7203-7220.

3-variable AMOC chaotic model

(*Sévellec and Fedorov, 2014*)





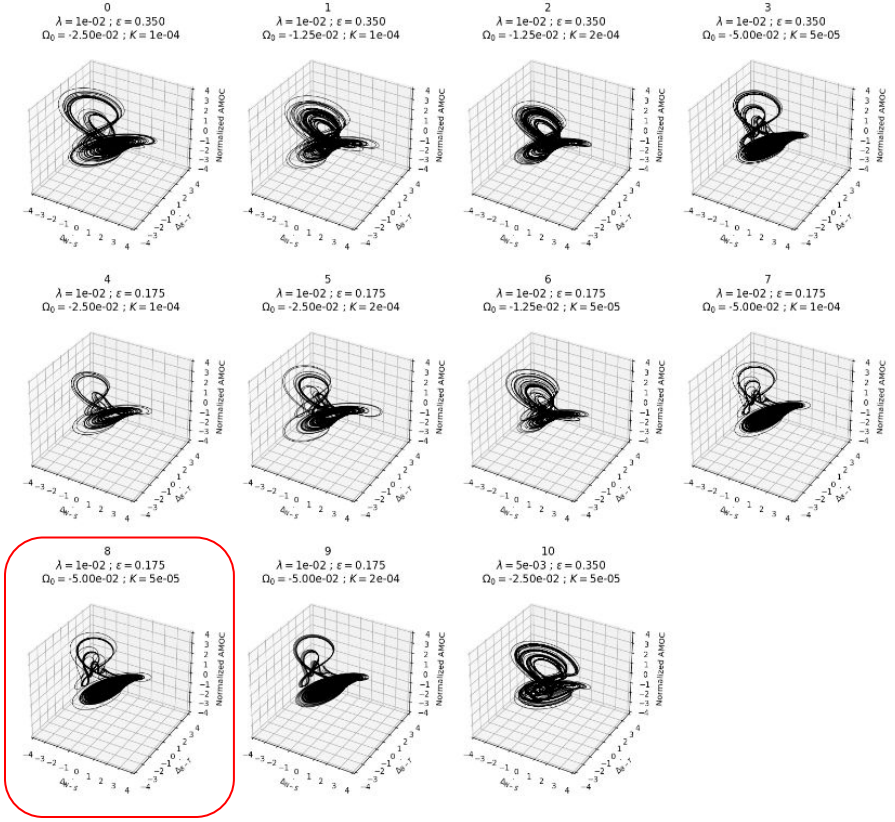
ω **overturning strength**

$$\frac{d\omega}{dt} = -\lambda\omega - \epsilon\beta S_{NS},$$
$$\frac{dS_{BT}}{dt} = (\Omega_0 + \omega) S_{NS} - K S_{BT} + \frac{F_0 S_0}{h},$$
$$\frac{dS_{NS}}{dt} = -(\Omega_0 + \omega) S_{NS} - K S_{NS}$$

Δ_{N-S}: **Meridional salinity gradient**

Δ_{B-T}: **Stratified salinity**

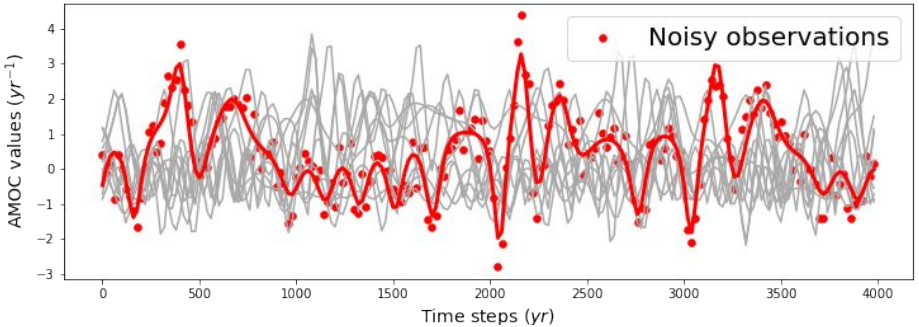
Experimental set up: generation of different versions of the idealized AMOC model



➔ **11 perturbed-parameter versions**

➔ **Leave-One-Out strategy**

➔ **Mimic 10 climate simulations and 1 observation**

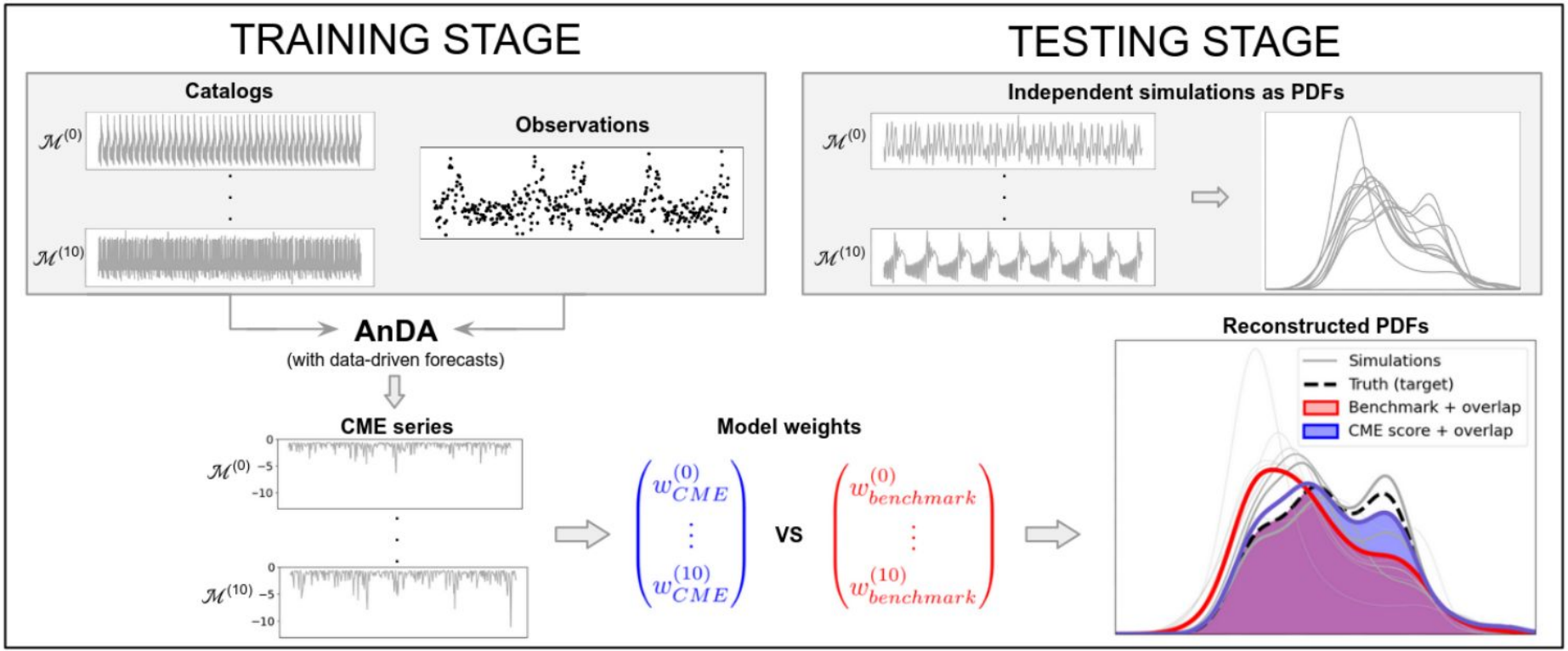


Schematic of the Leave-One-Out strategy

➔ **Compute 10 weights**

➔ **Approximate observation distribution**

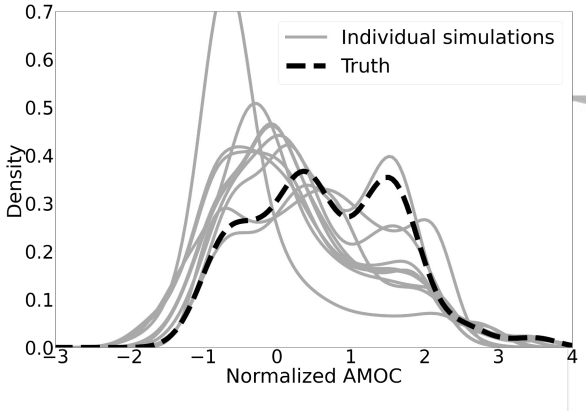
Experimental set up: generation of different versions of the idealized AMOC model



Application results for one experiment: applying the weights to reconstruct the truth

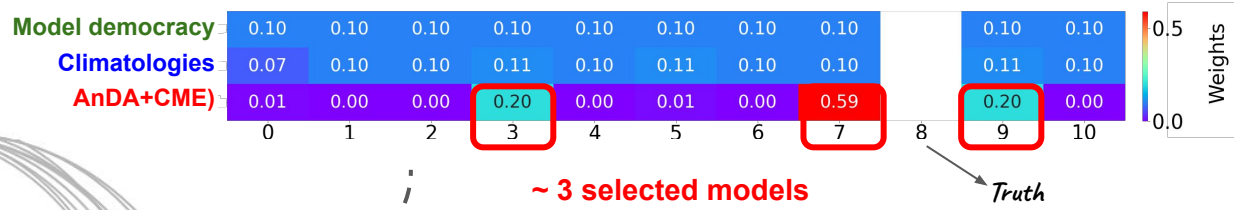
➔ **Out-of-training simulations**

PDFs simulations for each model



Weighting

Attributed weights to each model



Application results for one experiment: applying the weights to reconstruct the truth

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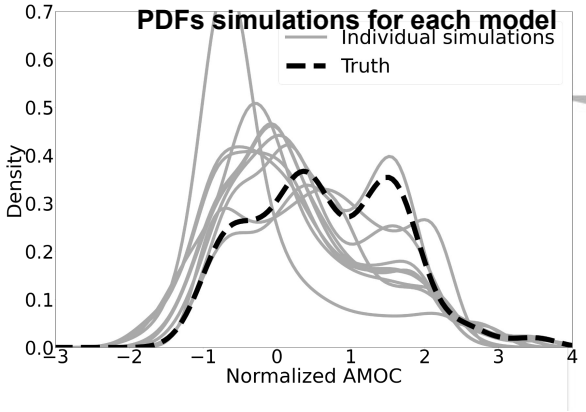
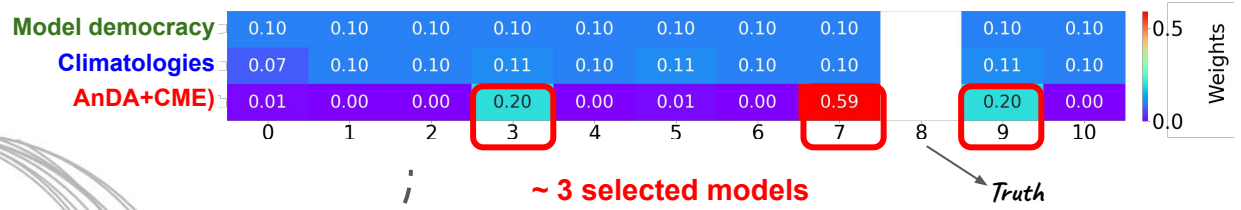


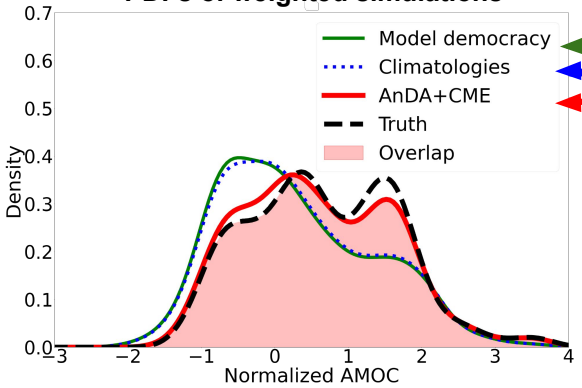
Attributed weights to each model



~ 3 selected models

Weighting

PDFs of weighted simulations



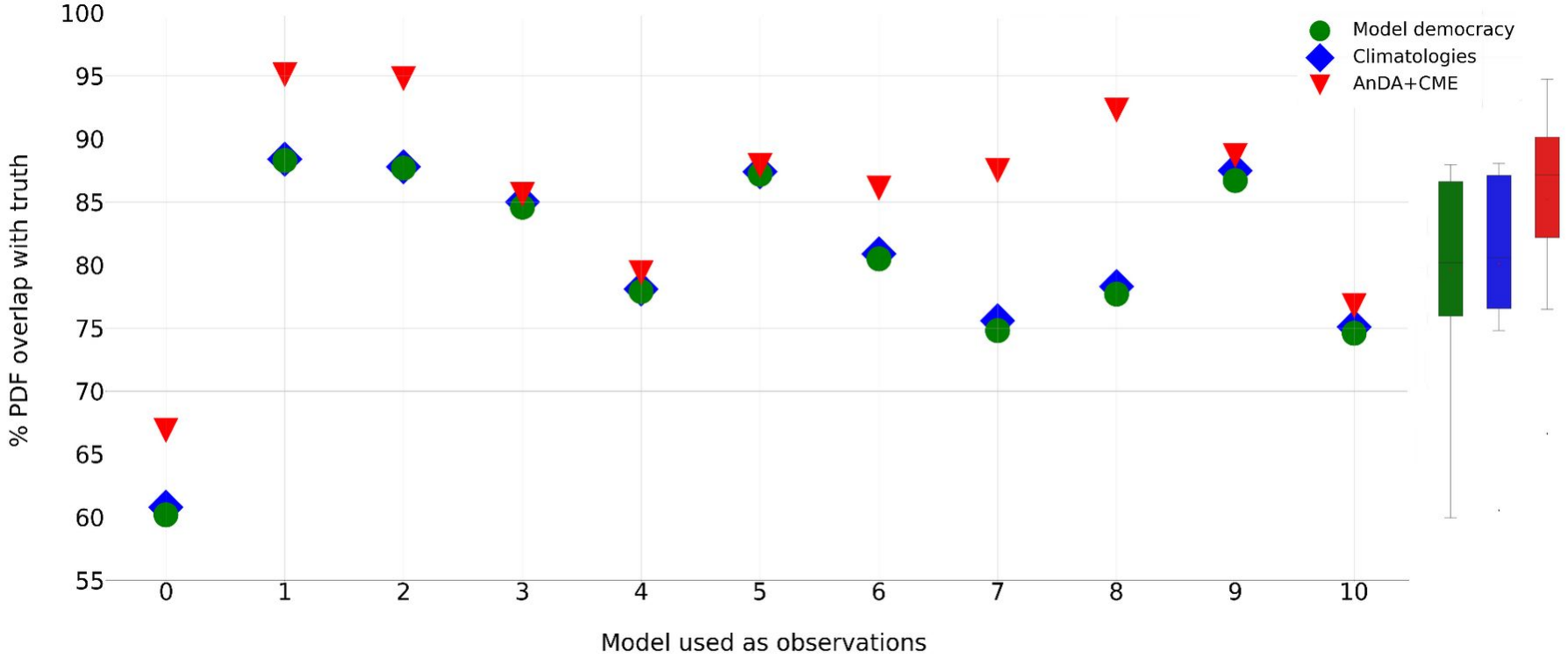
Results: reconstruction skillness

% PDFs overlap	One experiment
Model democracy	77.6
Climatologies	78.3 (+0.7)
AnDA+CME	92.3 (+14.7)

AnDA with CME outperforms model democracy

Application results: overall results on Leave-One-Out (LOO) experiments

LOO results: % PDF overlap between each weighted PDF and the true one



AnDA with CME performs at least as good as model democracy

Conclusion & perspectives

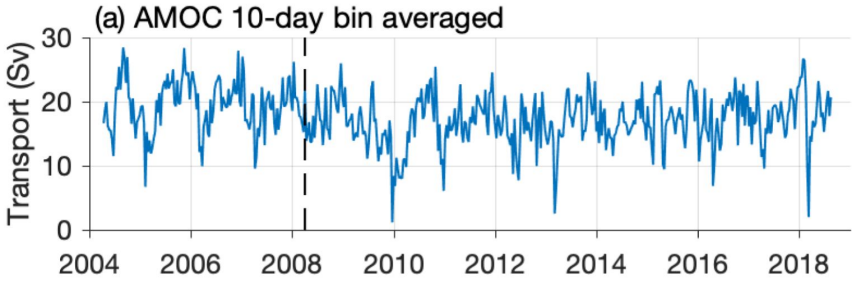
→ **Weight climate simulations using noisy observations**

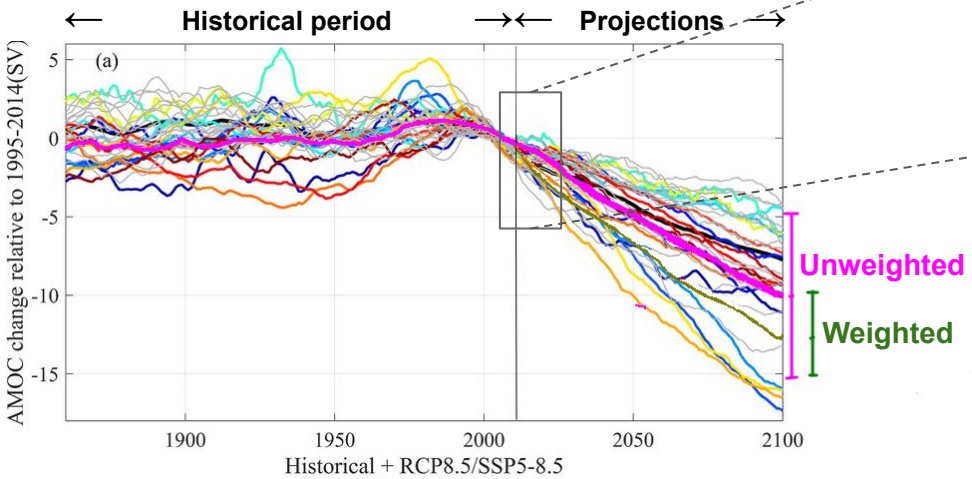
→ **Data-driven approach (no need to run climate models)**

→ **Combination of Data Assimilation & Machine Learning**

→ **Application to synthetic data of the AMOC**

→ **The proposed method outperforms “model democracy”**





Reference

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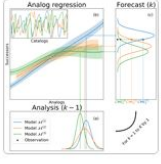
Juan Ruiz, Pierre Ailliot, Thi Tuyet Trang Chau, Pierre Le Bras, Valérie Monbet, Florian Sévellec, and Pierre Tandeo



Abstract

Data assimilation is a relevant framework to merge a dynamical model with noisy observations. When various models are in competition, the question is to find the model that best matches the observations. This matching can be measured by using the model evidence, defined by the likelihood of the observations given the model. This study explores the performance of model selection based on model evidence computed using data-driven data assimilation, where dynamical models are emulated using machine learning methods. In this work, the methodology is tested with the three-variable Lorenz model and with an intermediate complexity atmospheric general circulation model (a.k.a. the SPEEDY model). Numerical experiments show that the data-driven implementation of the model selection algorithm performs as well as the one that uses the dynamical model. The technique is able to select the best model among a set of possible models and also to characterize the spatiotemporal variability of the model sensitivity. Moreover, the technique is able to detect differences among models in terms of local dynamics in both time and space which are not reflected in the first two moments of the climatological probability distribution. This suggests the implementation of this technique using available long-term observations and model simulations.

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arigato gozaimasu!

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