Narrowing uncertainties in climate projections using data science tools

P. Tandeo[1], P. Ailliot[1,2], C. Bello[1], B. Chapron[3], T. Chau[4], R. Knutti[5], P. Le Bras[6,1], P. Naveau[4], V. Monbet[7], J. Ruiz[8], F. Sévellec[6], A.-M. Treguier[6]

IMT Atlantique, France[1]
Univ. Brest, France[2]
IFREMER, France[3]
LSCE-IPSL, France[4]
ETH Zurich, Switzerland[5]
IUEM, France[6]
Univ. Rennes I, France[7]
Univ. Buenos Aires, Argentina[8]

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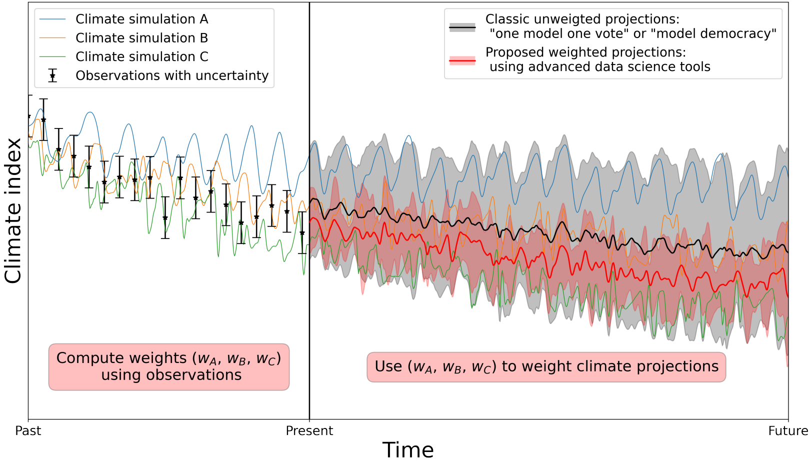
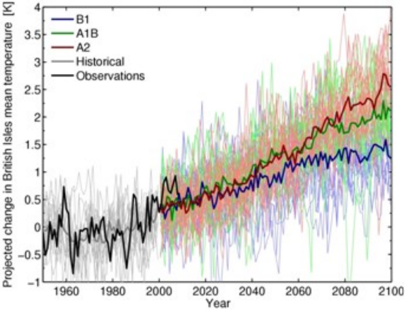
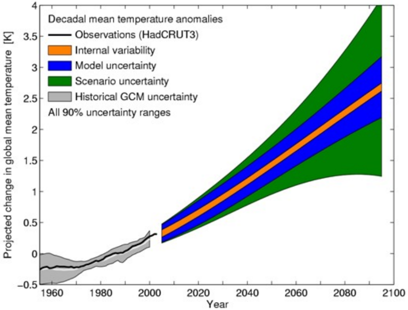
Context and main goal



- In the IPCC → ensemble of **unweighted projections** ("one model one vote" or "model democracy", [Knutti, 2010])
- Idea → **learn weights** from historical observations and simulations, then **propagate weights** to climate projections

Climate uncertainties revealed by CMIP

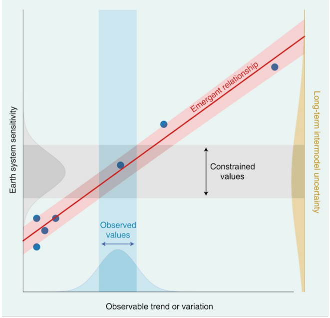




Source: [Hawkins and Sutton, 2011]

- Climate projections are sensitive to internal, model and scenario uncertainties
- **Potential to narrow uncertainties**, especially in **regional climate predictions** [Hawkins and Sutton, 2009]

New at IPCC: emergent constraints



Source: [Eyring et al., 2019]

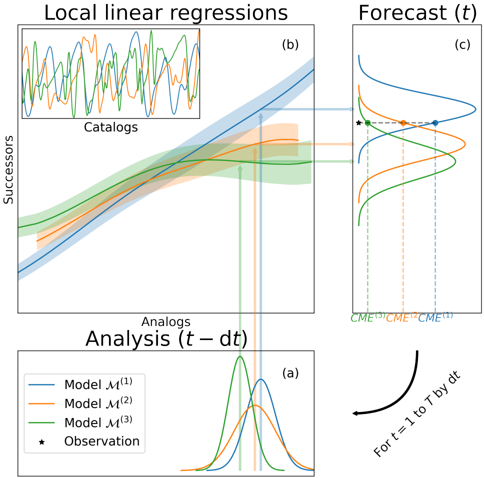
Pros:

- Easy to implement (projection using linear regression)
- Easy to understand (synthetic graphical representation)
- Do not weight climate simulations (not directly)

Cons:

- Causality not obvious (especially for large horizons)
- Low number of samples to fit the regression
- Questionable linear relationship and homoscedasticity

Proposed approach: use advanced data science methods



Three main steps:

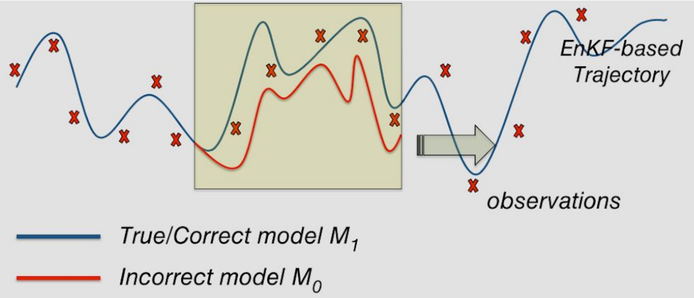
- (a) **Data assimilation** (ensemble Kalman filter)
- (b) **Data-driven forecasting** (local linear regression)
- (c) **Distance obs-forecasts** (contextual model evidence)

Ingredient 1: (a) EnKF + (c) contextual model evidence

Contextual model evidence in data assimilation (CME):

$$\mathcal{L}\left(\mathrm{y}(t)|\mathcal{M}_{(i)}\right) \propto \exp\left(-\mathrm{d}_{(i)}(t)^\top \Sigma_{(i)}(t)^{-1}\mathrm{d}(t)\right) \qquad (1)$$

with the **innovation** defined by its mean and covariance:
$\mathrm{d}_{(i)}(t) = \mathrm{y}(t) - \mathrm{Hx}^f_{(i)}(t)$ and $\Sigma_{(i)}(t) = \mathrm{HP}^f_{(i)}(t)\mathrm{H}^\top + \mathrm{R}$.



Source: [Carrassi et al., 2017]

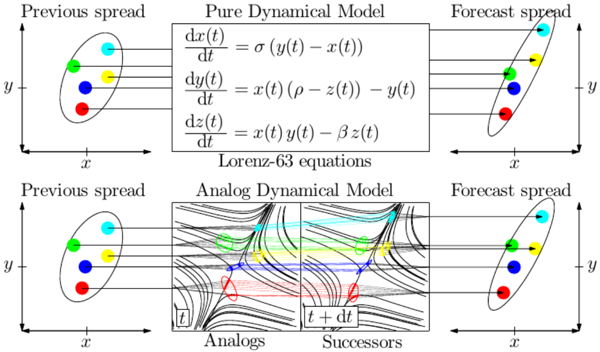
Ingredient 2: (a) EnKF + (b) analog forecasting

Analog forecasting within data assimilation (AnDA):

$$\mathsf{x}(t) = \mathcal{A}\left(\mathsf{x}(t - \mathrm{d}t), \boldsymbol{\eta}(t)\right) \quad (2)$$

$$\mathsf{y}(t) = \mathcal{H}\left(\mathsf{x}(t)\right) + \boldsymbol{\epsilon}(t) \quad (3)$$

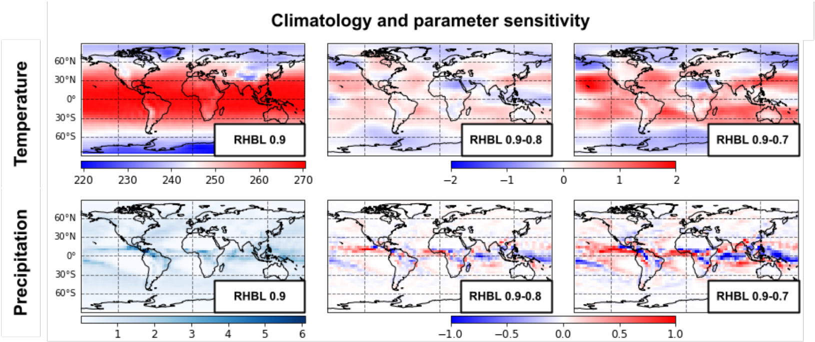
with $\mathcal{A}$ the **analog forecasting** operator [Lguensat et al., 2017].



Source: [Tandeo et al., 2015]

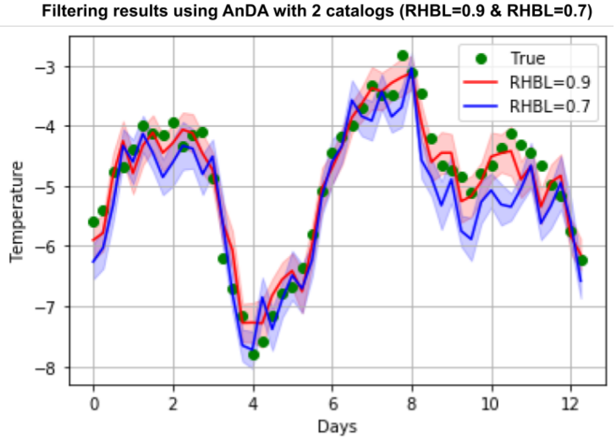
Ingredients 1 + 2: (a) EnKF + (b) AF + (c) CME

- Tested on a **simplified GCM** (SPEEDY, [Molteni, 2003]):
  - 7 vertical levels, 96×48 horizontal grid
  - simple physics (convection, clouds, radiation, boundary layer)
- Relative Humidity threshold in the Boundary Layer:
  - RHBL $= 0.9 \rightarrow$ the "true" model
  - RHBL $= 0.8 \rightarrow$ slightly imperfect model
  - RHBL $= 0.7 \rightarrow$ imperfect model

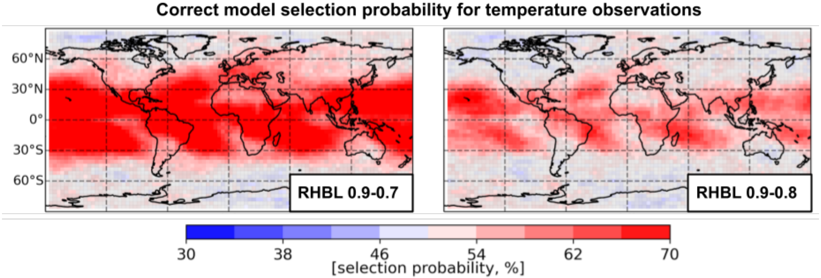


Ingredients 1 + 2: (a) EnKF + (b) AF + (c) CME

- Analog data assimilation details:
  - EnKF with 40 members with adaptive inflation [Miyoshi, 2011]
  - 30-years catalogs for 3 parameterizations (RHBL 0.9, 0.8, 0.7)
  - 3D local domains (3 vertical levels, 3×3 horizontal grid)
  - 3 years of noisy observations from RHBL 0.9 (std $= 0.7K$)

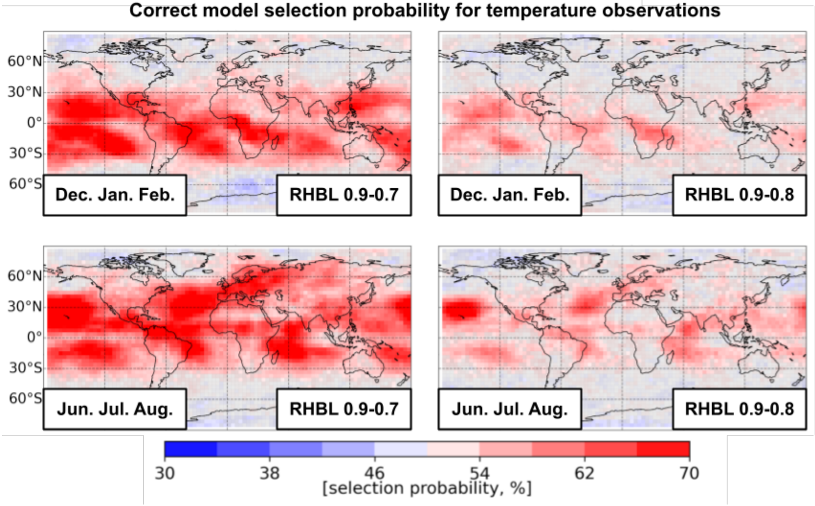


Ingredients 1 + 2: (a) EnKF + (b) AF + (c) CME



- Results about model identification (in space):
  - tropical-subtropical regions affected by model imperfections
  - degree of imperfection is captured (RHBL 0.7 $<$ 0.8)

Ingredients 1 + 2: (a) EnKF + (b) AF + (c) CME



- Results about model identification (in space and time):
  - sensibility to the RHBL parameter is evolving in time
  - detection of model imperfection more important in summers (i.e., when there is more convection observed)

Ingredients 1 + 2: (a) EnKF + (b) AF + (c) CME

Conclusions:

- Combination of **advanced data-science methods**
- Able to compare **short-term model dynamics**
- Ruiz et al., will be submitted soon to the *Journal of Climate*

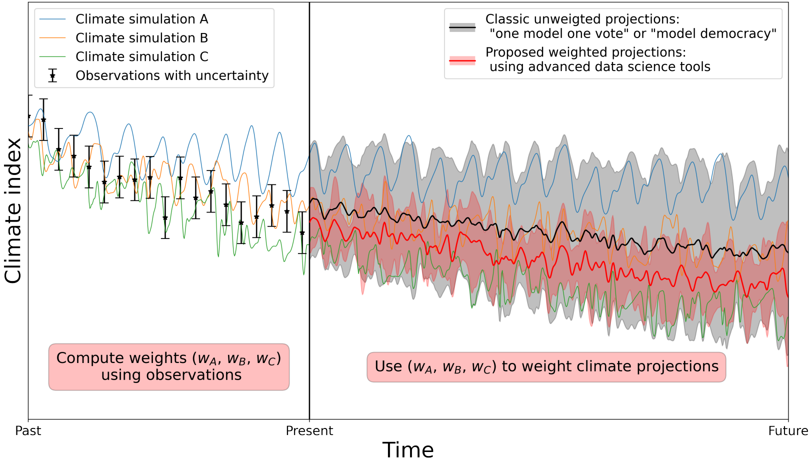
Pros:

- **Local approach** (sub-domain, given period, partial variables)
- **Low-cost procedure** (no need to run climate models)
- Capture **spatiotemporal differences** in model identifications

Cons:

- Need historical numerical simulations
- Need tuning (analogs, inflation, domain, observations)
- May seem complicated (but not so much!)

Next step: application to climate simulations



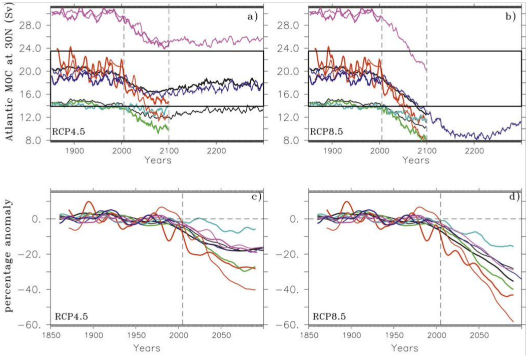
- Data → compare current observations to CMIP simulations
- Method → combine data-science methods (DA, AF, CME)
- Goal 1 → create weighted projections of climate metrics
- Goal 2 → reduce the uncertainty of climate projections

Next step: application to climate simulations

Specificity of climate simulations [Knutti et al., 2019]:

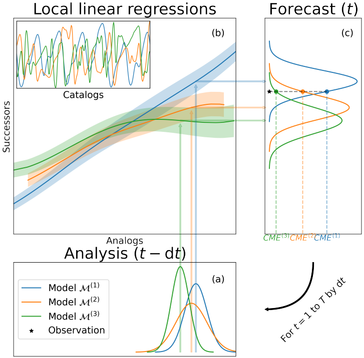
- **Interdependence** → many CMIP models share ideas, parts of code, or whole components (e.g., the sea ice model)
- **Performance** → some CMIP models are "good" at representing a specific climate index, other models are not
- Simulations are sometimes **biased** and need **standardization**

AMOC variations in CMIP5 for 2 RCP scenarios



Source: [Cheng et al., 2013]

Next step: application to climate simulations



Caveats and improvement of the methodology:

- (a) $\rightarrow$ deal with **model interdependence** (e.g., work with clusters of models), deal with **non-parametric** distributions
- (b) $\rightarrow$ find differences in the **short-term dynamics** of climate metrics (especially in the extremes), find **relevant dt**
- (c) $\rightarrow$ define more **flexible metrics** (e.g., optimal transport), find **relevant observations** (long time series, knowing noise)

Thank you for your attention! Any questions?

MAFALDA:

Multi-climate-model Analog Forecasting for Attributing Likelihoods using Data Assimilation

French ANR program

JCJC "young researcher"

Under evaluation (2nd round)

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