Selection of dynamic model using analog data assimilation

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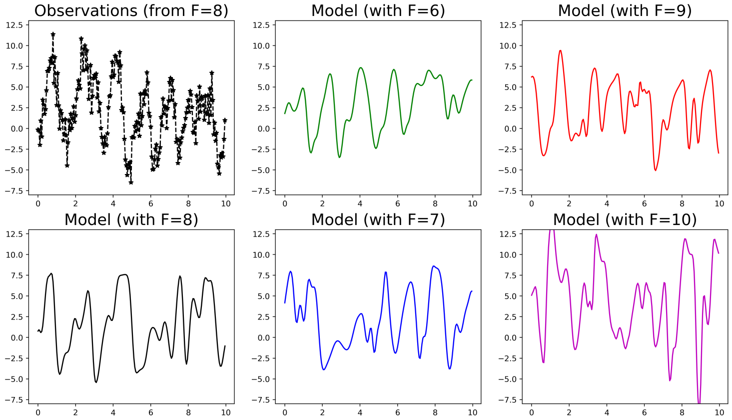
Context, notation and goal

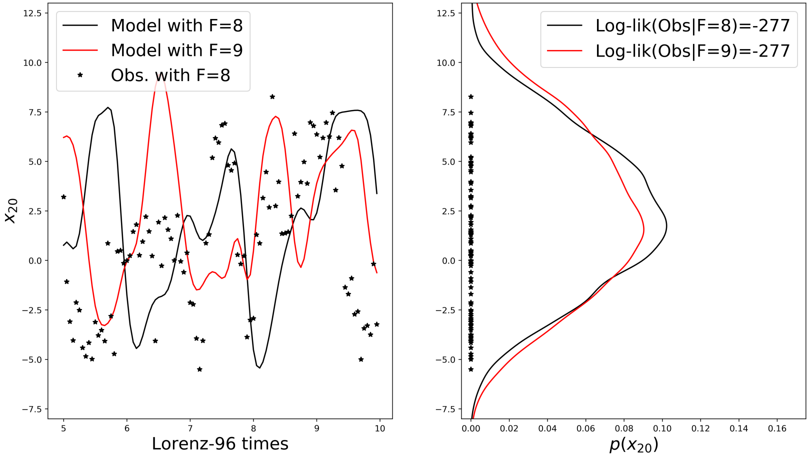
- Given a set of observations $\mathbf{y}$
- And p different dynamic models $\{\mathcal{M}_{(i)}\}_{i=1,\dots,p}$
- With independent realizations $\{\mathbf{x}_{(i)}\}_{i=1,\dots,p}$



- Here, we use the Lorenz-96 and different forcing terms F
- **How can we say which model "match" the observations?**

Solution 1: comparing climatological distributions

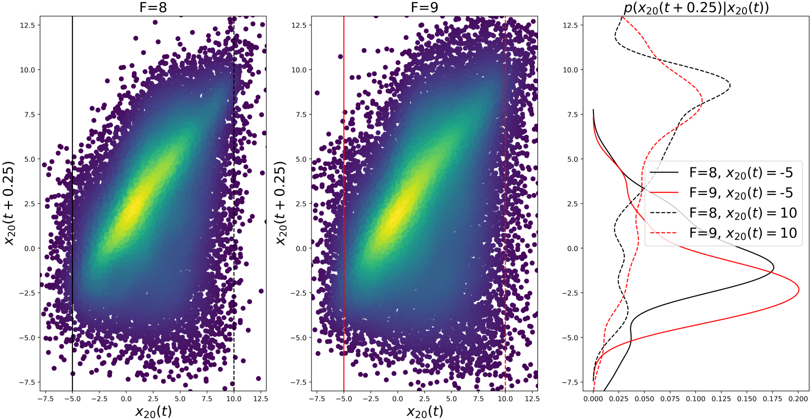
- Compare climatological (marginal) distributions
- $p\left(\mathbf{x}_{(i)}\right)$ $\underline{\text{VS}}$ $p\left(\mathbf{y}\right),\ \forall\ i = 1, \ldots, p$



- Work well if bias or different range of values
- Unable to detect models that are closed to the observations

Solution 2: comparing model dynamics

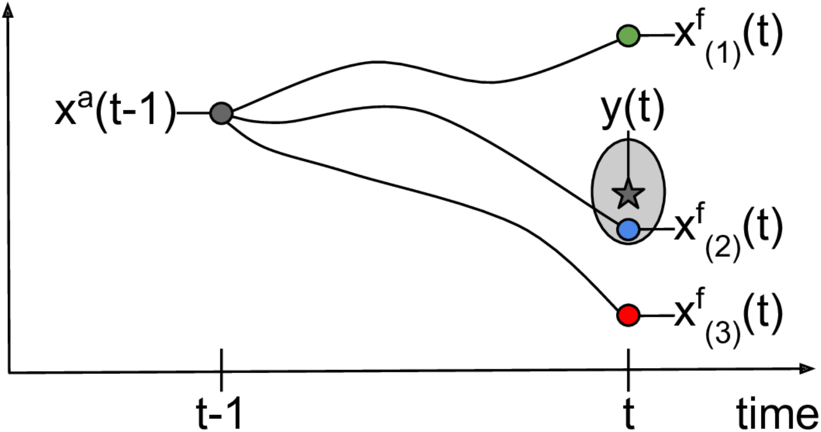
- Compare conditional distributions between consecutive times
- $p\left(\mathbf{x}_{(i)}(t)|\mathbf{x}_{(i)}(t-1)\right)$ <u>VS</u> $p\left(\mathbf{y}(t)\right)$, $\forall\ i = 1, \ldots, p$



- Dynamics are different depending on the models
- Differences appear in the extreme values
- Solution 2 (conditional) is preferred to solution 1 (marginal)

Comparing model dynamics using data assimilation

- Need to start from the best initial condition
- Need to deal with observation uncertainties
- Data Assimilation (DA) is the perfect candidate



- The idea is to evaluate, at each assimilation cycle, $p\left(\mathbf{x}^f_{(i)}(t)|\mathbf{x}^a(t-1)\right)$ <u>VS</u> $p\left(\mathbf{y}(t)\right)$, $\forall\ i = 1, \ldots, p$

Computing model evidence in DA

- Find a metric to compare model dynamics
- Contextual Model Evidence (CME) is a possible one
- Introduced in DA by [Carrassi et al., 2017, Metref et al., 2019]

In the nonlinear and Gaussian DA case:

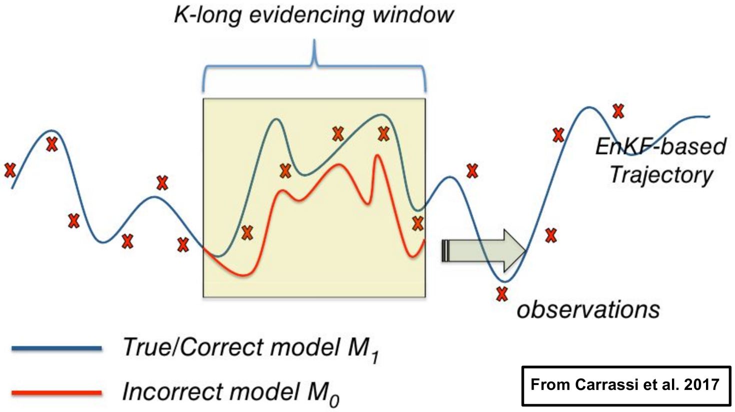
$$\mathrm{CME}_{(i)} = \prod_{t=1}^{T} \mathcal{L}\left(\mathbf{y}(t)|\mathcal{M}_{(i)}\right) \tag{1}$$

with the innovation likelihood given by:

$$\mathcal{L}\left(\mathbf{y}(t)|\mathcal{M}_{(i)}\right) \propto \exp\left(-\mathbf{d}_{(i)}(t)^{\top}\mathbf{\Sigma}_{(i)}(t)^{-1}\mathbf{d}(t)\right) \tag{2}$$

where $\mathbf{d}_{(i)}(t) = \mathbf{y}(t) - \mathbf{H}\mathbf{x}^{f}_{(i)}(t)$ and $\mathbf{\Sigma}_{(i)}(t) = \mathbf{H}\mathbf{P}^{f}_{(i)}(t)\mathbf{H}^{\top} + \mathbf{R}$

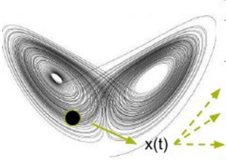
Pros and cons of model evidence in DA



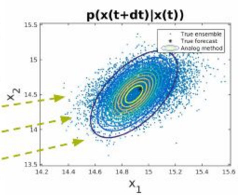
- Pros of CME in DA:
  - use observation ($\mathbf{R}$) and model error ($\mathbf{P}^f_{(i)}$) covariances
  - easy to compute at each DA cycle
- Cons of CME in DA:
  - need to run $\mathcal{M}_{(i)}$ to get $\mathbf{x}^f_{(i)}(t)$ and $\mathbf{P}^f_{(i)}(t)$, $\forall i$ and $\forall t$
  - need to run global model (potentially large)

Getting $p\left(\mathbf{x}_{(i)}(t) | \mathbf{x}^a(t-1)\right)$ using analogs

- Instead of running a model $\mathcal{M}_{(i)}$, use analog forecasting
- Analog forecasts naturally capture $\mathbf{x}^f_{(i)}$ and $\mathbf{P}^f_{(i)}$



Analogs (a_k): x_1, x_2, x_3 (time t)	Successors (s_k): x_1, x_2, x_3 (time $t + \mathrm{d}t$)
$(-0.33, +3.26, +25.51)$	$(+0.01, +3.23, +24.84)$
$(+0.01, +3.23, +24.84)$	$(+0.32, +3.20, +24.19)$
...	...
$(-2.76, -4.50, +19.18)$	$(-2.93, -4.71, +18.80)$
$(-2.93, -4.71, +18.80)$	$(-3.11, -4.95, +18.45)$

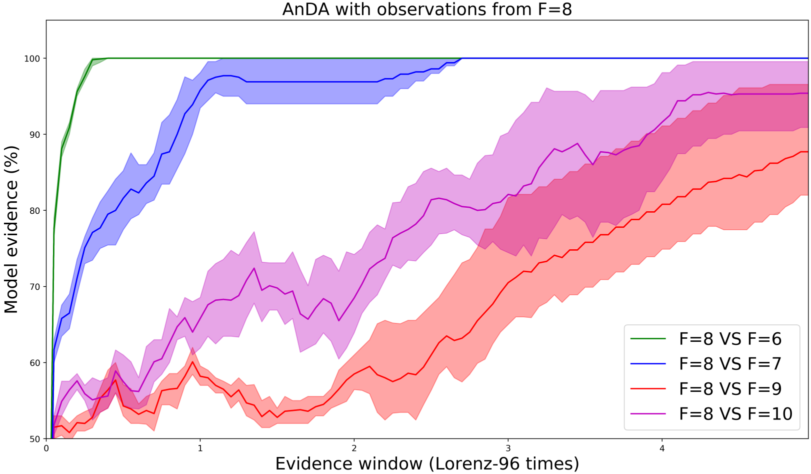


Catalog
(historical observations or numerical simulations)

- Analog forecasting can be easily plugged into DA algorithms
- The Analog Data Assimilation (AnDA) [Tandeo et al., 2015, Lguensat et al., 2017]
- Other forecasting methods can be considered (e.g., neural nets, kernel methods)

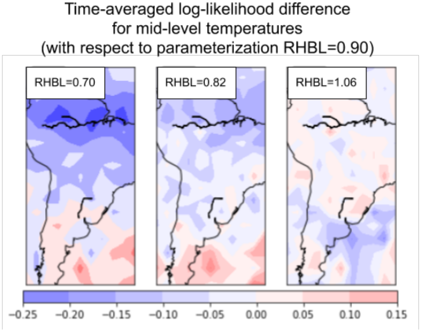
The computation of model evidence using AnDA

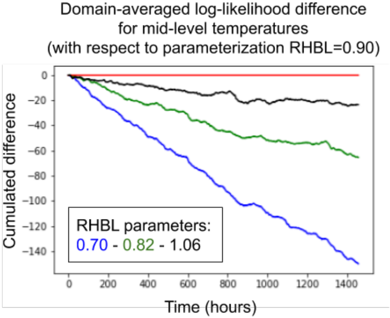
- Need sufficient catalog size to get good performance
- Results similar as the true DA (using model integration)
- Details given in [Chau, 2019]



The interest of AnDA: the locality

- AnDA can be applied to a part of the state
- Thus, AnDA is able to compute CME locally

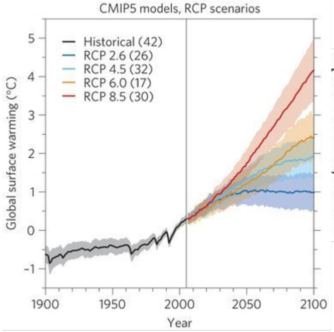




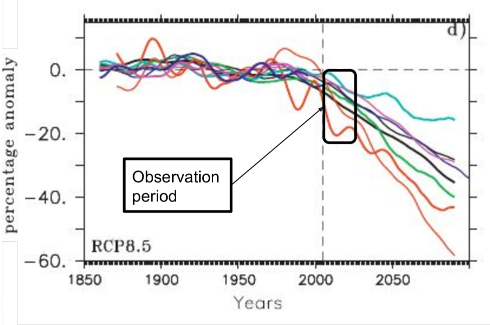
- Has been tested on a simple climate model (SPEEDY)
- 30 years or catalogs with different parameterizations
- Relative Humidity threshold in the Boundary Layer (RHBL = 0.70, 0.82, 0.90, 1.06)

Next step: application to climate simulations

- CMIP contains climate simulation runs for the future
- Different models (20) and scenarios (4) are considered
- For each scenario, each model has several members



RCP scenarios in CMIP simulations



Atlantic Meridional Overturning Circulation (AMOC) simulations from different climate models

- Goal 1 → create weighted projections of climate metrics
- Goal 2 → reduce the uncertainty of climate projections
- Data → compare current observations to climate simulations
- Method → use AnDA and the model evidence metric

Thank you for your attention!

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