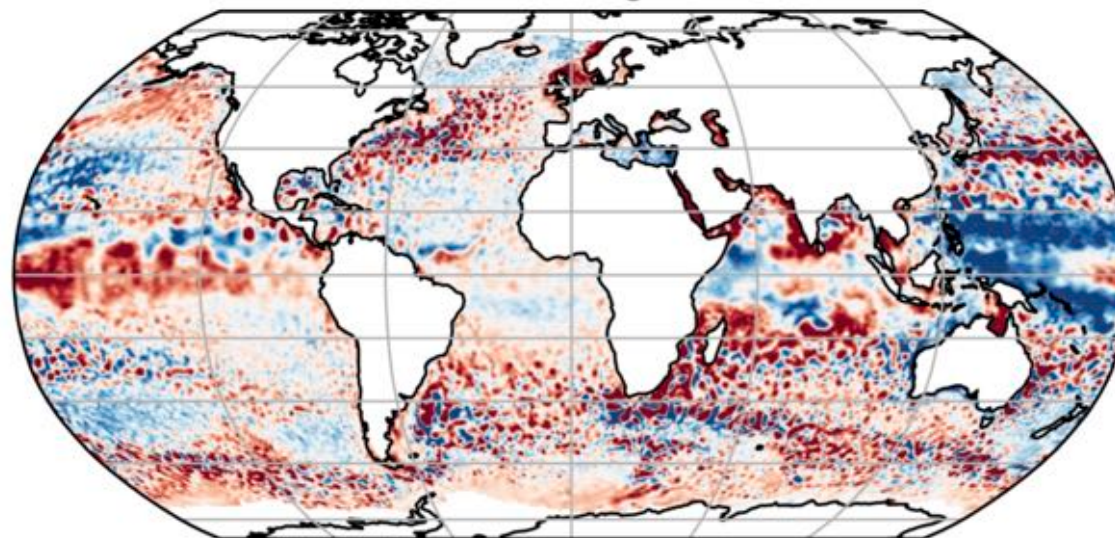


Atténuation de la variabilité chaotique observée par altimétrie

Thierry Penduff
Sally Close
Mickaël Lalande
Redouane Lguensat



Sabrina Speich



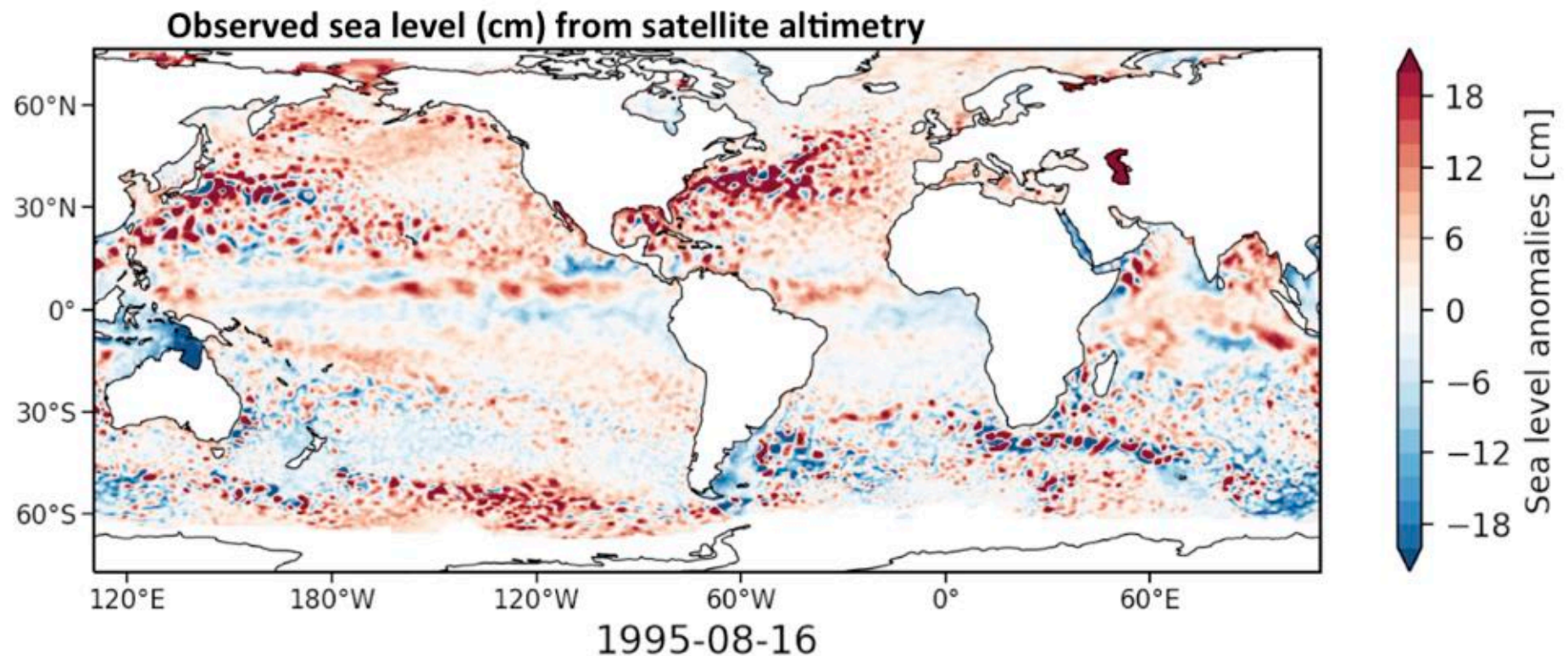
Outline

- ❑ **Forced & chaotic ocean variability**
- ❑ **Removing the chaotic component : a simple filter**
- ❑ **Removing the chaotic component : deep learning**
- ❑ **Conclusions and perspectives**

Forced and chaotic ocean variability

Penduff et al, 2011
Sérazin et al, 2015

- Oceanic evolution : 1 part is **forced** by the atmosphere
1 part is **chaotic** (random)



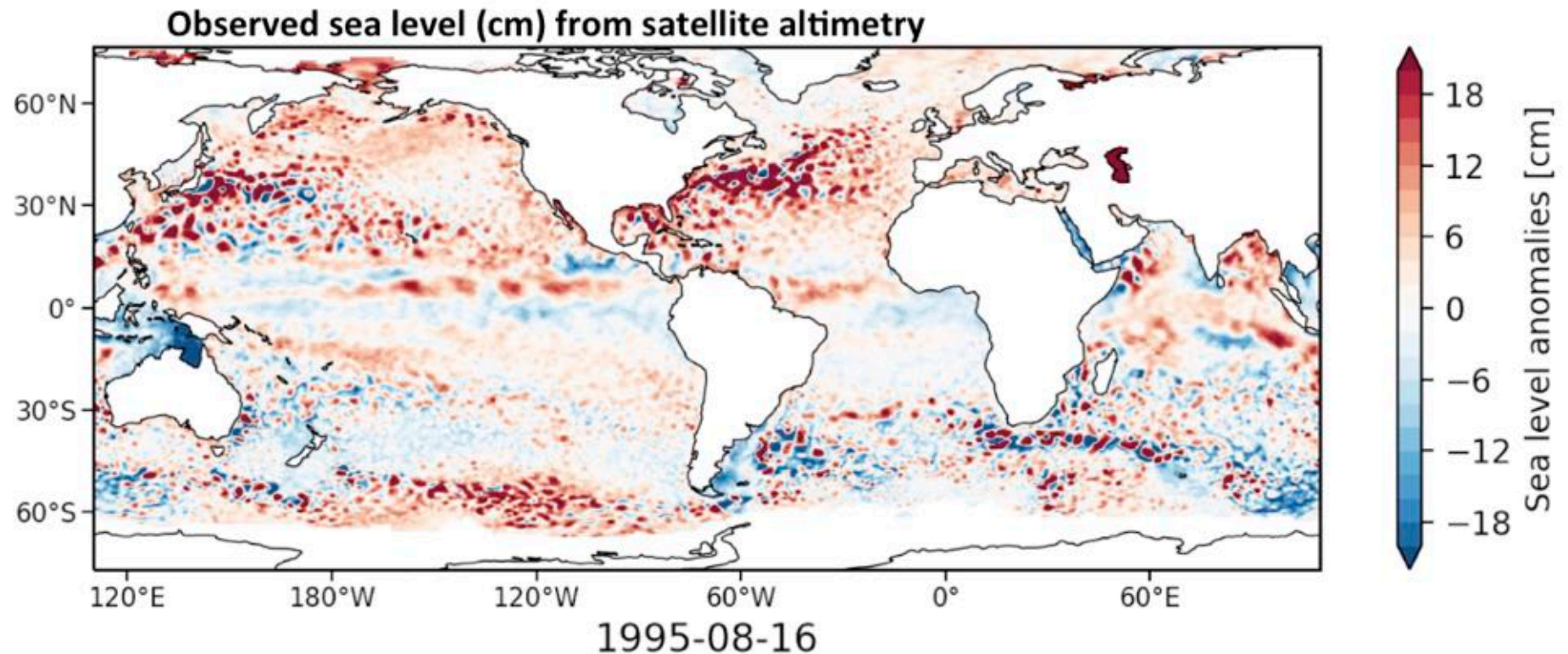
Forced and chaotic ocean variability

Penduff et al, 2011
Sérazin et al, 2015

Llovel et al, 2018

- Oceanic evolution : 1 part is **forced** by the atmosphere
1 part is **chaotic** (random)
- The **chaos** can mask the **forced** evolution locally

↑
*example : anthropogenic
sea level rise*

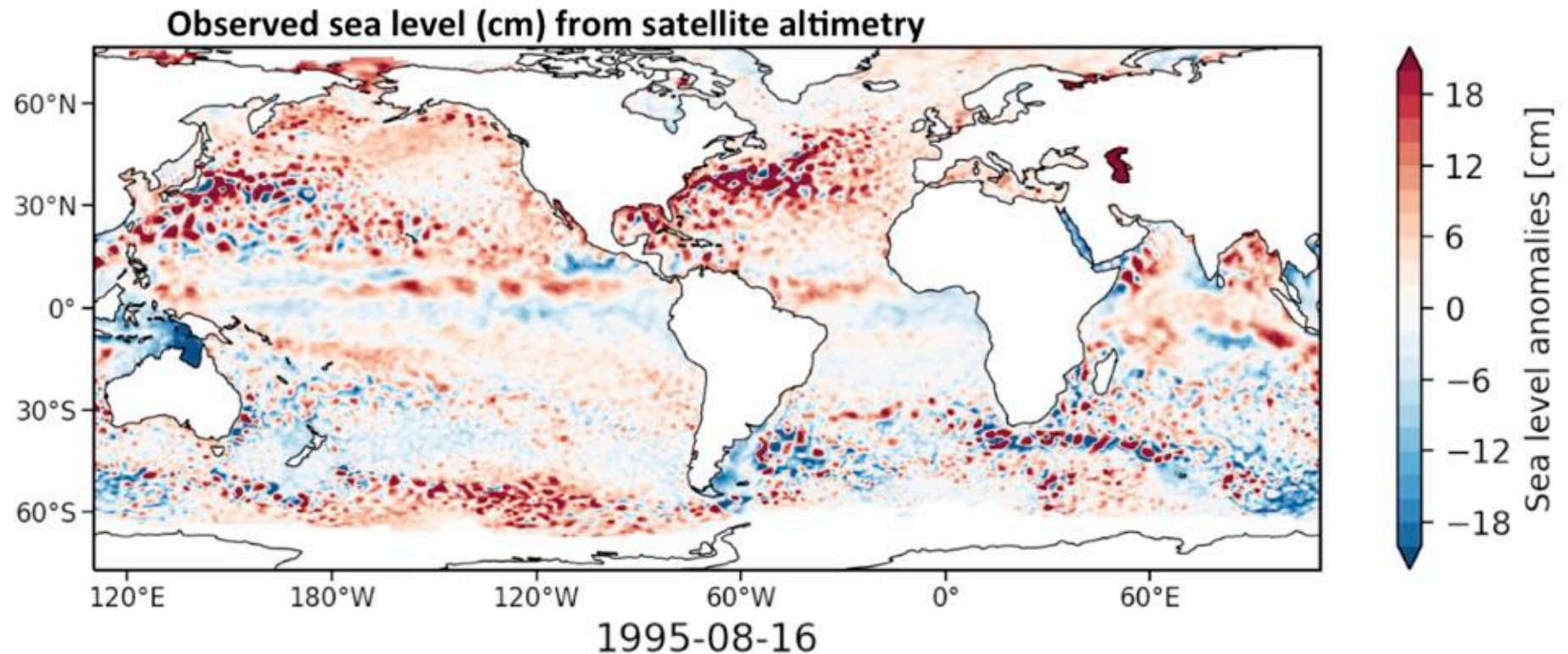


Forced and chaotic ocean variability

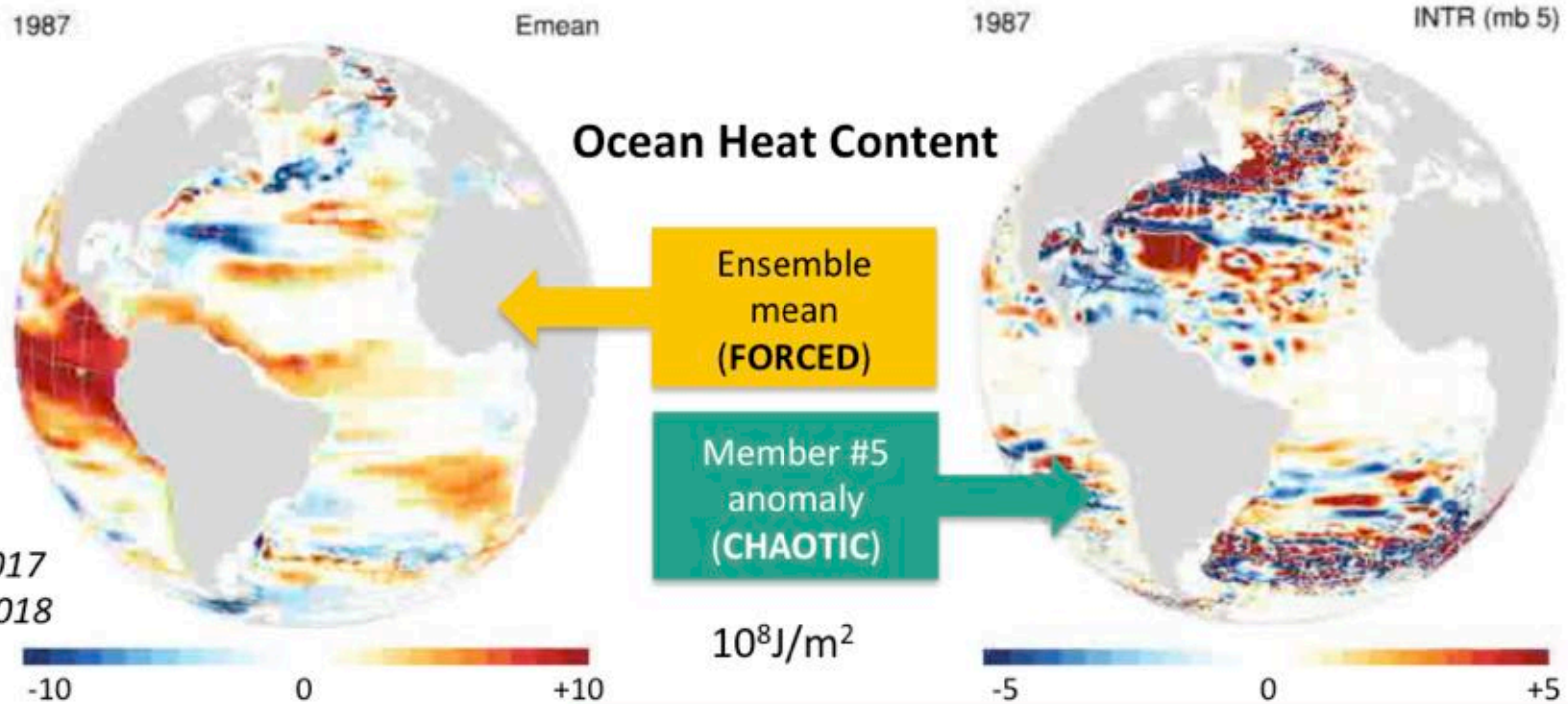
Penduff et al, 2011
Sérazin et al, 2015

Llovel et al, 2018

- Oceanic evolution : 1 part is **forced** by the atmosphere
1 part is **chaotic** (random)
- The **chaos** can mask the **forced** evolution locally
- **Extracting the forced evolution is crucial:**
observations alone ? → very difficult



Forced and chaotic ocean variability



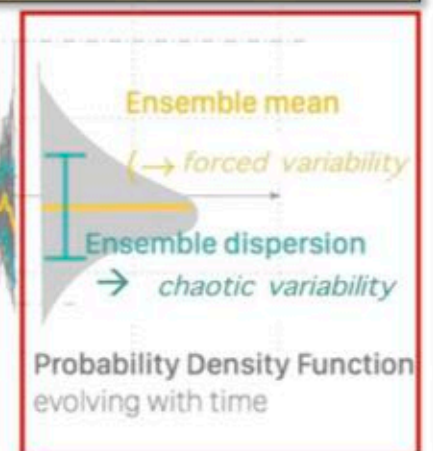
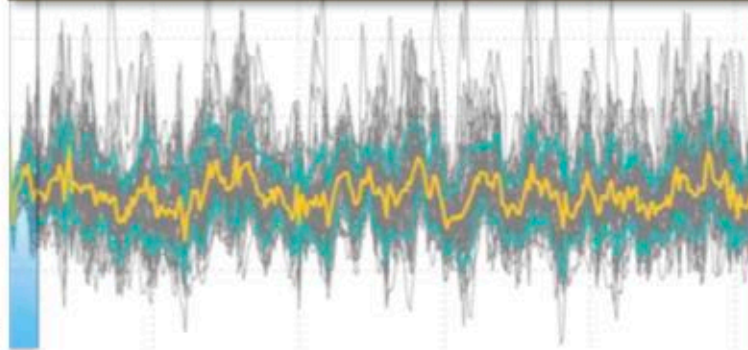
Sérazin et al, 2017
Penduff et al, 2018

OCCIPUT ensemble simulation :

- 50 global NEMO simulations ($1/4^\circ$)
- same forcing based on ERA-Interim
- slight initial perturbations

→ Separate forced and chaotic signals

Can we use ensemble simulations to estimate the forced signals in observations ?



Outline

- ❑ **Forced & chaotic ocean variability**
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- ❑ **Conclusions and perspectives**

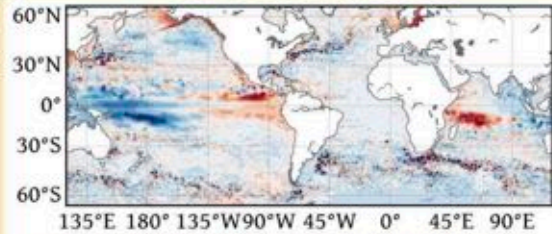
Ensemble run: forced variability

MODEL

member #1

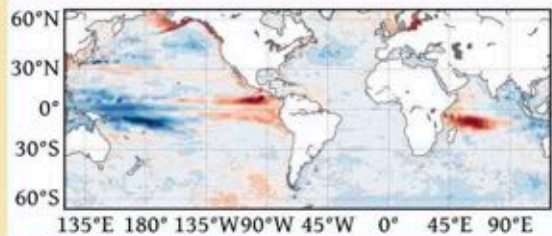
SLA Feb 24, 1998.

FULL



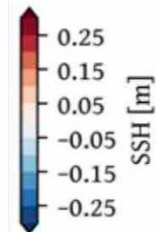
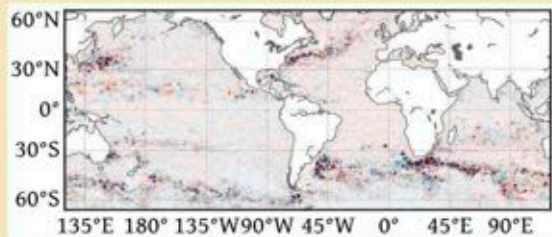
=

FORCED

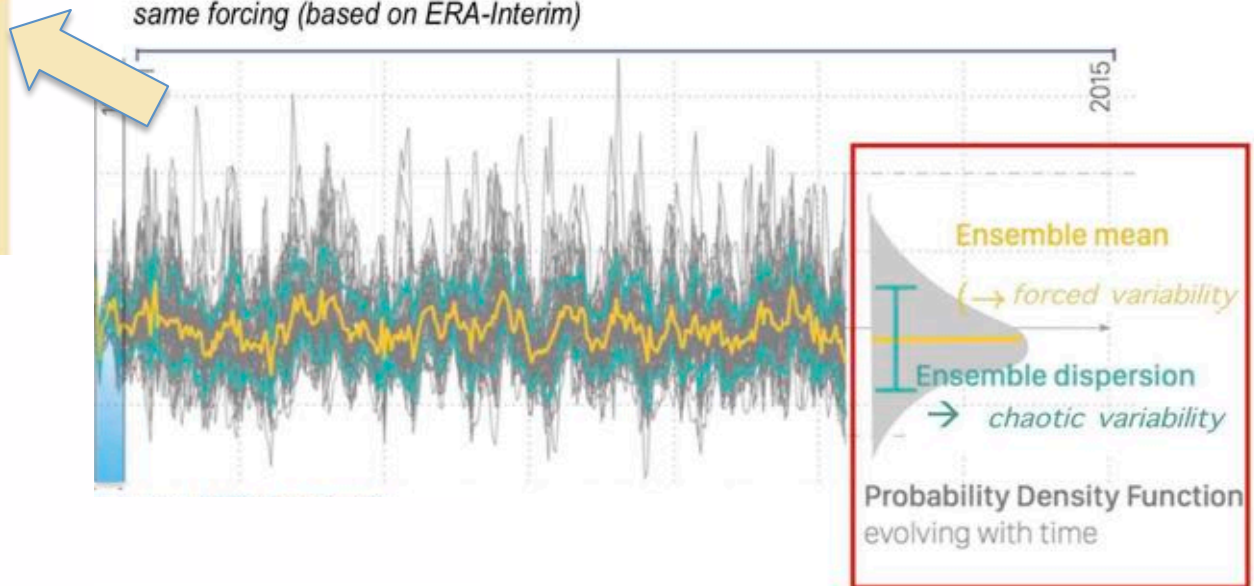


+

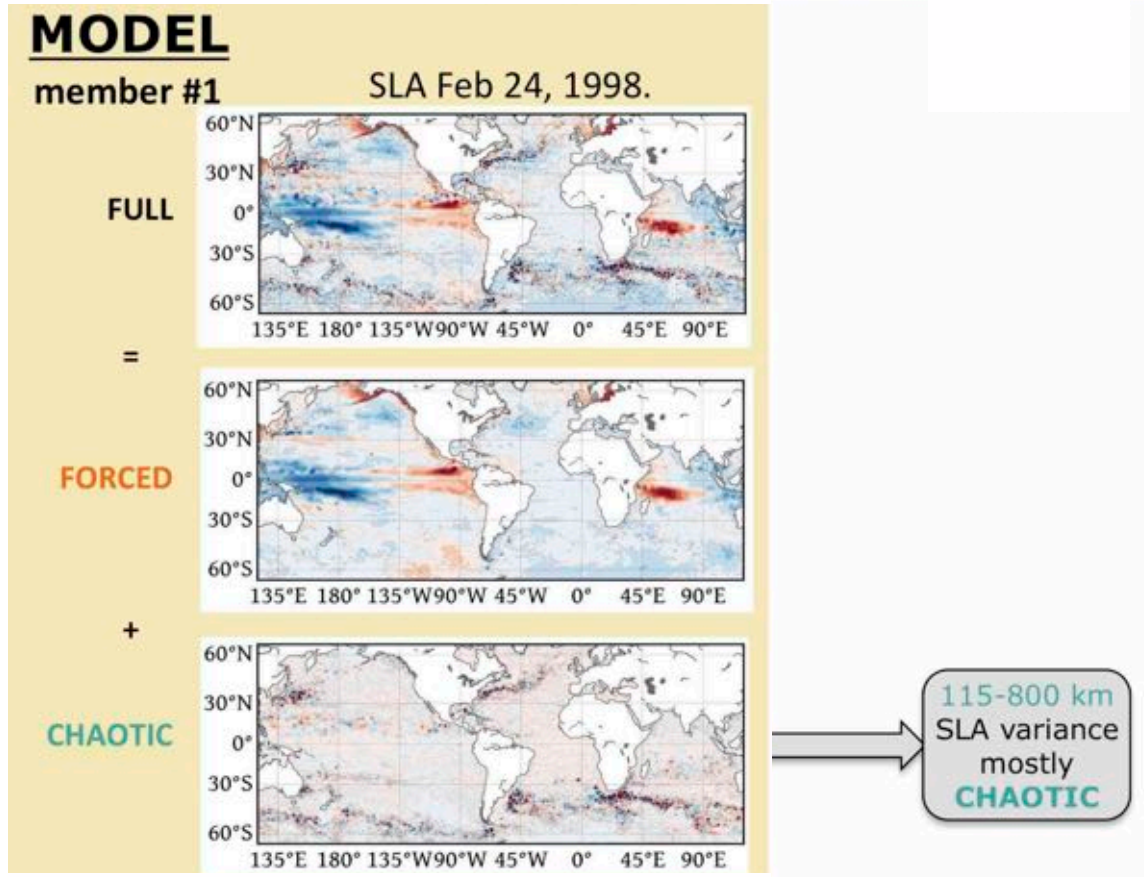
CHAOTIC



same forcing (based on ERA-Interim)

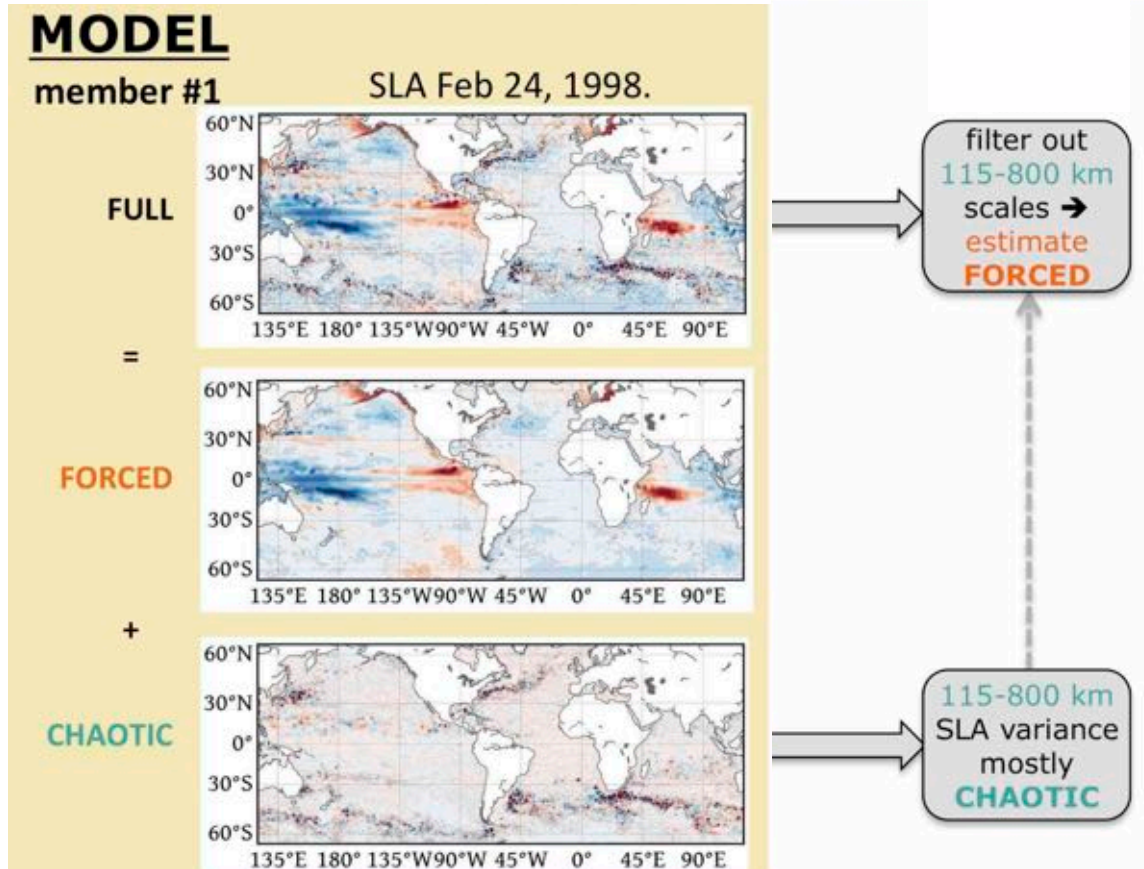


Ensemble run: forced variability



Close et al, in revision

Ensemble run: forced variability



Close et al, in revision

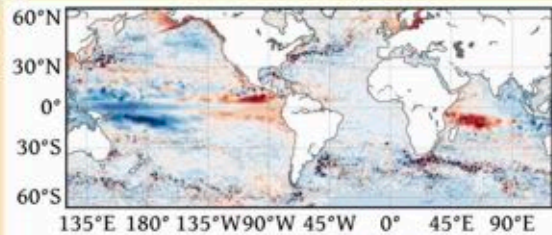
Ensemble run: forced variability estimate (filter)

MODEL

member #1

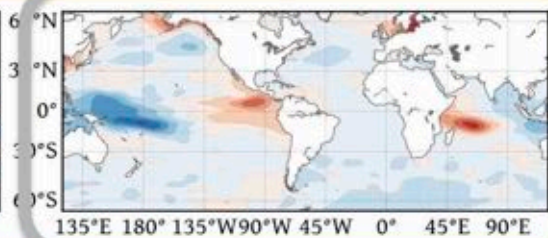
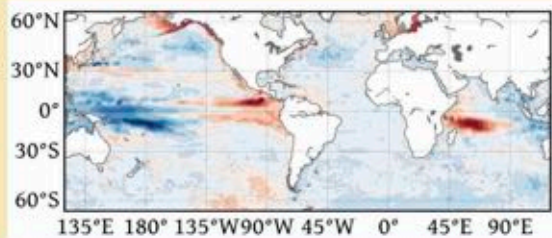
SLA Feb 24, 1998.

FULL



filter out
115-800 km
scales →
estimate
FORCED

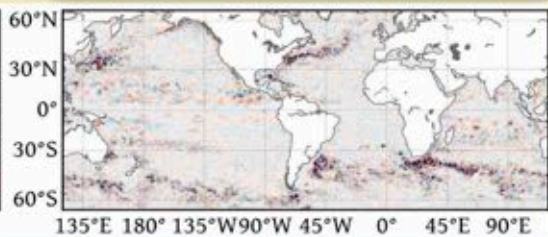
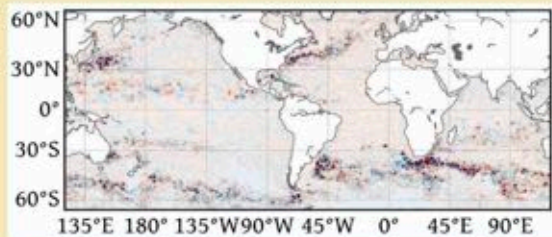
FORCED



FORCED timeseries :
 $\text{Corr}_T(\text{true, estimated}) \sim 0.9$

+

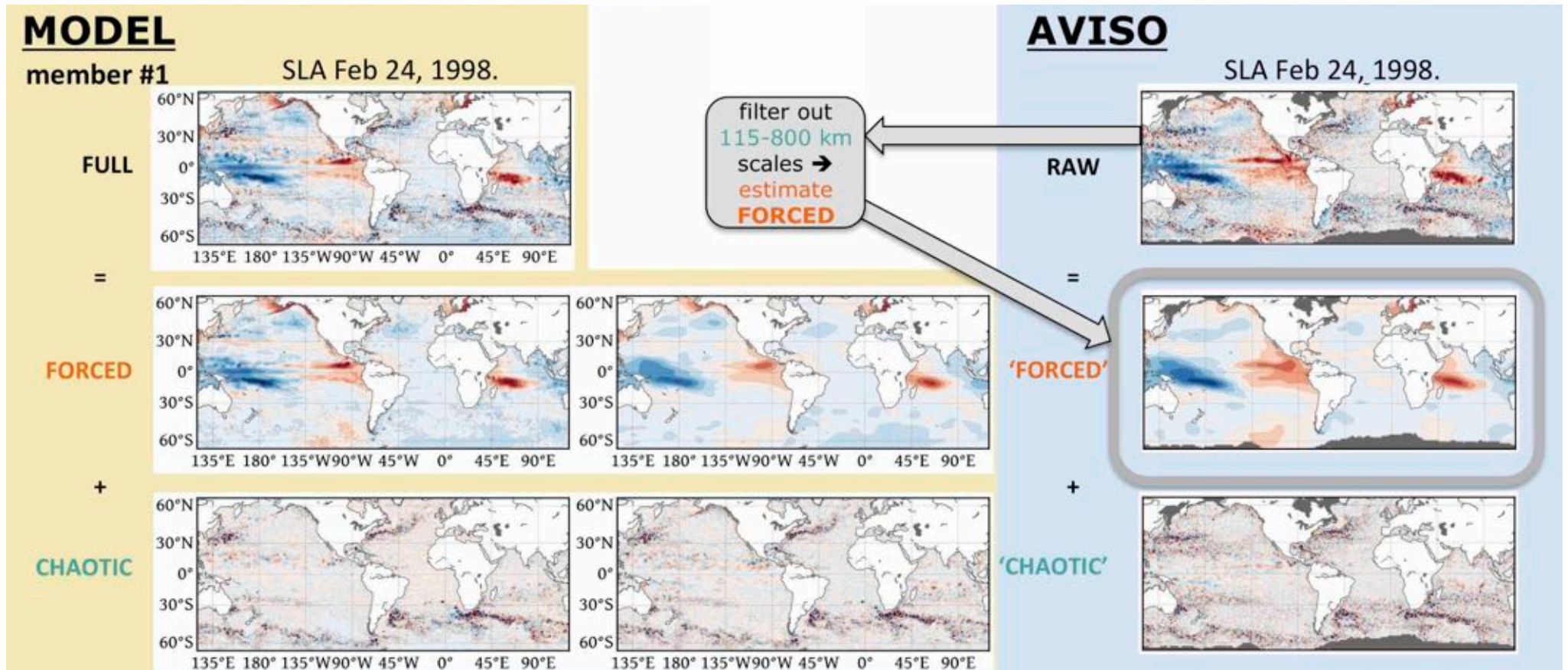
CHAOTIC



CHAOTIC timeseries
 $\text{Corr}_T(\text{true, estimated}) \sim 0.9$

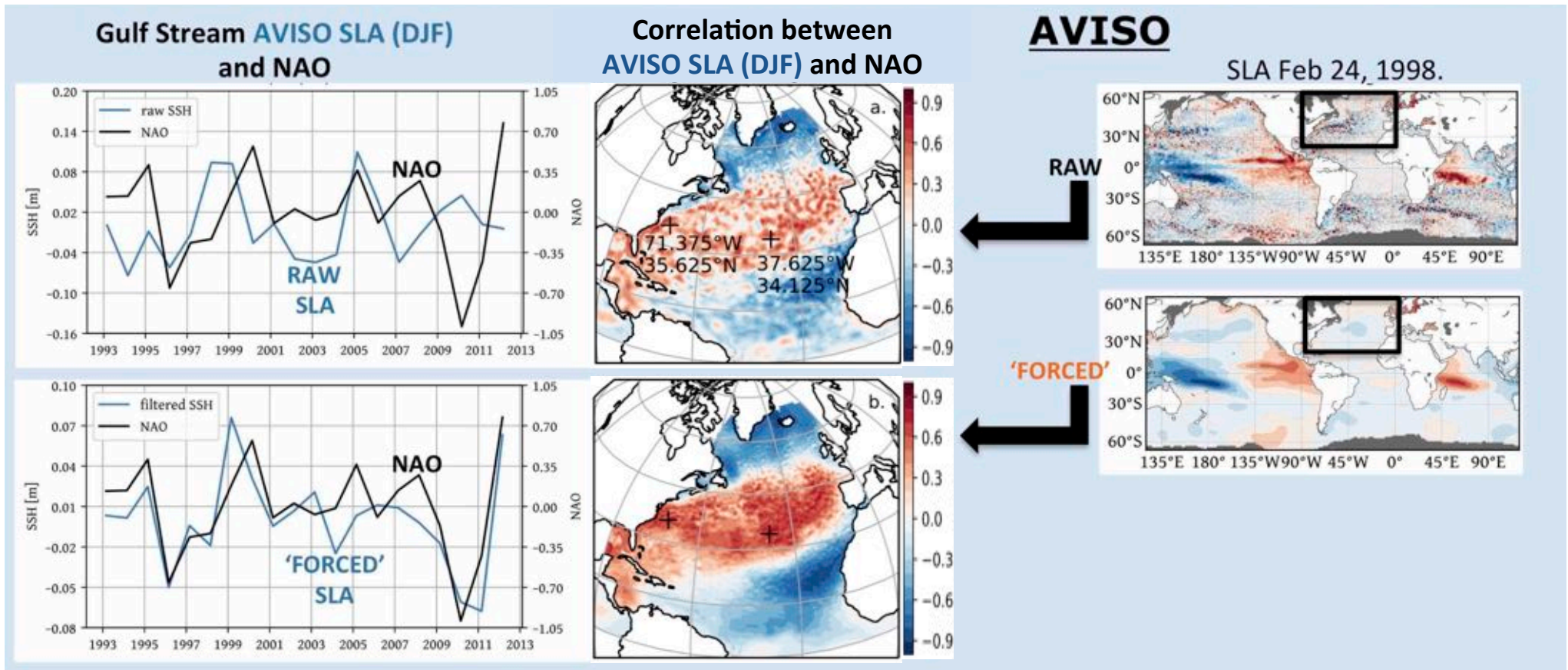
Close et al, in revision

Observations: forced variability estimate (filter)



Close et al, in revision

Observations: forced variability estimate: response to the atmosphere



Can we improve this forced variability estimator through deep learning ?

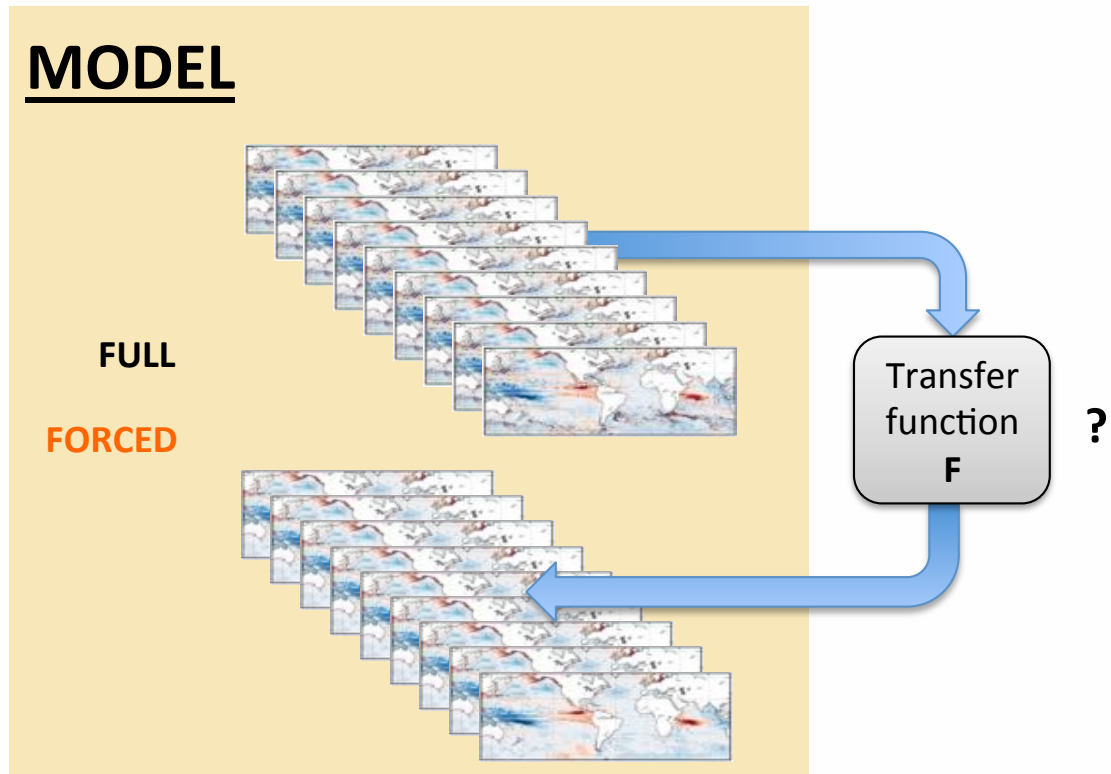
Close et al, in revision

Outline

- ❑ **Forced & chaotic ocean variability**
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forced variability estimate: Deep Learning

TRAINING



forced variability estimate: Deep Learning in Zones 1+2+3

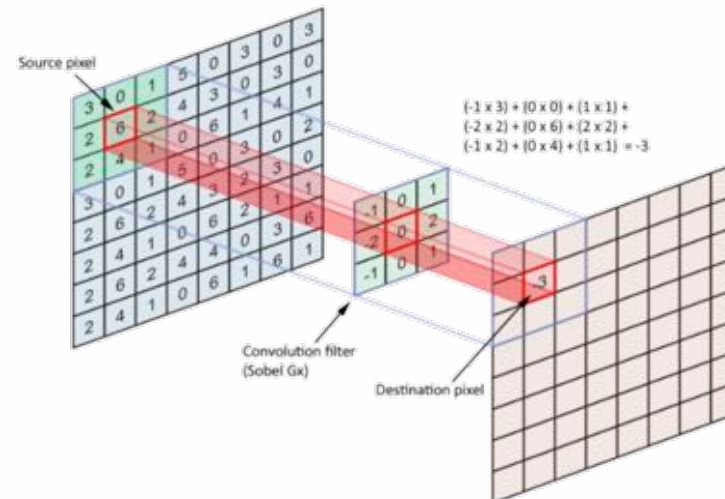
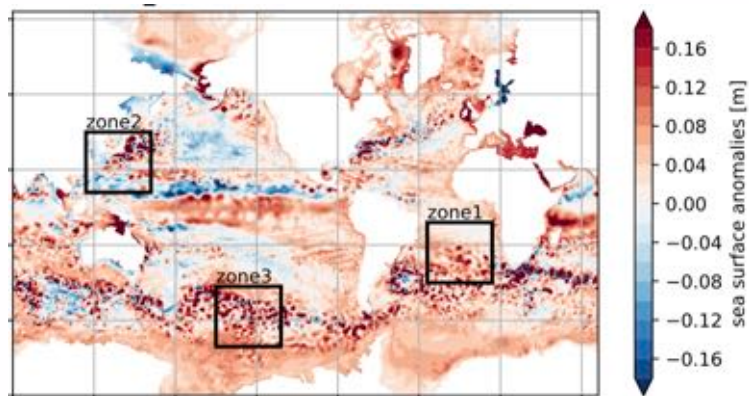
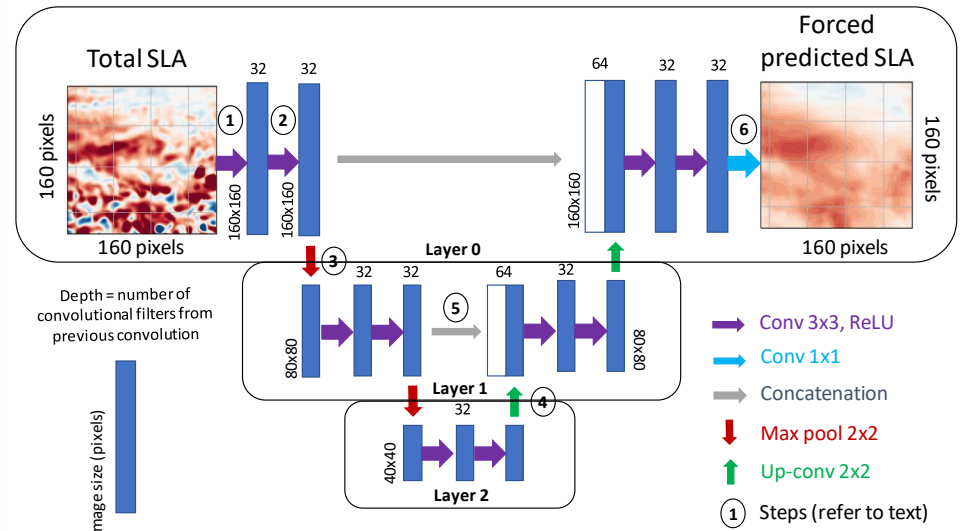
TRAINING

MODEL Local - Certain members, days

Learning the

Transfer function **F**

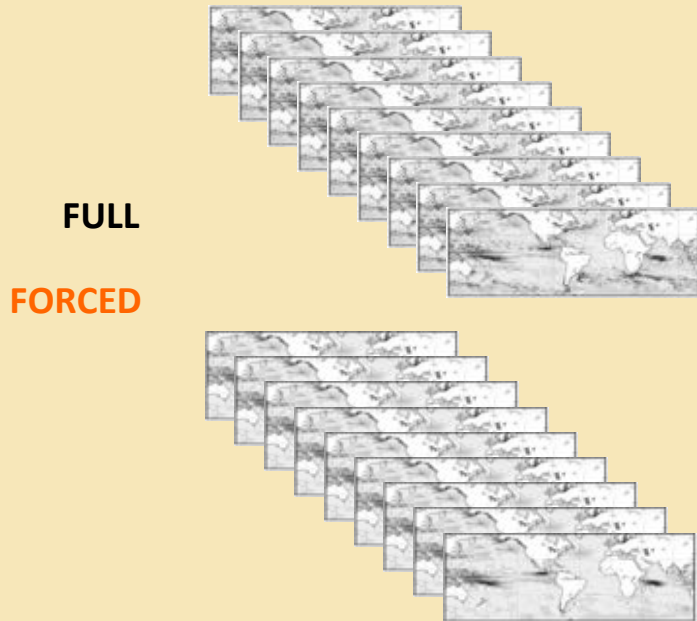
Convolutional Neural Network : U-net (Ronneberger et al. 2015)



forced variability estimate: Deep Learning in Zones 1+2+3

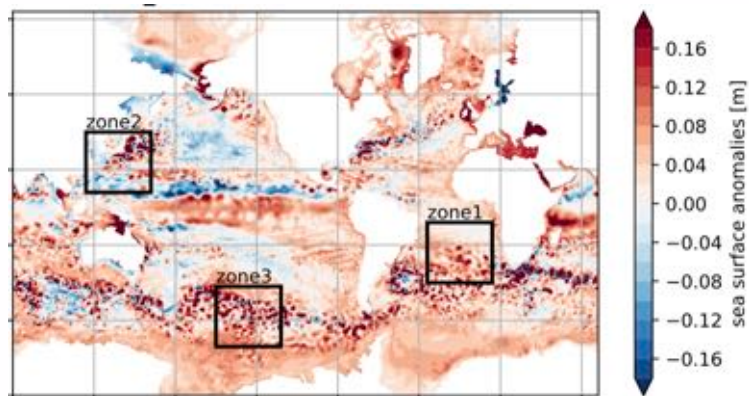
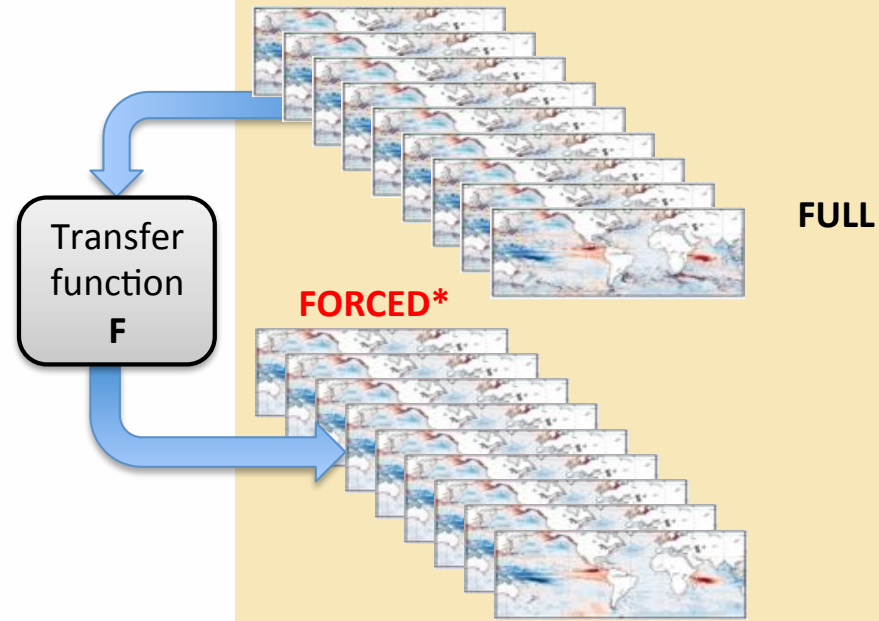
TRAINING

MODEL Local - Certain members, days



EVALUATION

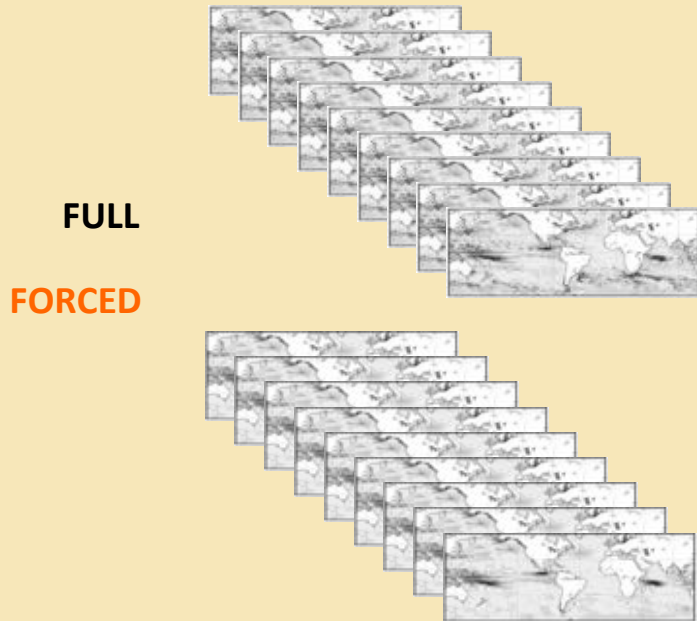
MODEL Global - Unseen members, days



forced variability estimate: Deep Learning in Zones 1+2+3

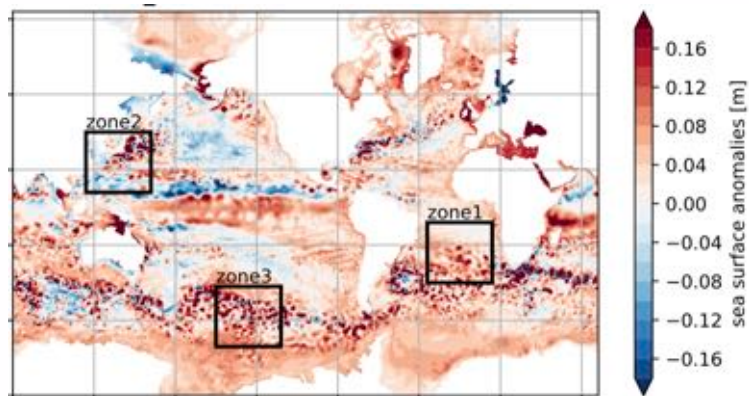
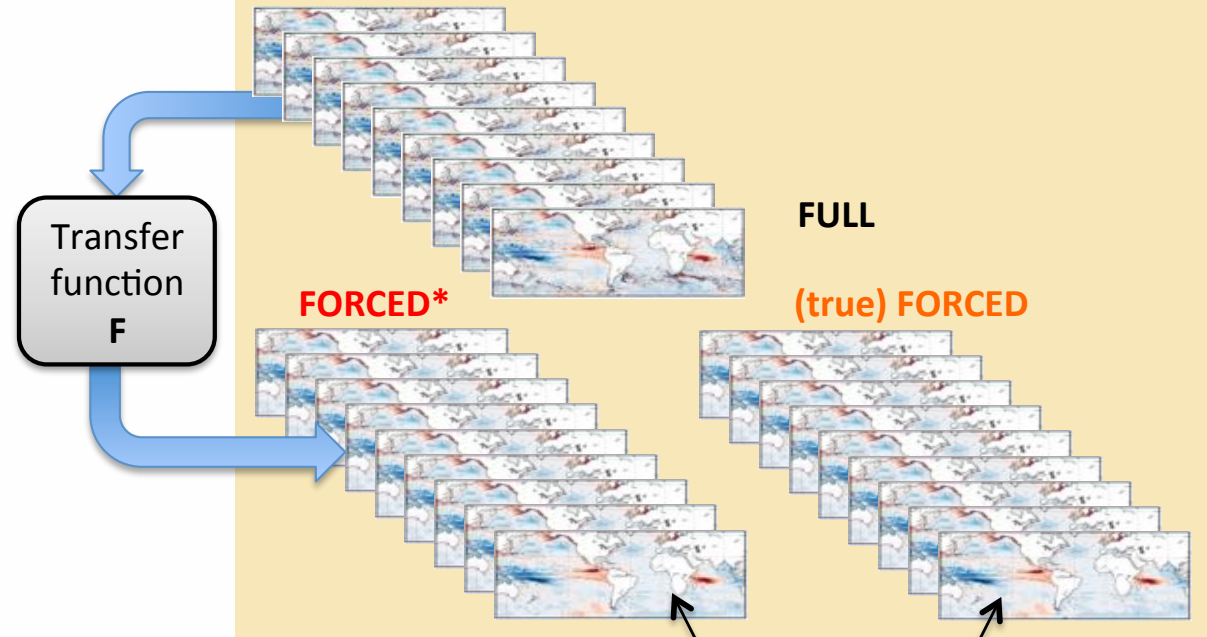
TRAINING

MODEL Local - Certain members, days

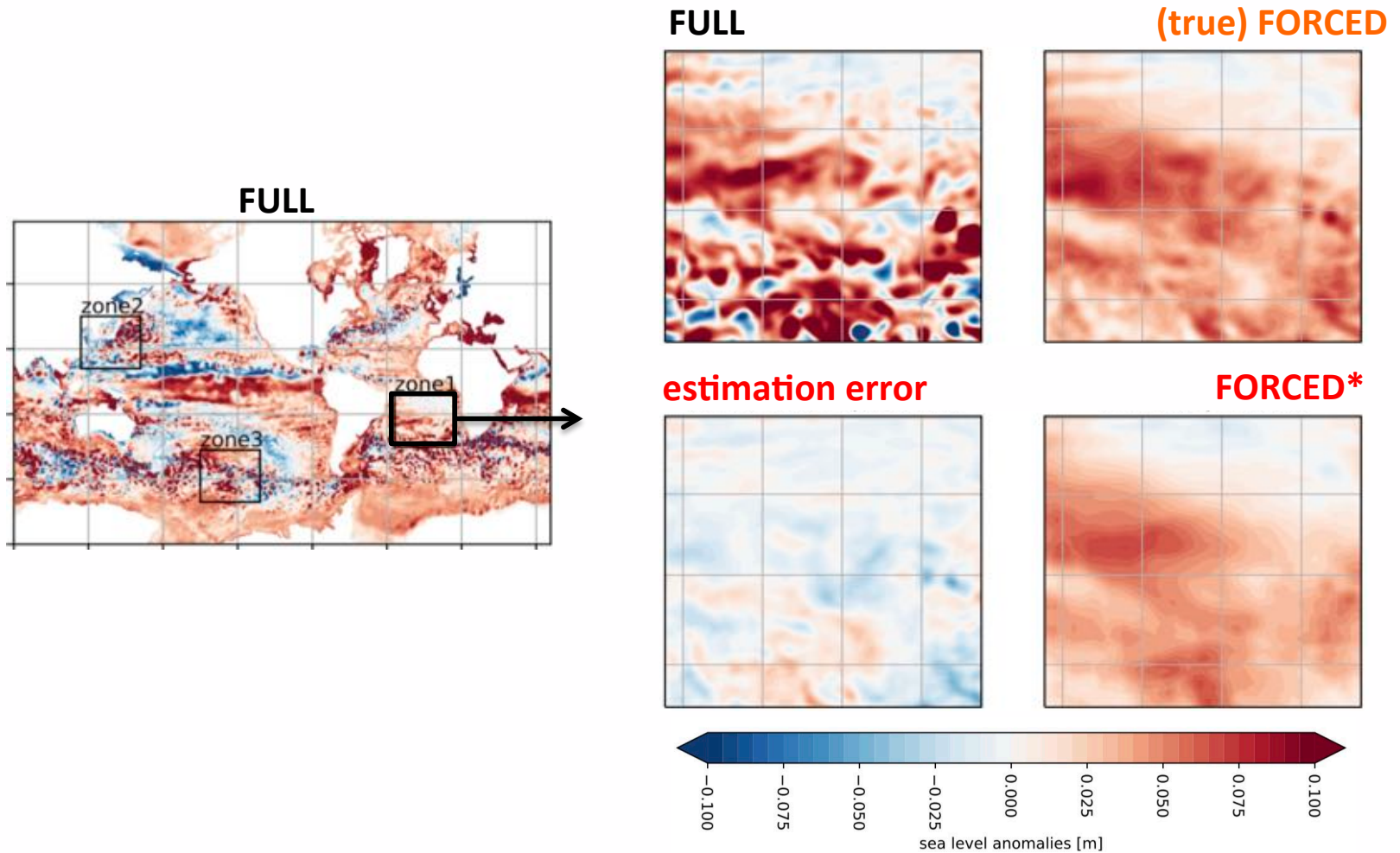


EVALUATION

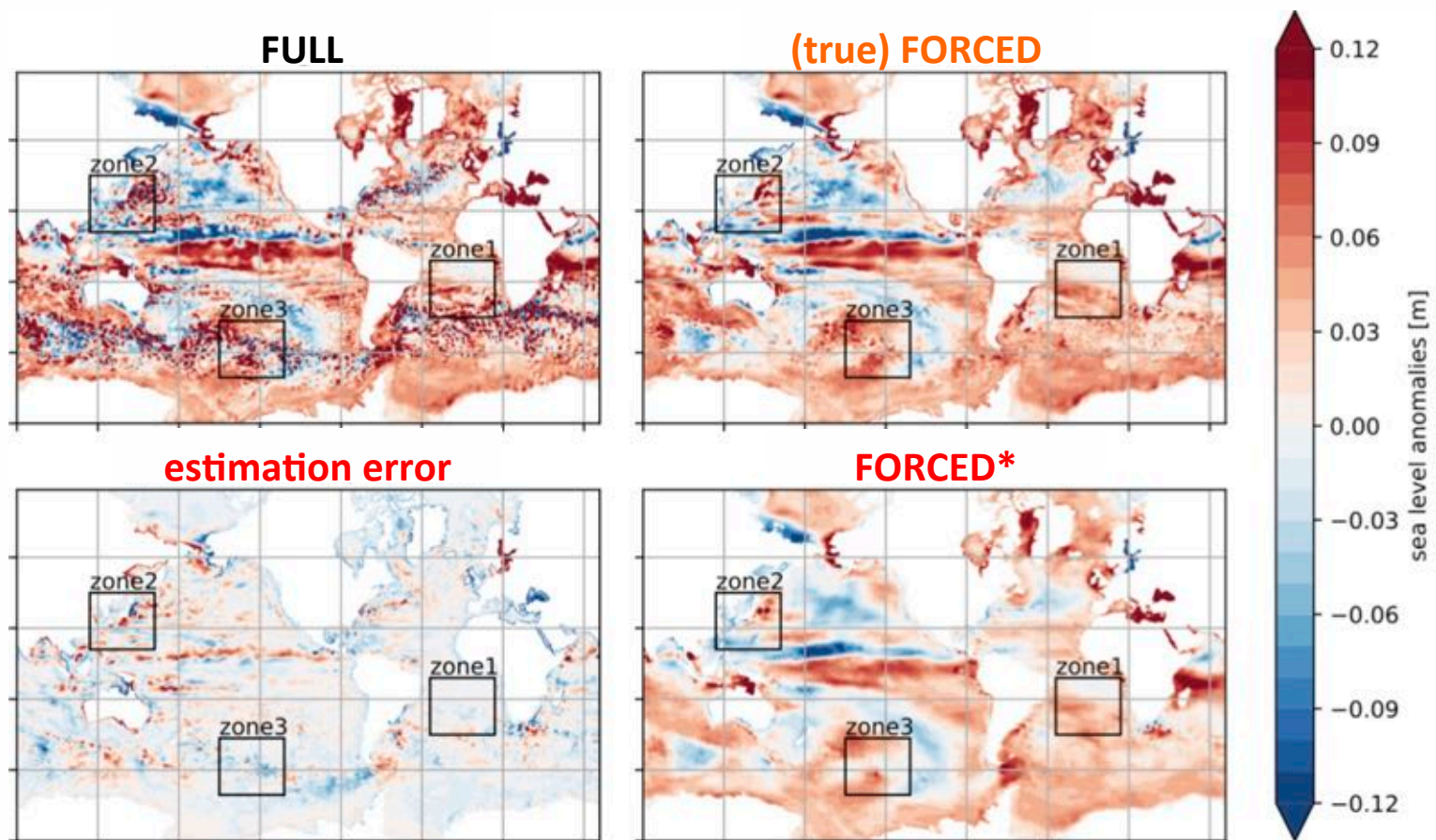
MODEL Global - Unseen members, days



forced variability estimate: Deep Learning in Zones 1+2+3

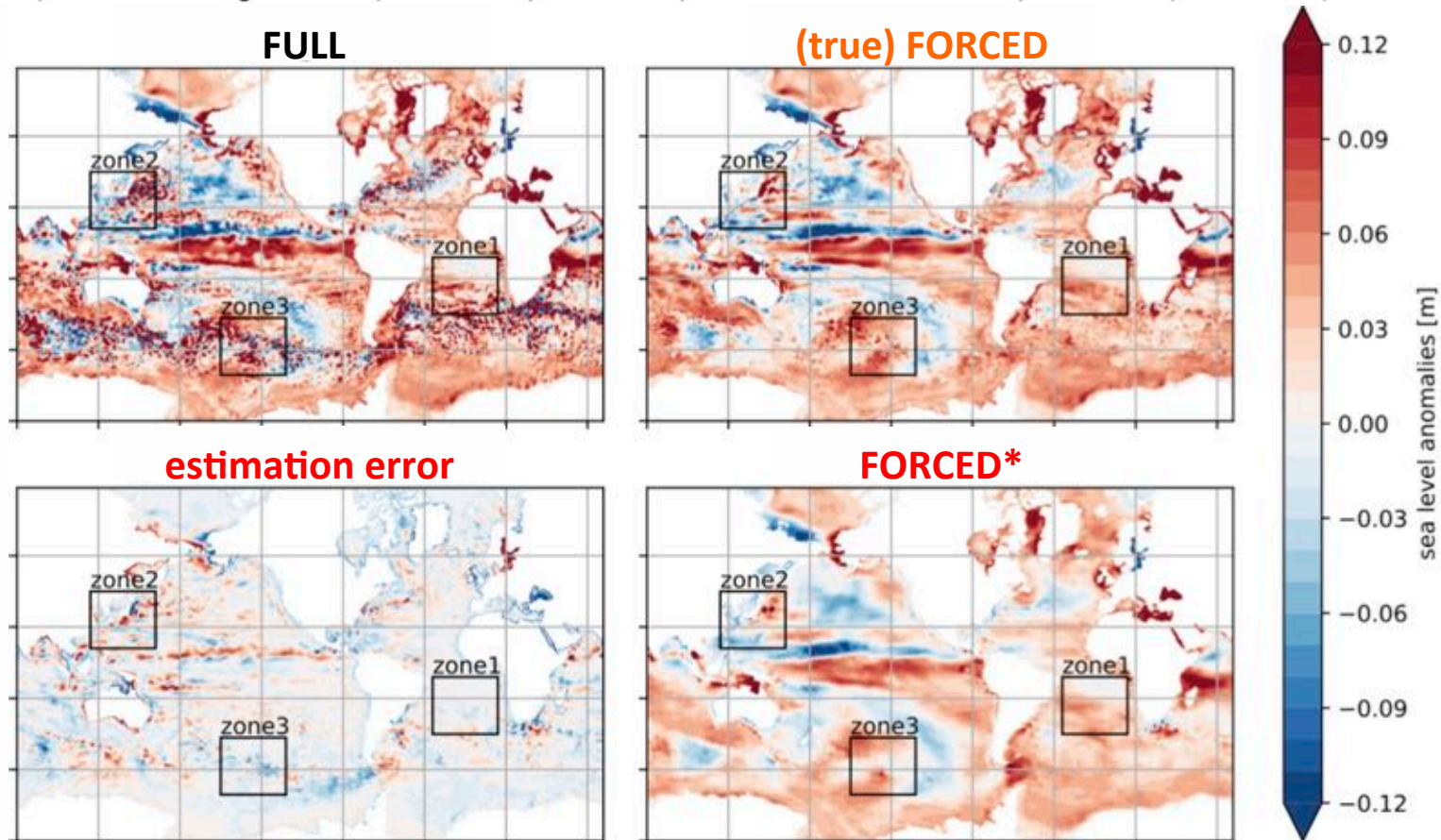
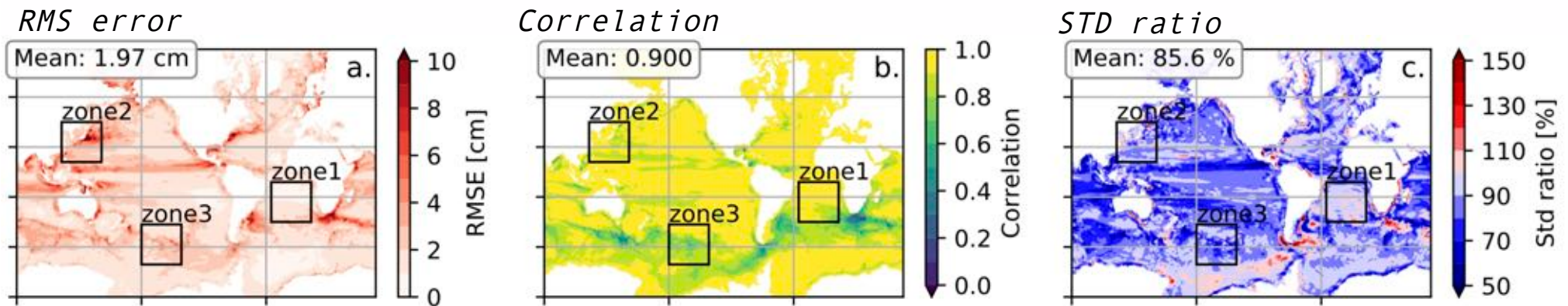


forced variability estimate: Deep Learning in Zones 1+2+3



forced variability estimate: Deep Learning in Zones 1+2+3

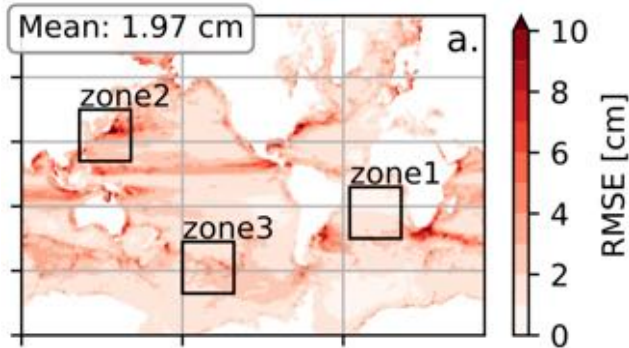
DL



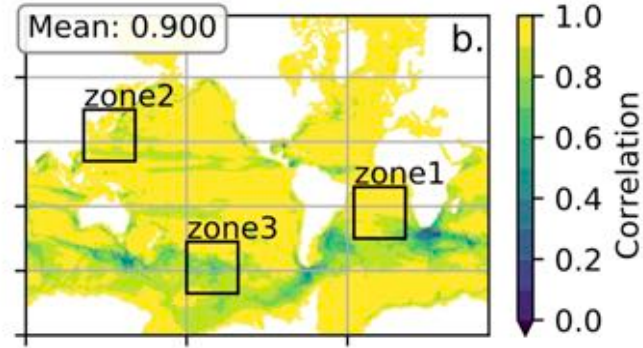
forced variability estimate: Deep Learning vs Filter

DL

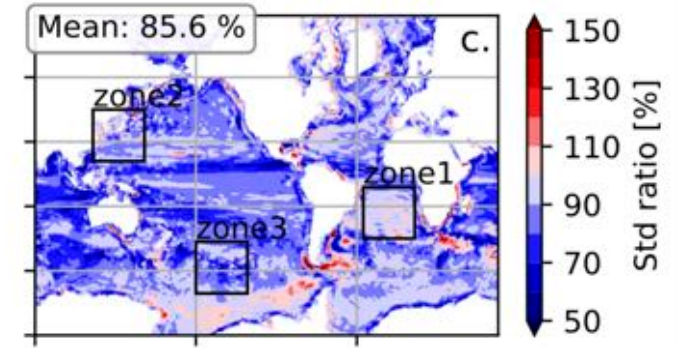
RMS error



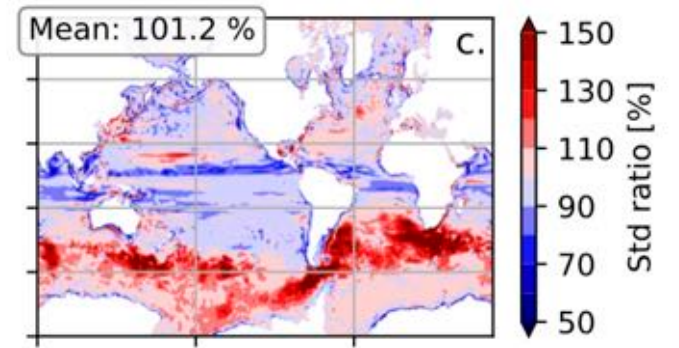
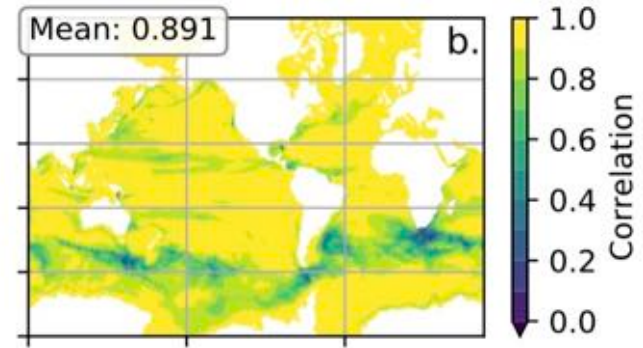
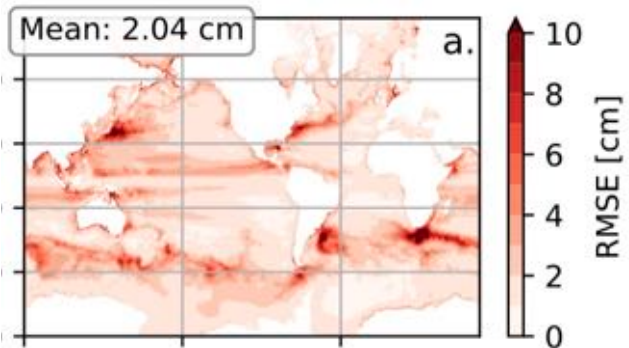
Correlation



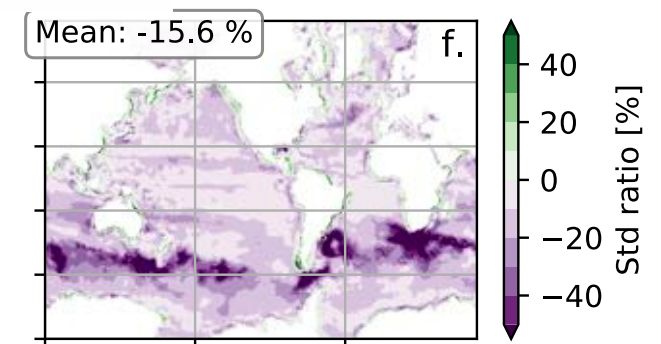
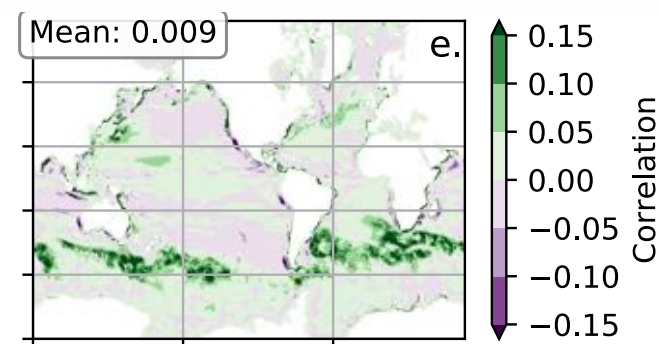
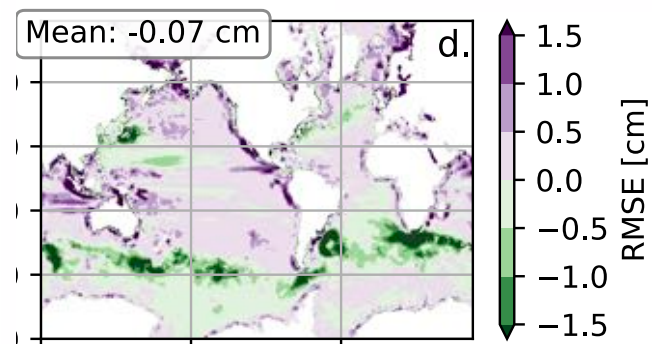
STD ratio



Filter



Difference DL — Filter



Conclusion

DL denoising → « deterministic » signals

Perfectible but promising

Self-adapting to specific regions

Potential applications for other variables

New tools → new questions

Still exploratory

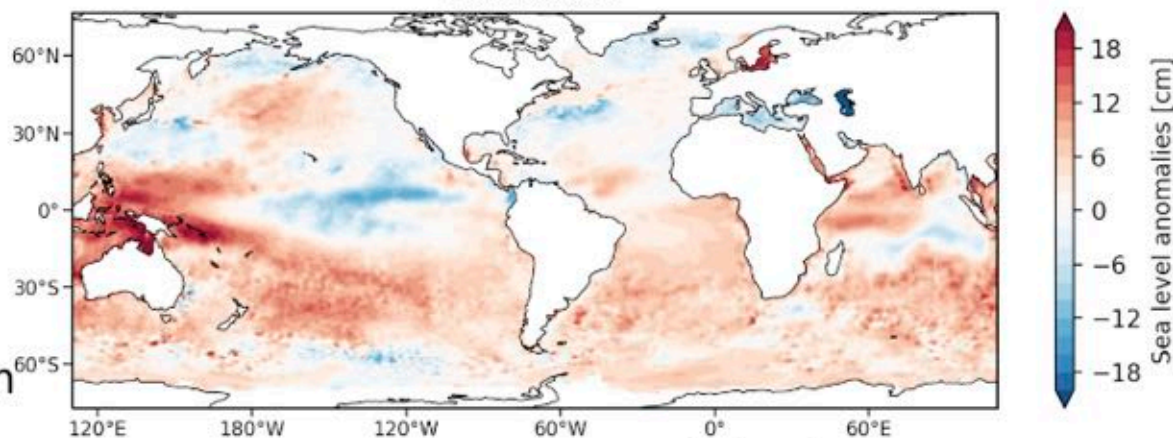
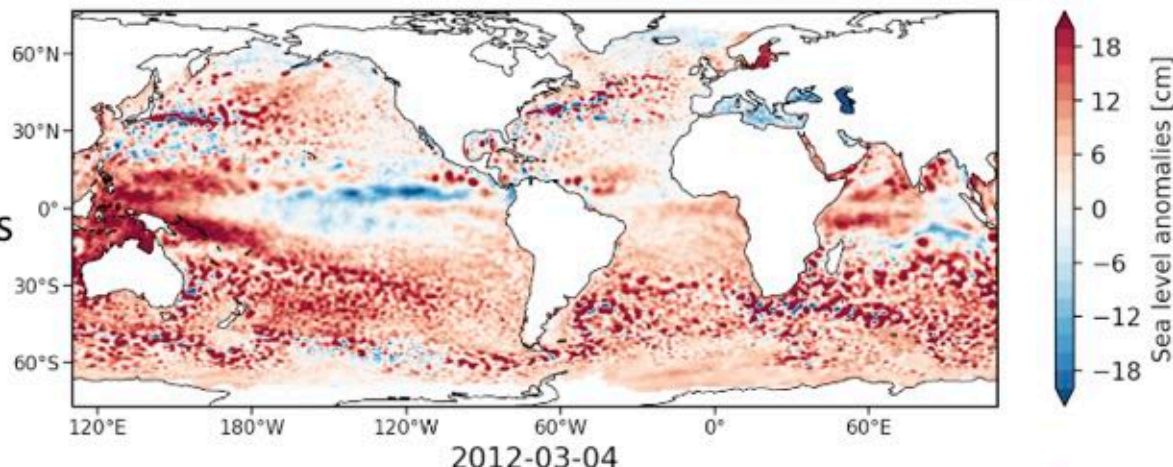
New insights into natural systems

→ other perspectives of AI

Data mining, classification

Subgrid-scale closures, data assimilation

**Original
Altimetric Observations**



**« Deterministic »
Altimetric Observations:
Forced by the atmosphere**