Attenuating the ocean chaotic variability in altimetric observations: from band-pass filtering to machine learning

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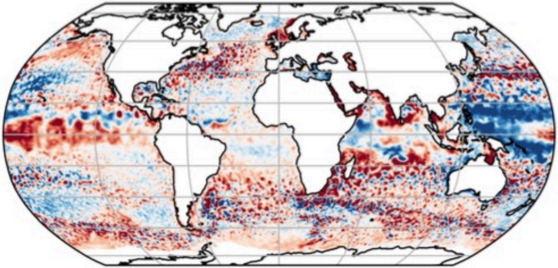


Outline

- ❑ <u>**Forced & chaotic ocean variability**</u>
- ❑ **Attenuating the chaotic component : a simple filter**
- ❑ **Attenuating the chaotic component : deep learning (DL)**
- ❑ **Conclusions and perspectives**

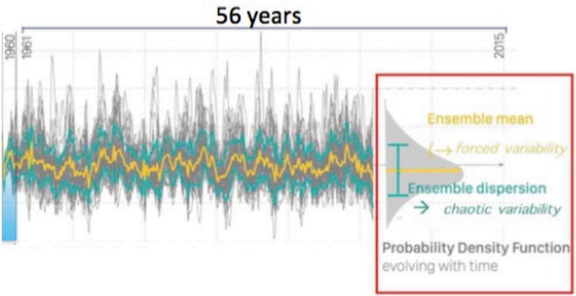
Forced and chaotic ocean variability

- Sea-level evolution : 1 part is forced by the atmosphere : deterministic
  1 part is intrinsic to the ocean : chaotic
- The chaos can mask the forced evolution locally
- **Extracting the forced evolution is crucial:**
  observations alone ? ➔ very difficult
  ensembles simulation ? ➔ **yes**
  ex: forced SLA trends (W. Llovel's talk last Monday)

OCCIPUT ensemble simulation :

- 50 global ocean simulations (1/4°)
- slight initial perturbations
- same observed atmospheric forcing

➔ **Separate forced and chaotic signals**



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- Attenuating the chaotic component : deep learning
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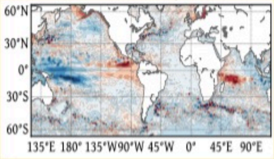
Ensemble run: forced & chaotic variability

MODEL

member #1 SLA Feb 24, 1998.

FULL



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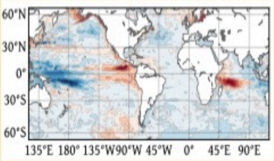
FORCED



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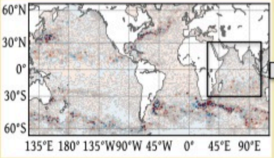
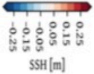
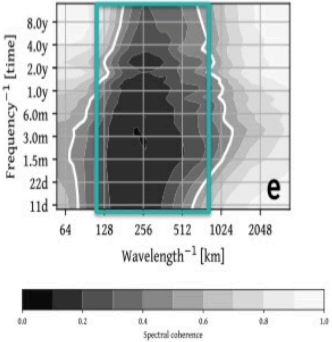
CHAOTIC





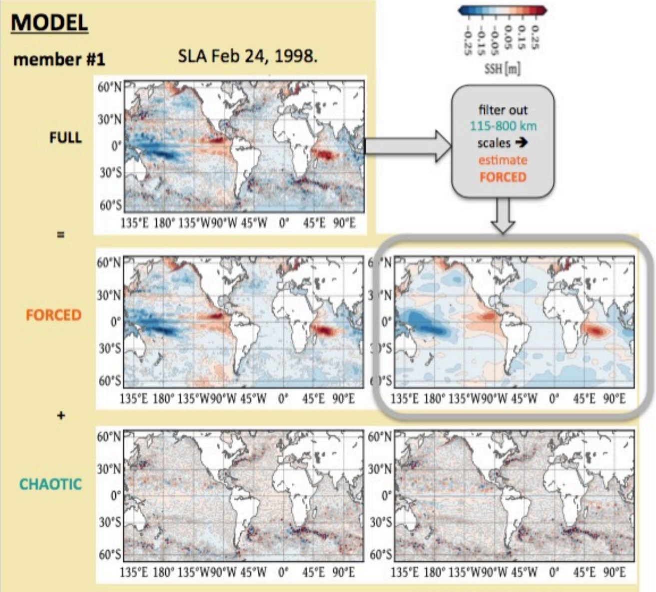
115-800 km
SLA variance
mostly
CHAOTIC

spectral coherence
(full, forced)



Close et al. (in revision)

Ensemble run: forced variability estimate (filter)



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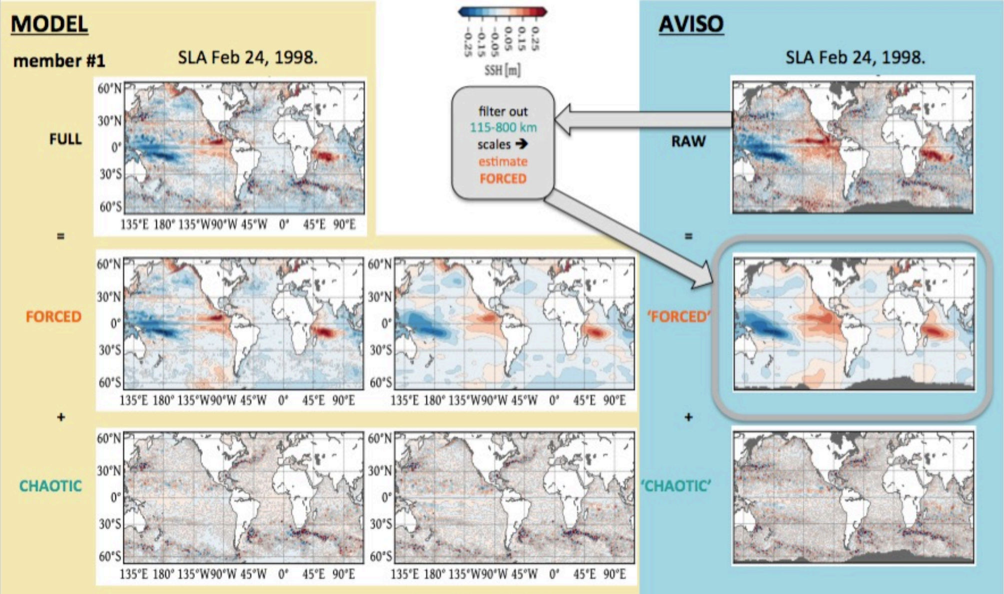
FORCED timeseries :
Corr$_T$ (true,estimated) ~ 0.9

CHAOTIC timeseries
Corr$_T$ (true,estimated) ~ 0.9

Observations: forced variability estimate (filter)



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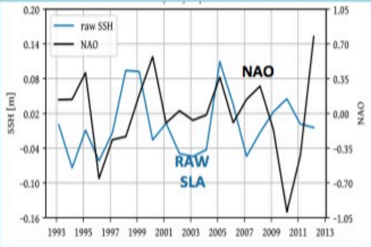
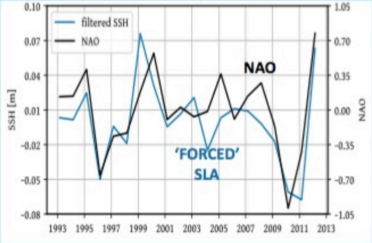
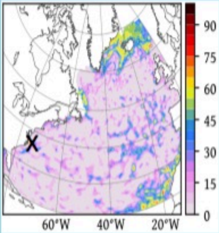
Observations: forced variability estimate: response to the atmosphere

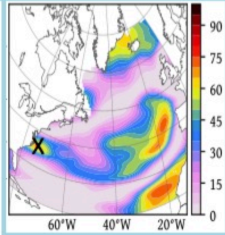
Gulf Stream AVISO SLA (DJF) and NAO





%variance of AVISO SLA (DJF) explained by NAO

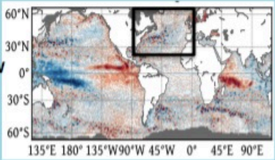




AVISO

SLA Feb 24, 1998.

RAW



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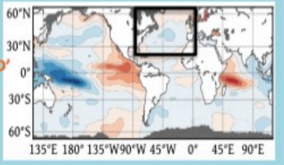

Can we improve this forced variability estimator through deep learning ?

Close et al. (in revision)

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forced variability estimate: DL in Zones 1+2+3

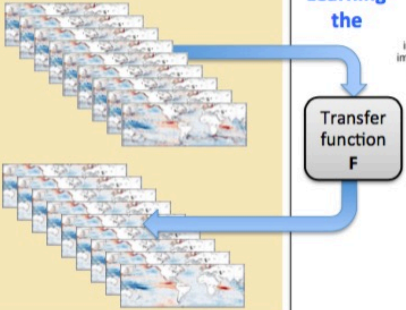
M. Lalande et al
in prep.

TRAINING

MODEL Local - Certain members, days

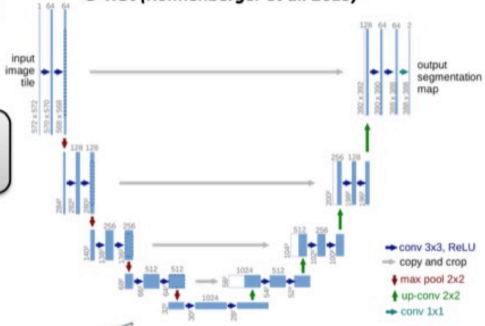
FULL

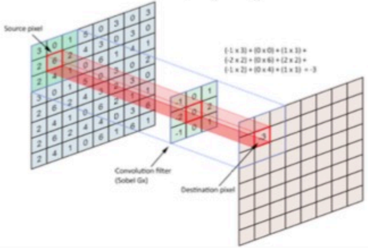
FORCED

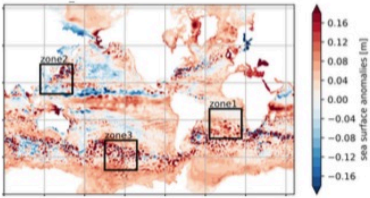


Learning the

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







forced variability estimate: DL in Zones 1+2+3

M. Lalande et al
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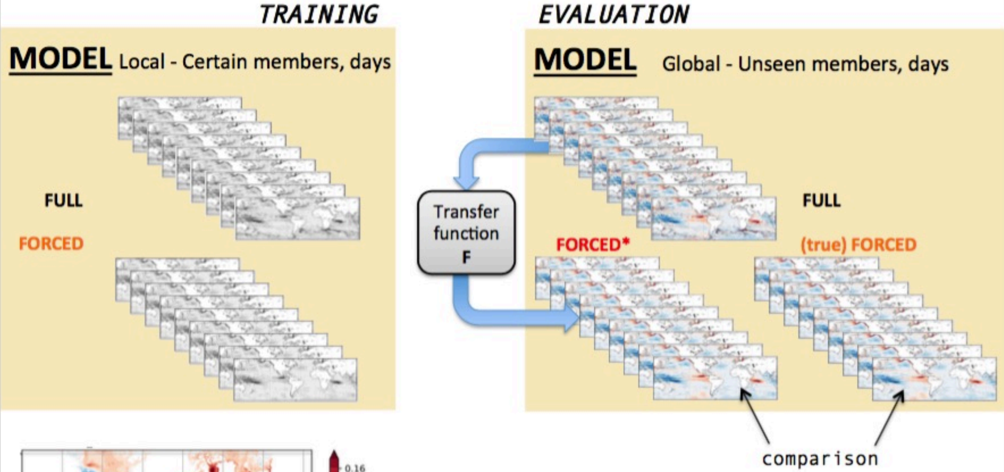

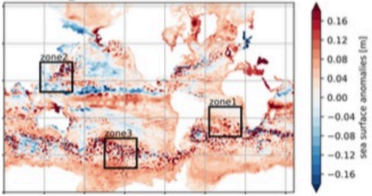

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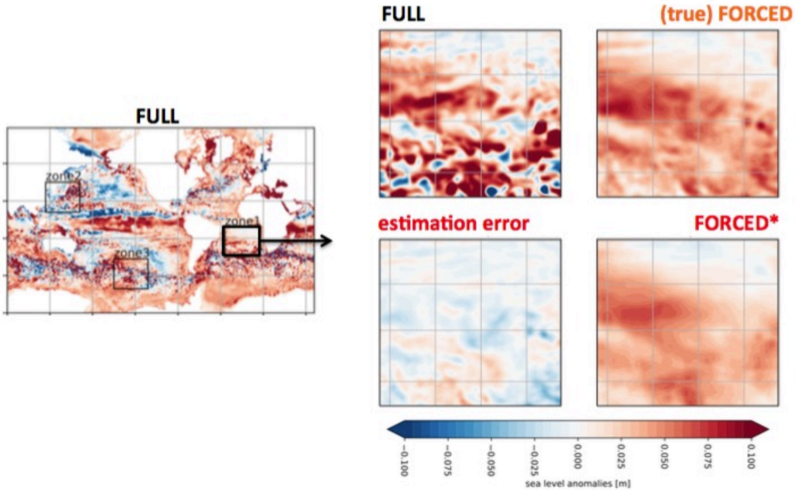
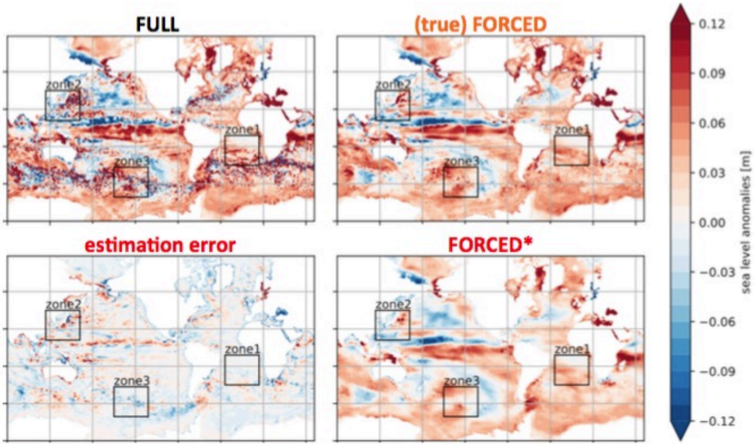
in prep.



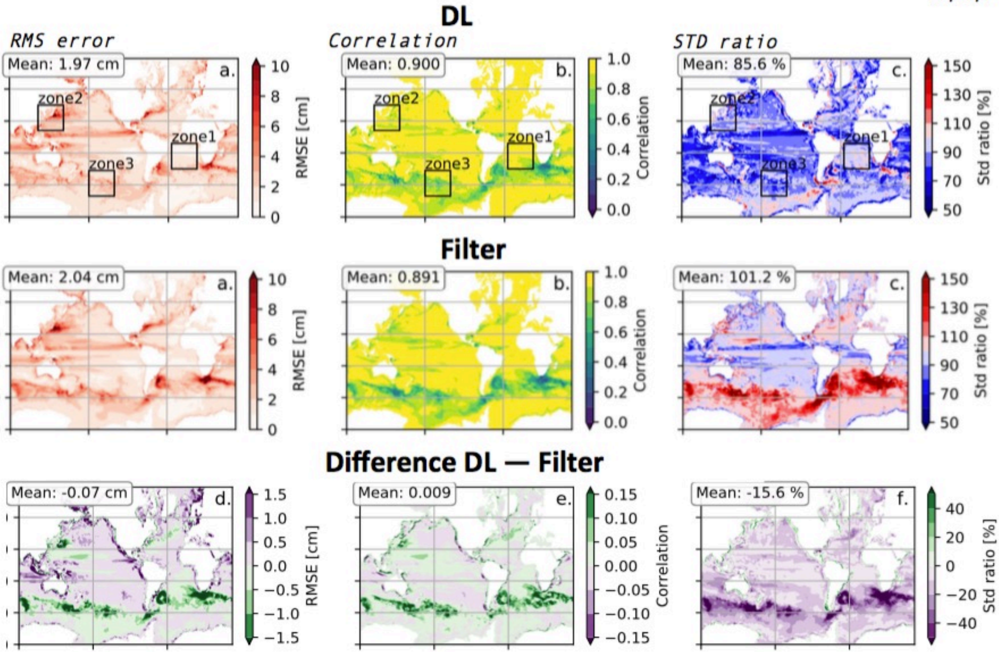
forced variability estimate: DL in Zones 1+2+3

M. Lalande et al in prep.



forced variability estimate: DL vs Filter

M. Lalande et al in prep.



Sea-level Observations: forced signals (DL Zones 1+2+3)

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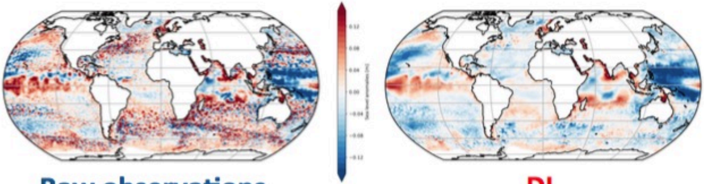
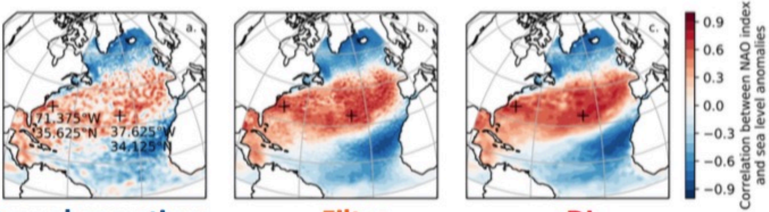
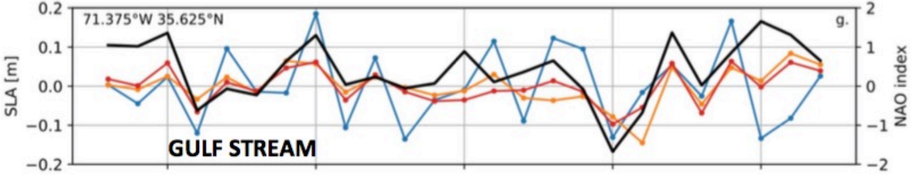


Raw observations DL



Raw observations Filter DL



Conclusions

- Multi-scale **Sea-level evolution**
  - Partly driven by the atmosphere (& anthropogenic signals) : « deterministic »
  - Partly driven by the oceanic intrinsic variability : « chaotic »
  - « Chaos » may hamper the attribution of observed « deterministic » signals
- Filters & CNN: **denoising tools** to estimate deterministic signals
  - Perfectible but promising
  - CNN: Self-adapting to specific regions
  - Potential applications for other variables
- AI: new tools to address **new oceanographic questions**
  - Regime classifiers, climate-relevant filters, etc
  - New insights into complex natural systems
  - Still exploratory phase