Laboratoire des Sciences du Climat et de l'Environnement
LSCE (UMR 8212)

Institut des géosciences de l'environnement

Institut Pierre Simon Laplace

Reconstruction of Sub-grid-scale Buoyancy Fluxes from Large-Scale ocean Variables

Anna Denvil-Sommer

Senior Research Associate at the University of East Anglia, UK

V. Balaji, J. Deshayes,
J. Le Sommer, A. Albert

29 January 2021

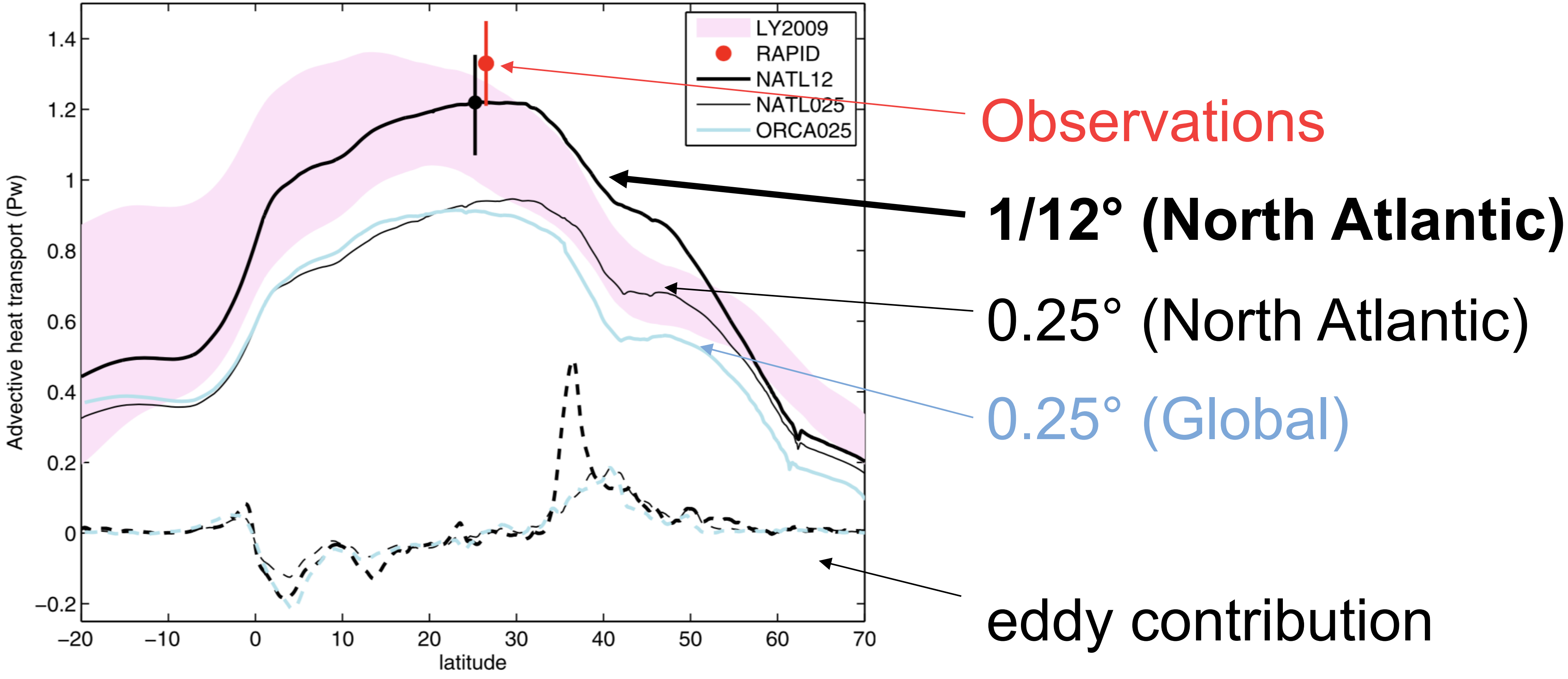
HRMES

Outline

- Introduction
    - Mesoscale, Ocean models resolution and Machine Learning approaches
- Data
    - Data used: high resolution models not observations!
- Method
    - Challenge for Machine Learning approaches
- First results
- Conclusion

Introduction, Role of ocean mesoscale processes

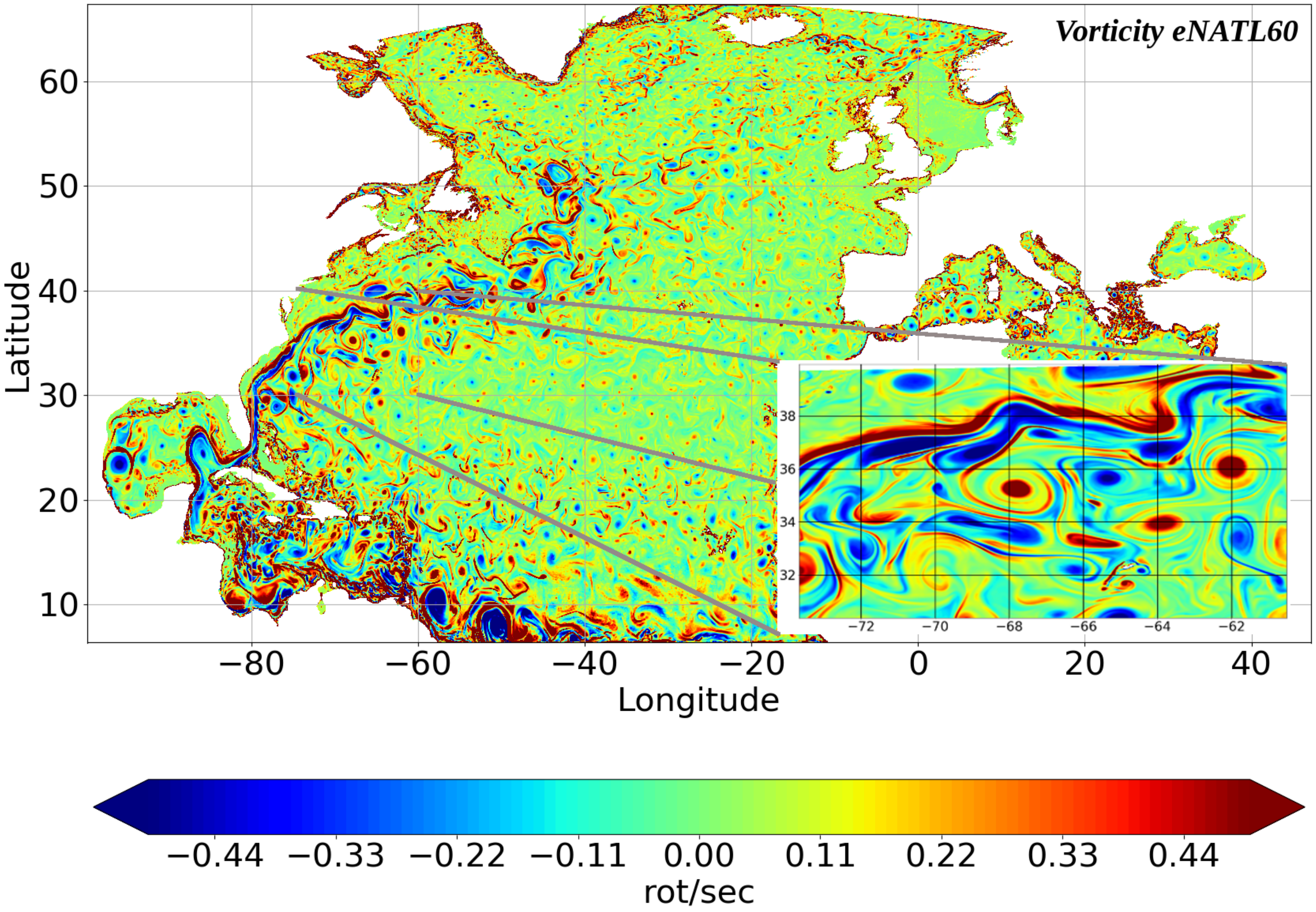
- Meridional heat transport 1993-2004 in the North Atlantic



Treguier et al., 2012

Introduction, Ocean models and Machine Learning

- The finite resolution of ocean models
- Meso-scale eddies not fully resolved in CMIP6 models
- Computational cost (15m h for 1 year)
- Require a high viscosity and dissipation to maintain numerical stability



Introduction, Ocean models and Machine Learning

- Machine learning methods for reconstruction of subgrid processes:
- <u>Atmosphere:</u>
- Brenowitz and Bretherton, 2018 : **FFNN** for apparent heating and moistening in the near-global aqua-planet
- Gentine et al., 2018 : **NN** for convection parameterization in the SuperParameterized aquaplanet global model
- + Rasp et al., 2018
- <u>Ocean:</u>
- Bolton and Zanna, 2019; 2020 : **CNN** for subgrid eddy momentum forcing in a high-resolution quasi-geostrophic ocean model

Reconstruction of w'b'

- baroclinic instability → mesoscale features
- baroclinic instability - quantified through the term of u'b' eddy buoyancy flux
- Gent-McWilliams (GM) parametrization

$$u^{\bar{\prime}}b' = K(\nabla T)$$

$$w'b' = f(\bar{T}, \bar{S}, \bar{u}, \bar{v}, \bar{w}, \nabla\bar{T}, \nabla\bar{S}, \nabla\bar{u}, \nabla\bar{v}, \nabla\bar{w})$$

Data. NEMO eNATL60 and ORCA1

- ***eNATL60 : regional training data →*** $w'b', \bar{T}, \bar{S}, \bar{u}, \bar{v}, \bar{w}$

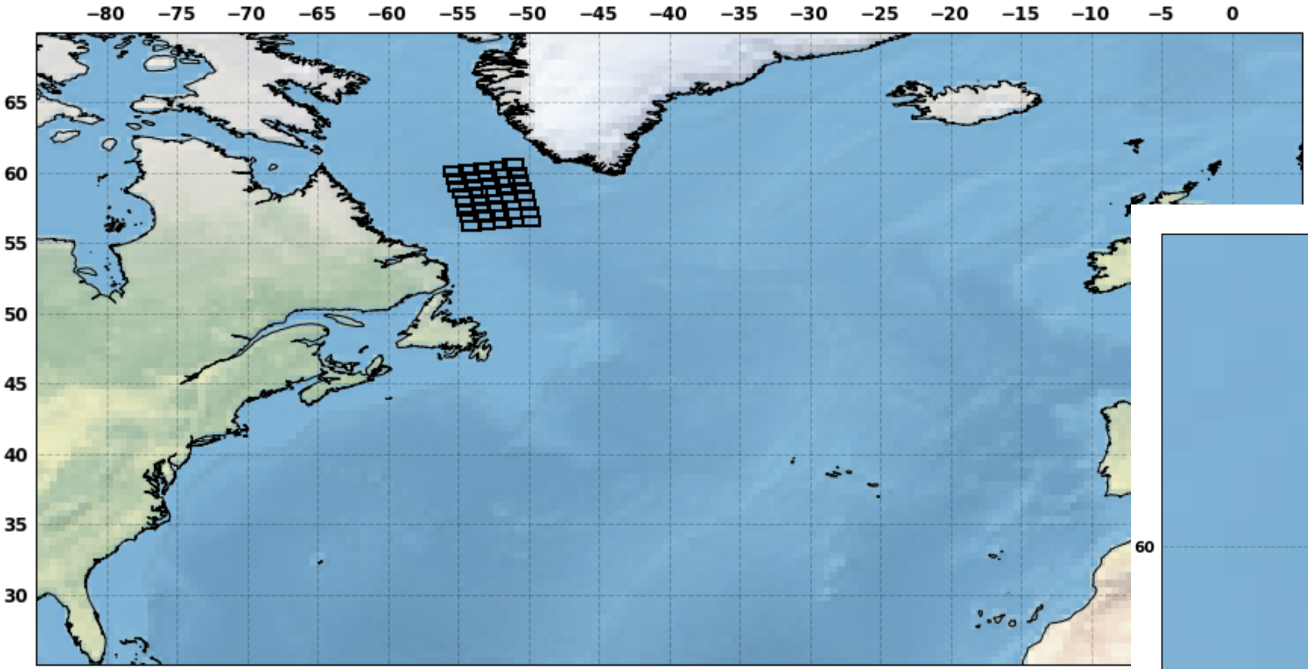
- Basin-scale configuration of NEMO : 6°N up to the polar circle;
- 1/60°, 300 vertical levels, 1h
- salinity (S), temperature (T), 3 components of ocean current velocity (u,v,w) and sea surface height (SSH)

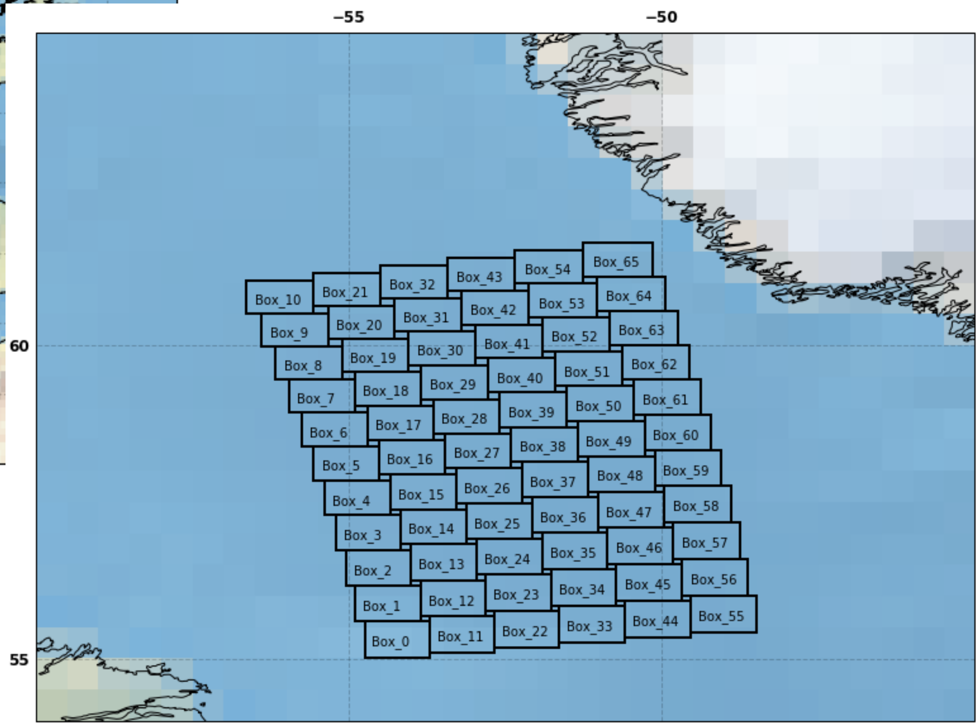
ORCA1 : global data for prediction → $\bar{T}, \bar{S}, \bar{u}, \bar{v}, \bar{w}$

- 1° x 1°, 75 levels, daily resolution
- S, T, (u,v,w) and SSH

Region

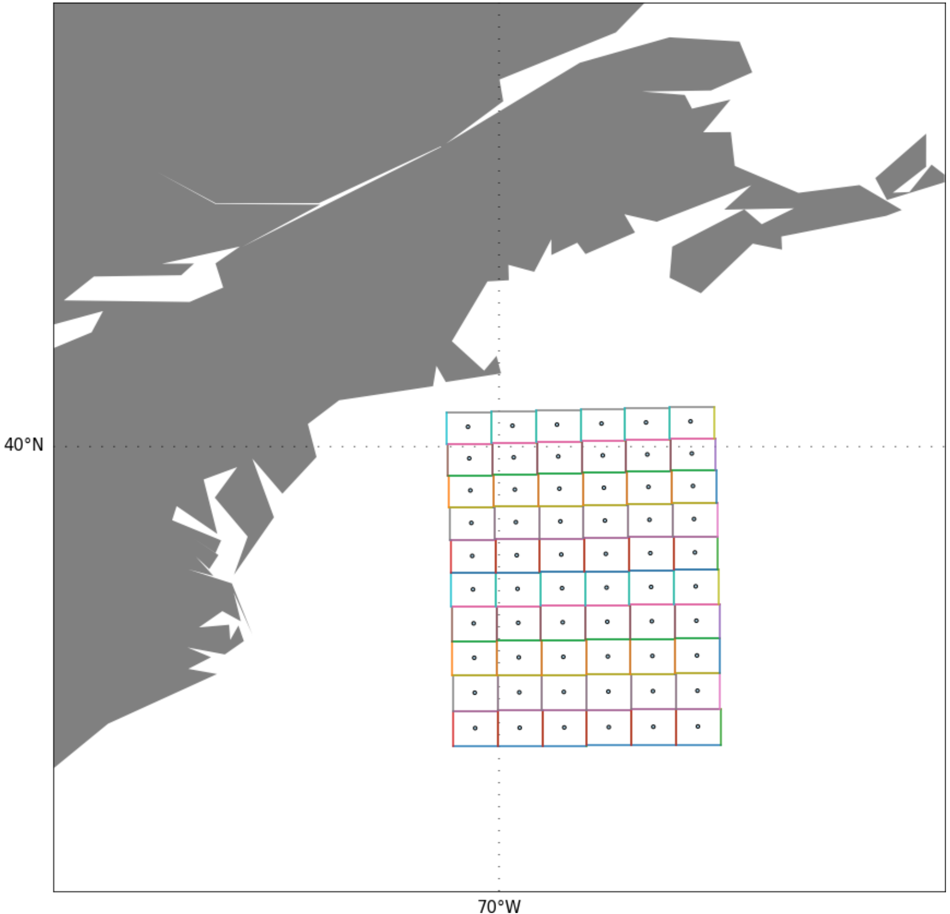
- Labrador Sea: 56º-61ºN, 55º-50ºW, min depth = 2955.2122m

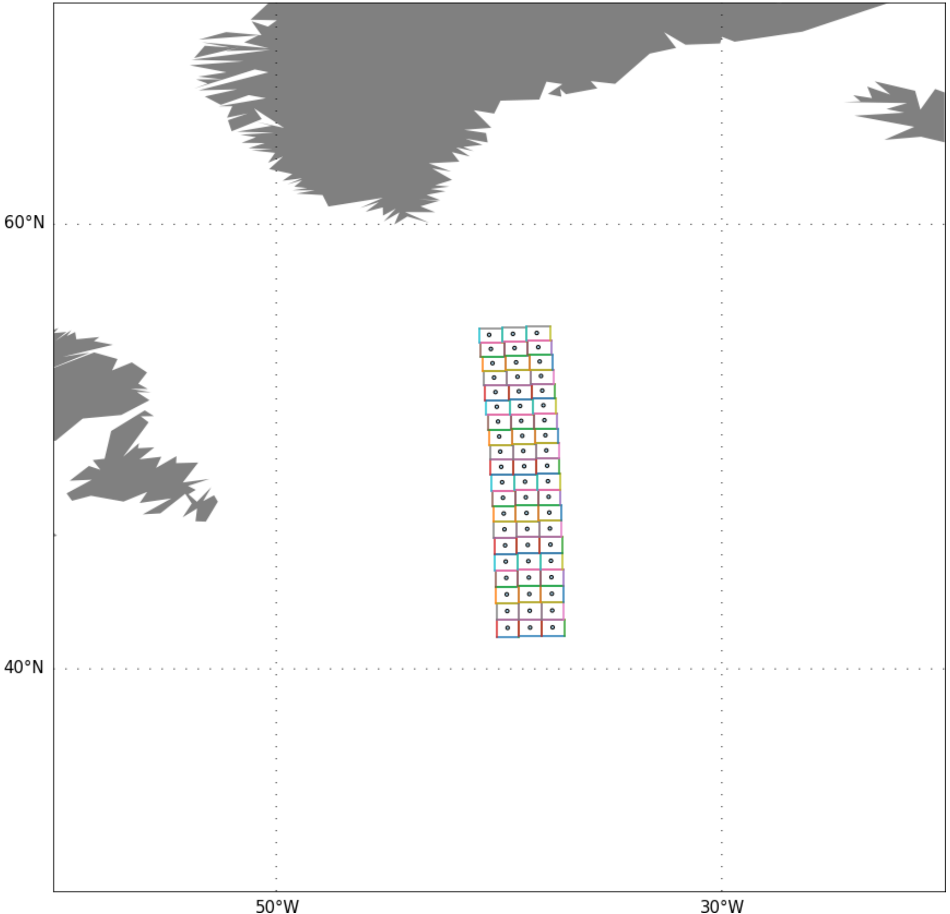




Other Regions

- Gulf Stream and the Middle of North Atlantic Ocean

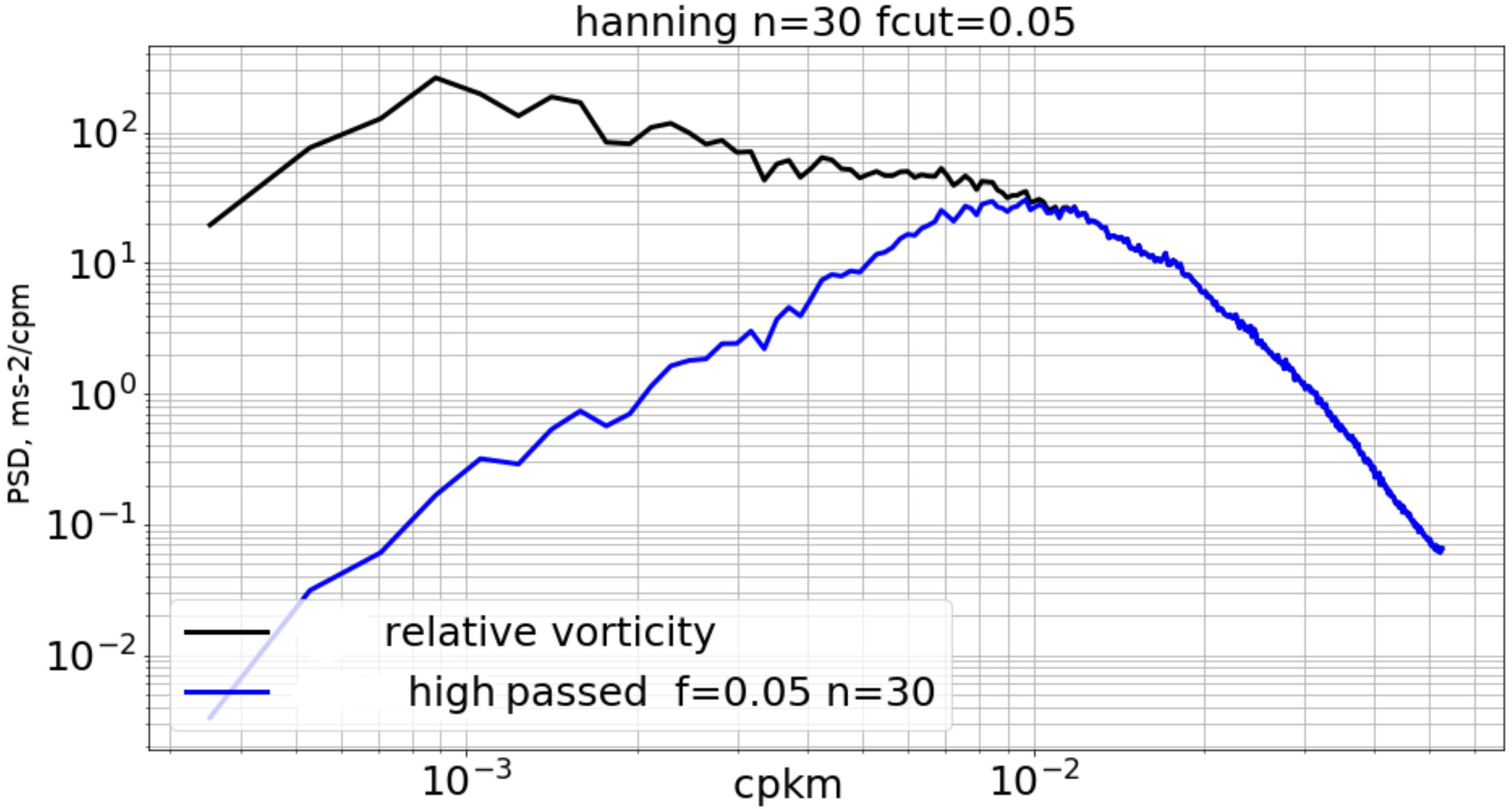




Pre-processing

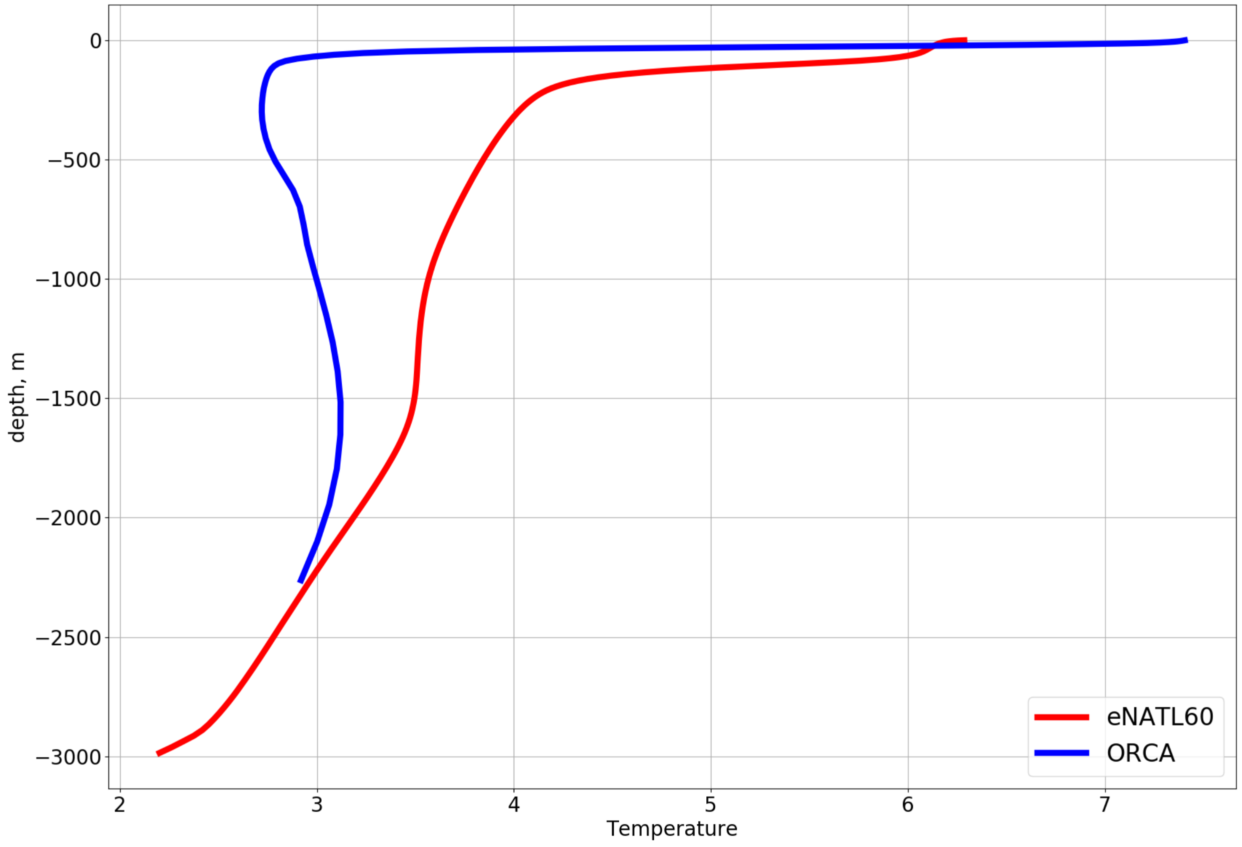
Filtering eNATL60: low-pass spatial filter with Hanning window

$\bar{T}, \bar{S}, \bar{u}, \bar{v}, \bar{w} \longrightarrow w', b'$



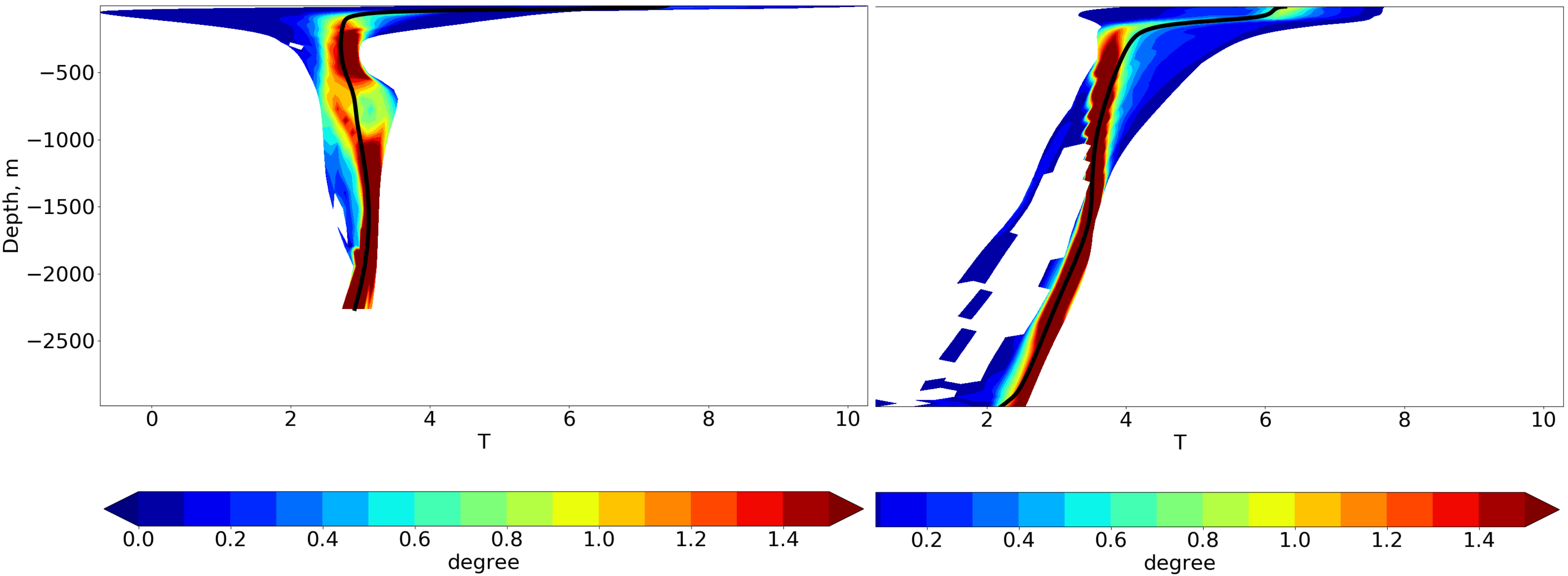
Implementation, Profiles comparison

- Mean Temperature profile : over LS zone for 100 days from 1/07/2009



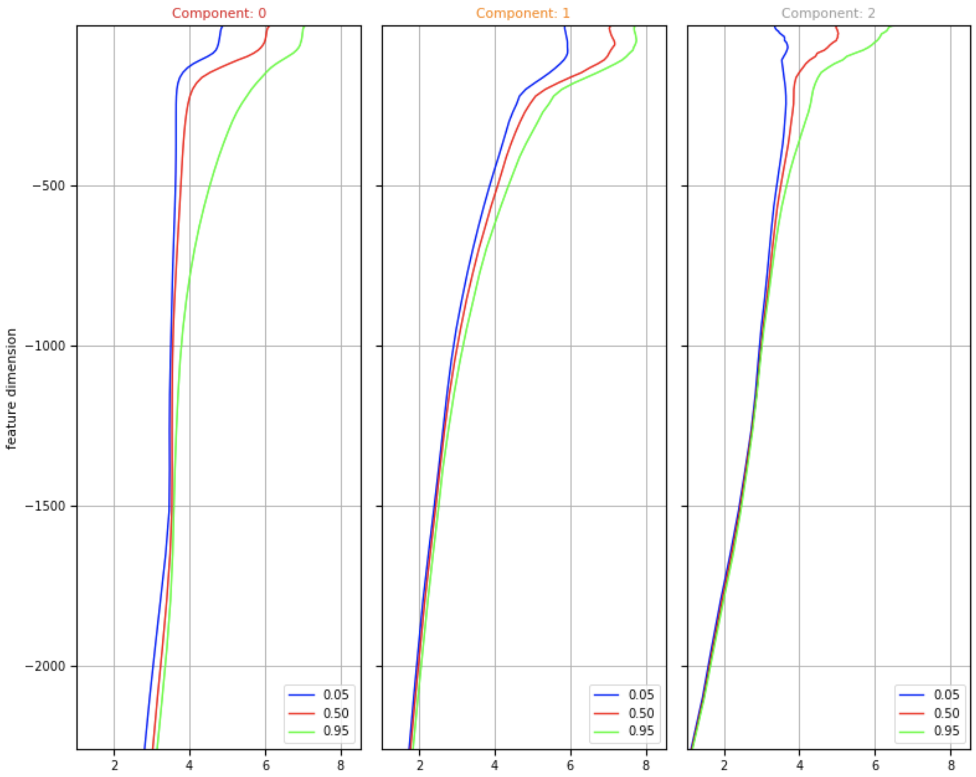
Profiles comparison

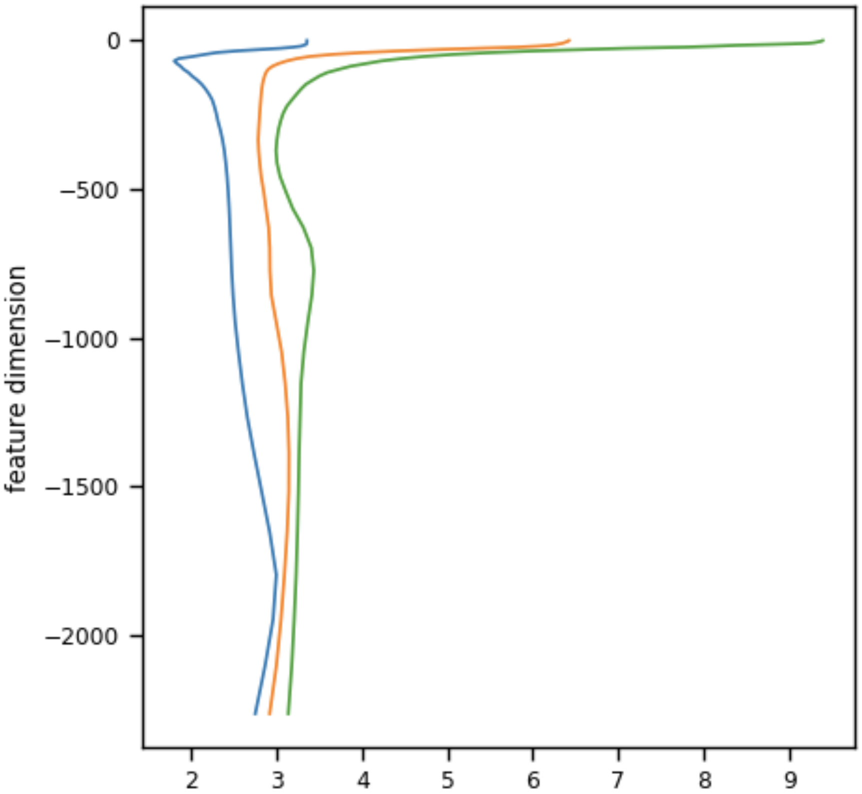
- Mean Temperature profile + PDF



Profiles comparison

Classification: Gaussian Mixture Model (GMM)





Conclusion and perspectives

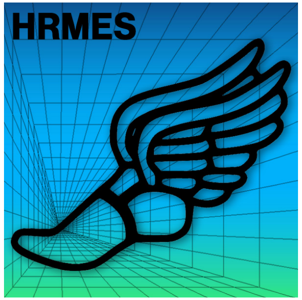
1. Extra-challenge: how will we manage the difference in vertical profiles that is inevitable?

2. Effect of filtering has to be better understood.

3. What is the role of differences between profiles?

4.Big Data problem.

5. First tests of Neural Network to reconstruct $w'b'$



Thank you !

Laboratoire des Sciences du Climat et de l'Environnement
LSCE (UMR 8212)