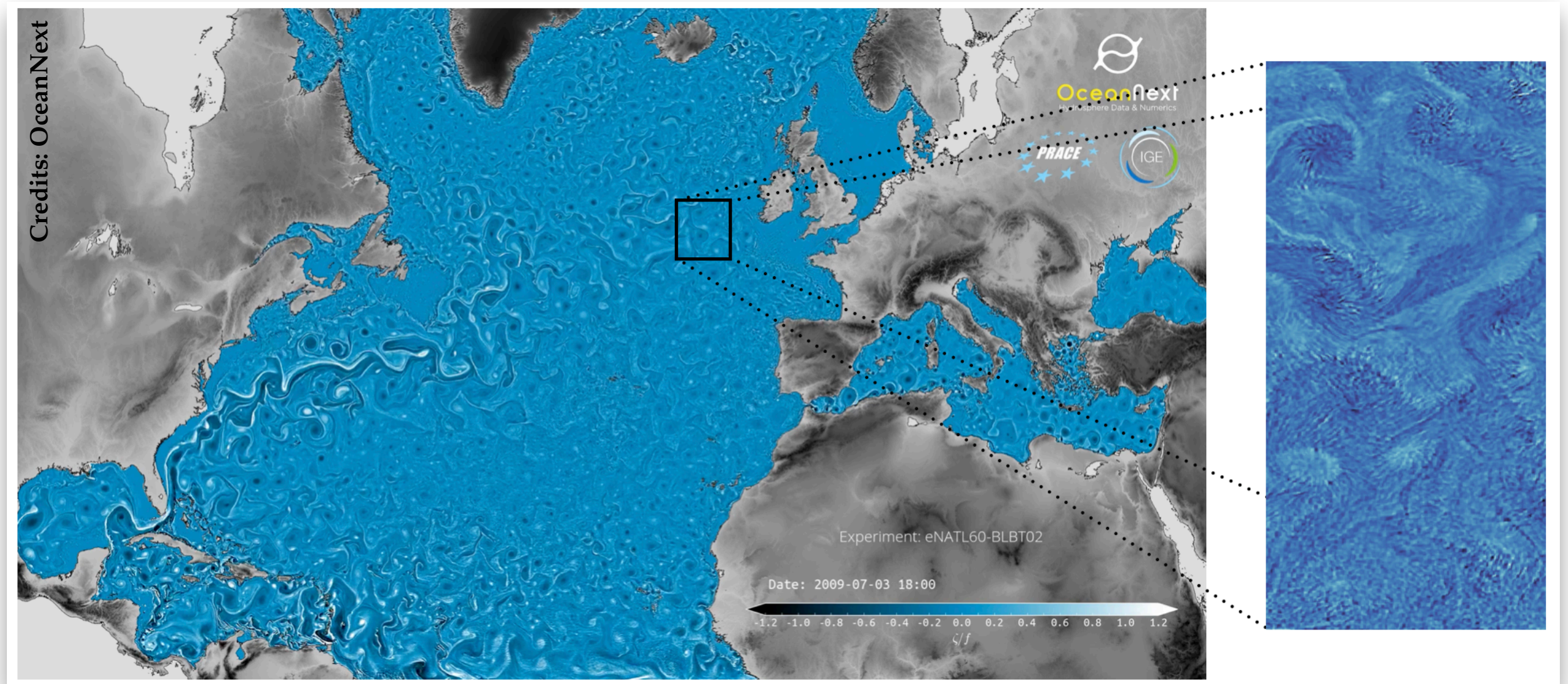




ANR Melody meeting

Filtering tide-generated internal waves using Convolutional Neural Networks

Redouane Lguensat

Postdoc @ LOCEAN-LSCE / Sorbonne University



Institut
Pierre
Simon
Laplace



Collaborators

FILTERING INTERNAL TIDES FROM WIDE-SWATH ALTIMETER DATA USING CONVOLUTIONAL NEURAL NETWORKS

Redouane Lguensat^{*1}, *Ronan Fablet*², *Julien Le Sommer*¹, *Sammy Metref*¹, *Emmanuel Cosme*¹,
*Kaouther Ouenniche*², *Lucas Drumetz*², *Jonathan Gula*³

¹ Université Grenoble Alpes, CNRS, IRD, Grenoble INP, IGE; Grenoble, France

² IMT Atlantique, LabSTICC, Université Bretagne Loire; Brest, France

³ Ifremer, LOPS; Brest, France

- ❖ This presentation is based on materials from Lguensat et al. 2020 accepted for publication in IEEE IGARSS. A preprint can be found in arxiv.org

Motivation

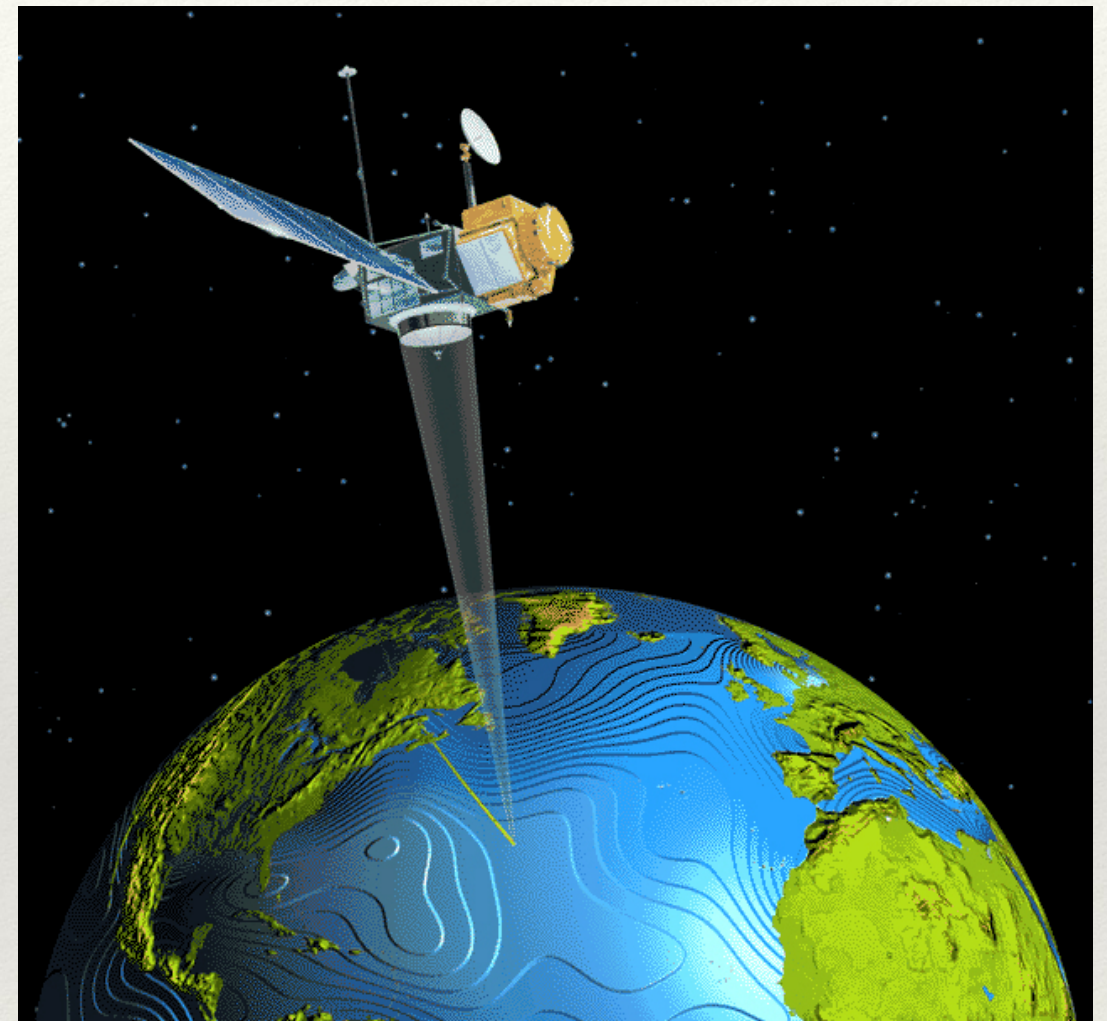
- ❖ At fine scale (<100km), ocean dynamics combine two dominant classes of motions with distinct properties: **baroclinic eddies** (balanced motions) and **internal gravity waves** (unbalanced motions)

Ocean dynamics

Balanced motions



Unbalanced motions



(Image: NASA)

These two classes of motions are expected to be observed by the Surface Water and Ocean Topography (**SWOT**) satellite altimeter.

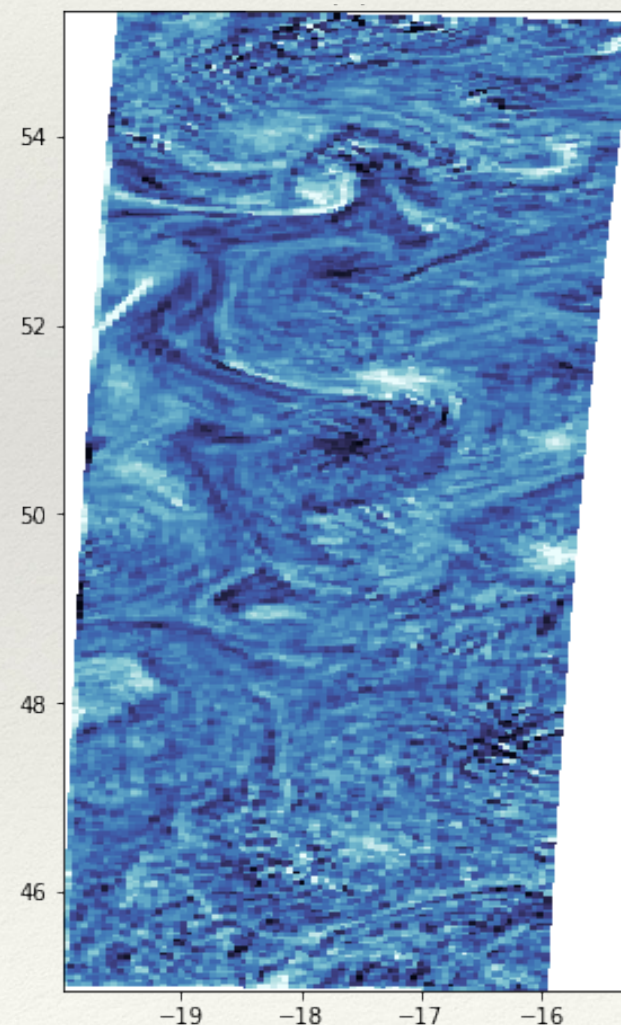
Problem statement

One of the main oceanographic objectives of the SWOT mission is the study of mesoscale and submesoscale eddies **without** the interference of tidal signals

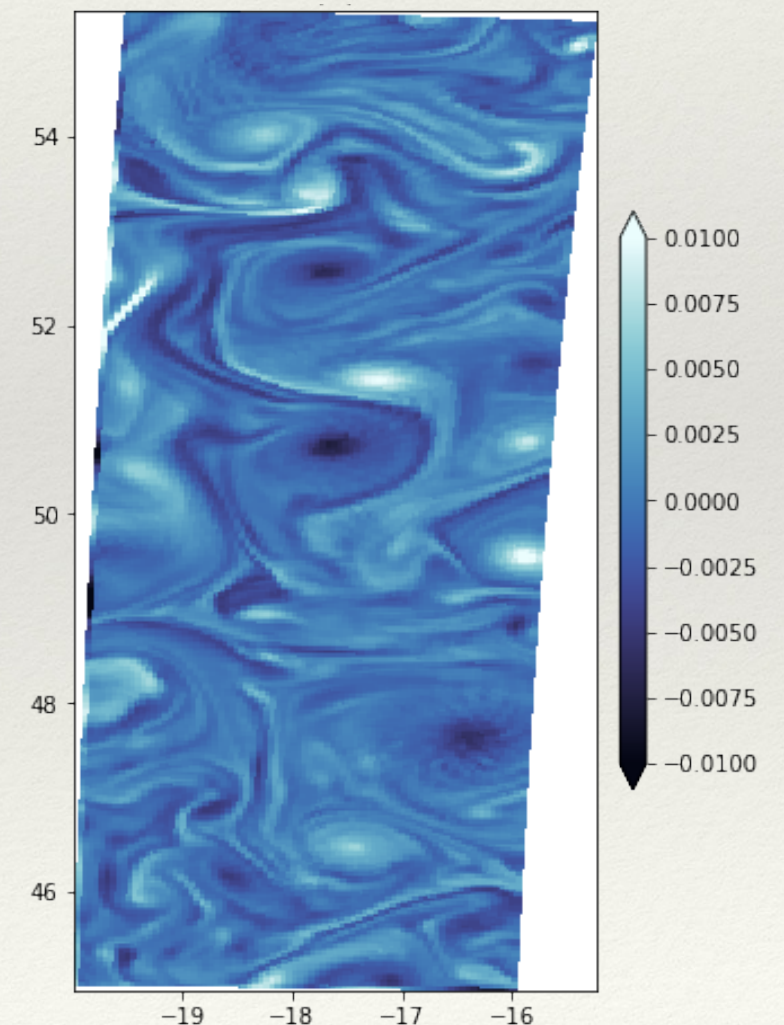


Need to filter out the contribution of wave motions from Sea Surface Height (SSH) measurements

Total vorticity field



Filtered vorticity



Existing methods

Several established methods have been used to separate balanced and unbalanced motions in the past, such as:

- Helmholtz Decomposition
- Lagrangian filtering
- Spectral splitting
- Low-pass temporal filters
- etc..

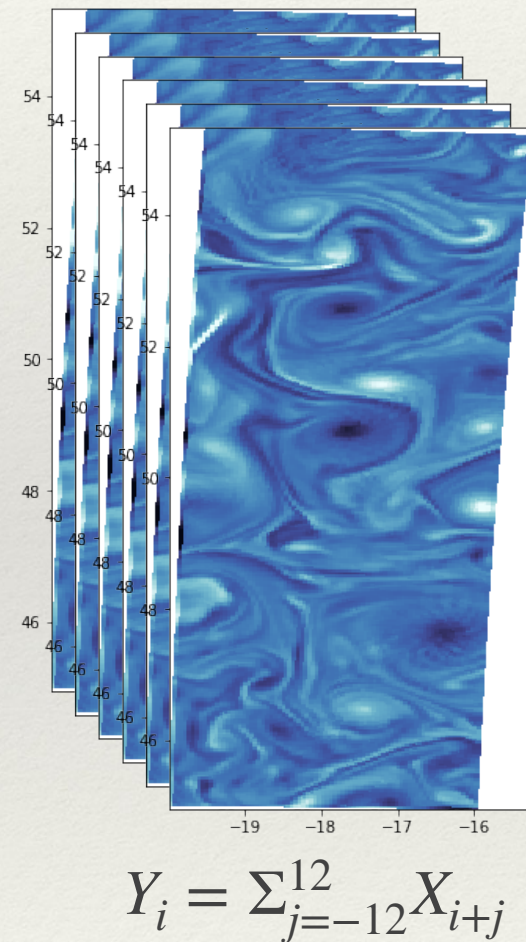
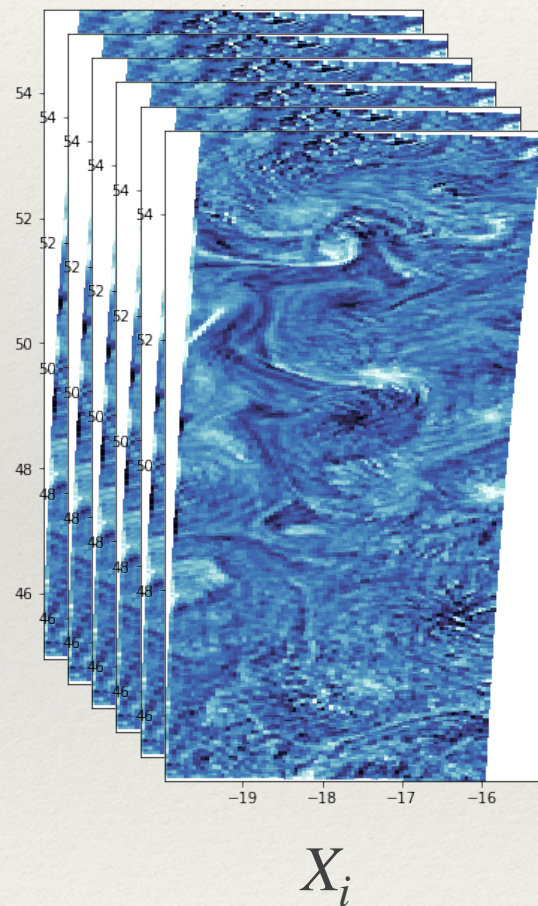
Caveat: these methods assume the availability of high temporal sampling SSH data (ex: hourly data)

At the best, SWOT will provide daily SSH maps (Fast sampling phase - CalVal period)

Proposed method

Given a high-resolution ocean numerical model (here NEMO-eNATL60, $1/30^\circ$ spatial resolution, hourly data), use one of the state-of-the-art solutions, then run a supervised learning technique to emulate the process

Total SSH
vorticity



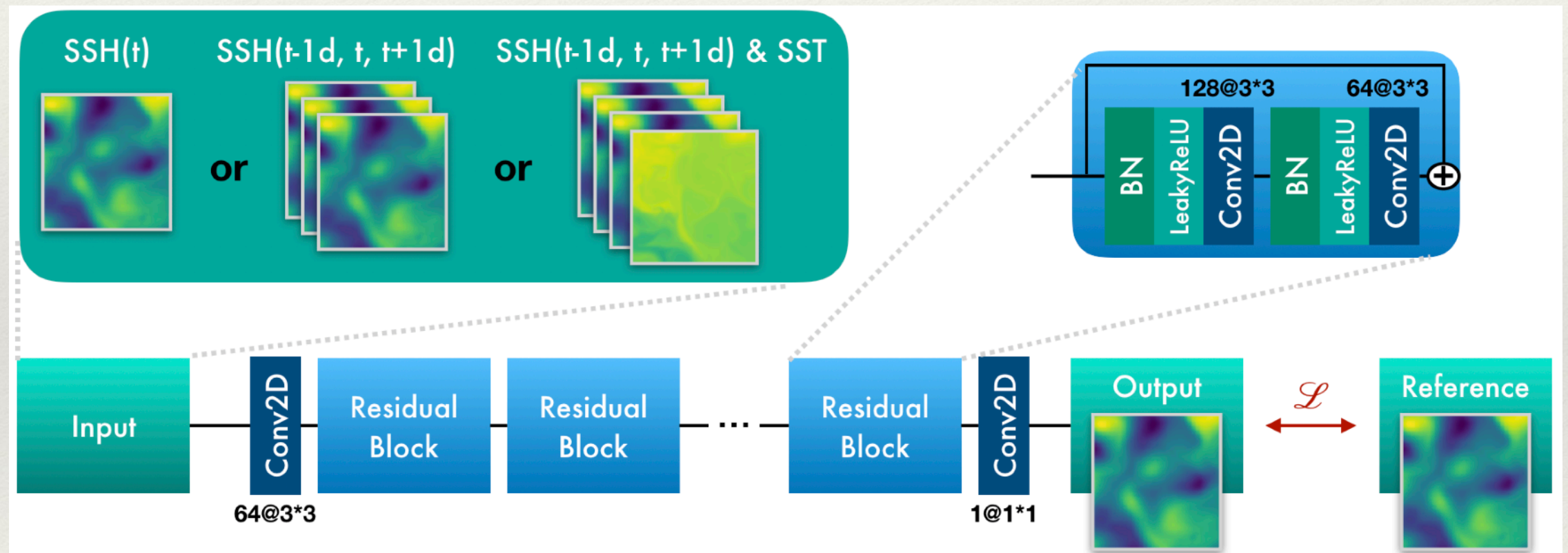
Example:

Simple
temporal box
car filter
(24h average)

Goal: using supervised learning to find a mapping between X_i and Y_i
This is a hard problem by construction

Proposed technique: ConvNets

We train different convolutional neural networks depending on the available **daily** input data, we can also include other variables such as Sea Surface Temperature (SST). The architecture is a Convolutional ResNet:

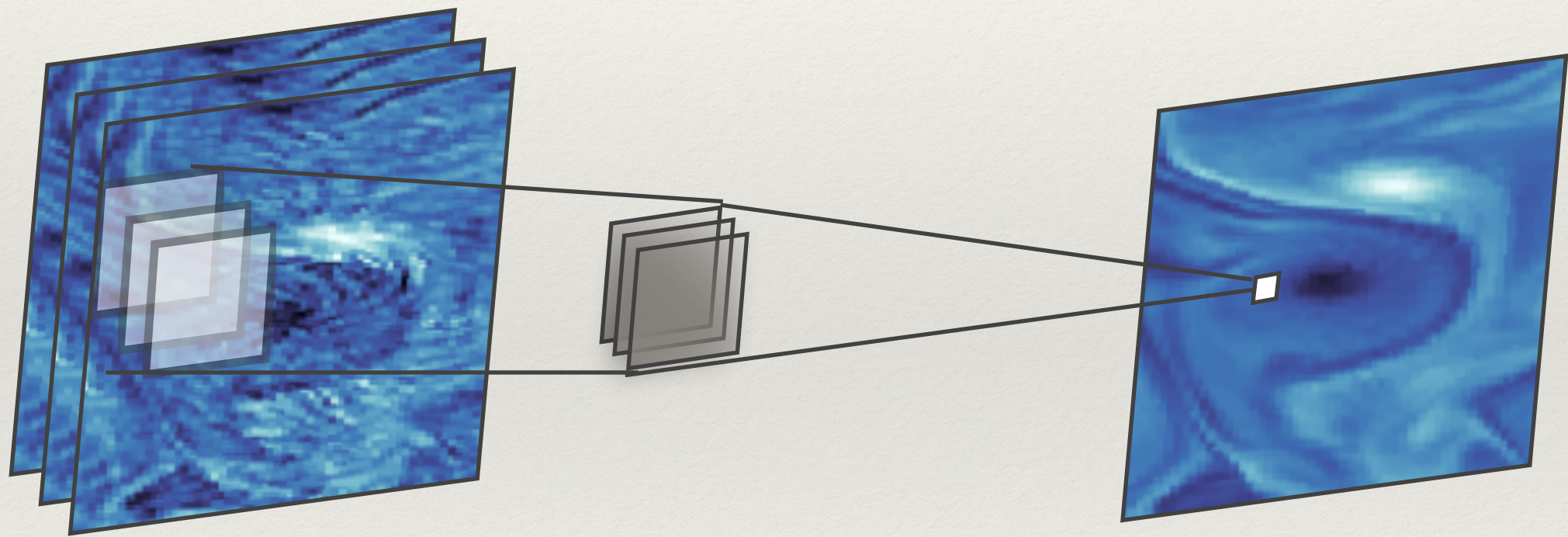


Importantly, we found that using a loss function that combines $MSE(SSH)$ and MAE of laplacian of SSH (related to vorticity) leads to a better reconstruction

$$\mathcal{L} \left(Y_i, \hat{Y}_i \right) = \left\| Y_i - \hat{Y}_i \right\|^2 + \alpha \left| \nabla^2 Y_i - \nabla^2 \hat{Y}_i \right|$$

Baseline for comparison

Using the 3 SSH input setting, we train a **one** convolutional **linear** layer with **one** 3D filter, this simulates the best linear spatial filter that could be used to filter out the wave motions, and is used as our baseline

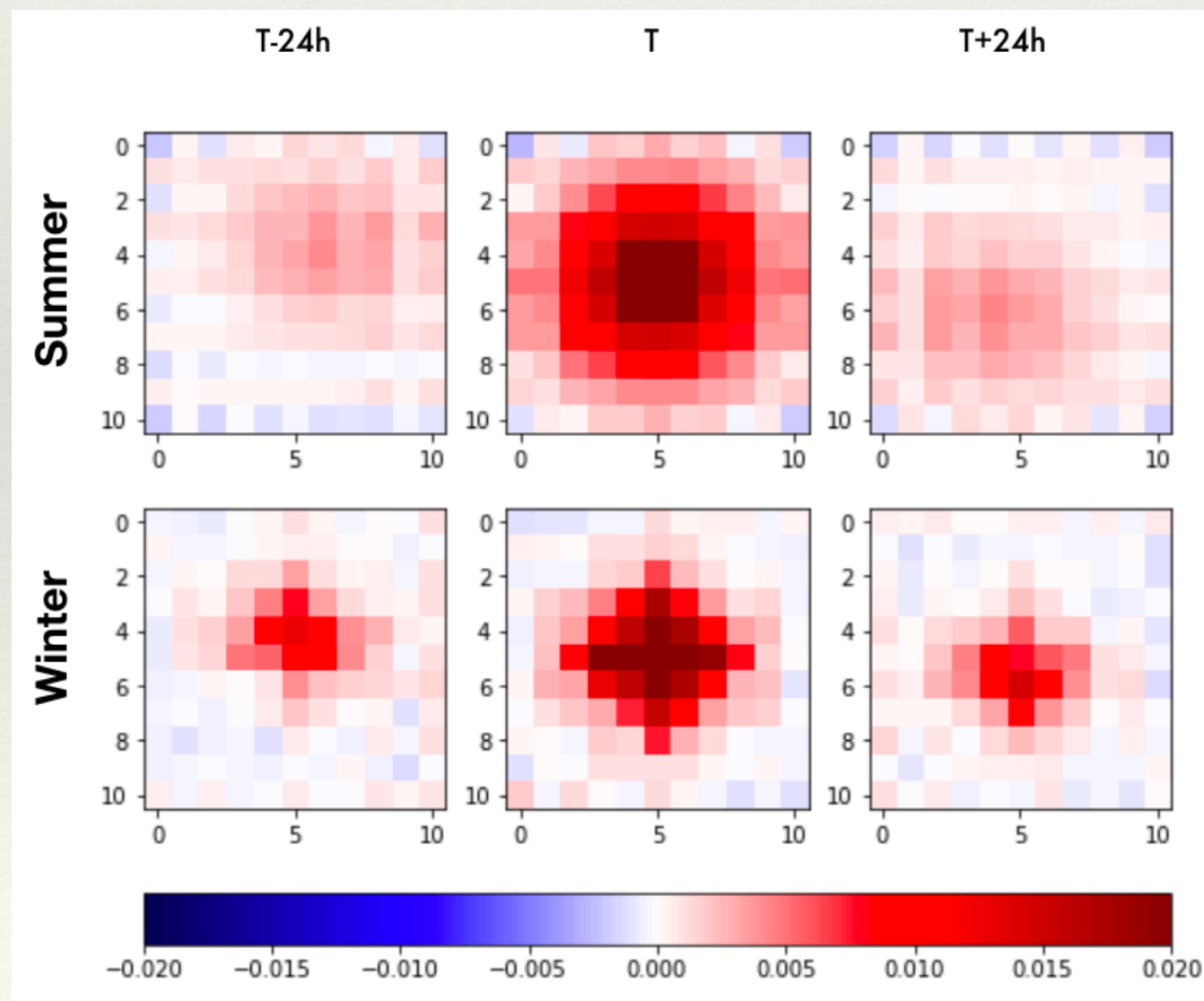


After train we can visualize the learned filters

Baseline for comparison

Two datasets are used for training, one for **summer** and one for **winter**.

The learned linear filters show the differences between the ocean dynamics in summer and winter. They are close to Gaussian filter distributions but with different cutoff frequencies

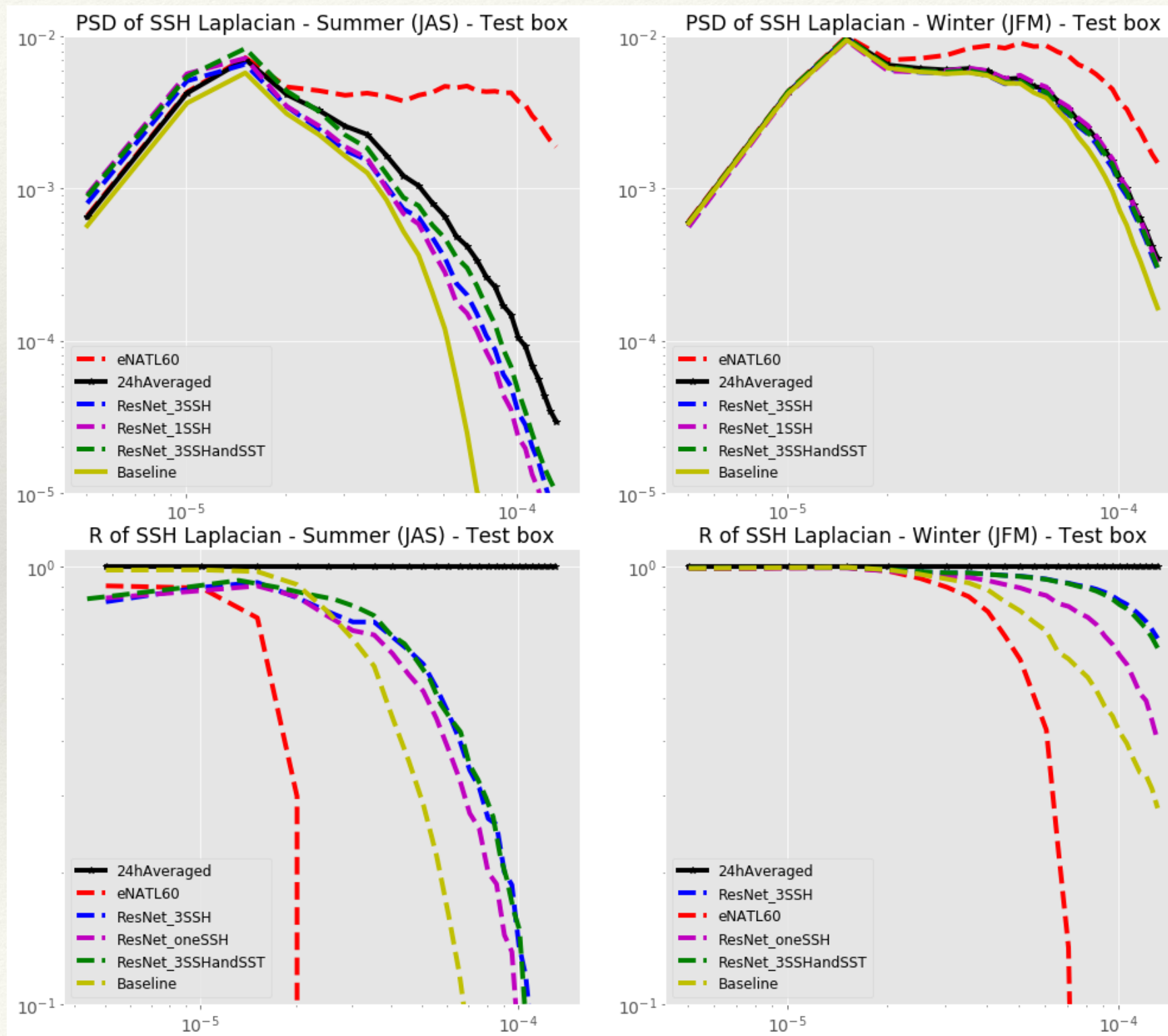


Comparison with ConvNets

- ❖ For **summer** and **winter**. We run experiments with as an input:
 - * 1 SSH: SSH at time t
 - * 3 SSH: SSH at times $t-24h$, t , $t+24h$
 - * 3 SSH 1 SST: SSH at times $t-24h$, t , $t+24h$ and SST at time t
- ❖ Training details can be found in our paper, with some tricks to train ResNets efficiently
- ❖ For comparison we use PSD (power spectral densities) and R a ratio of relative reconstruction quality:

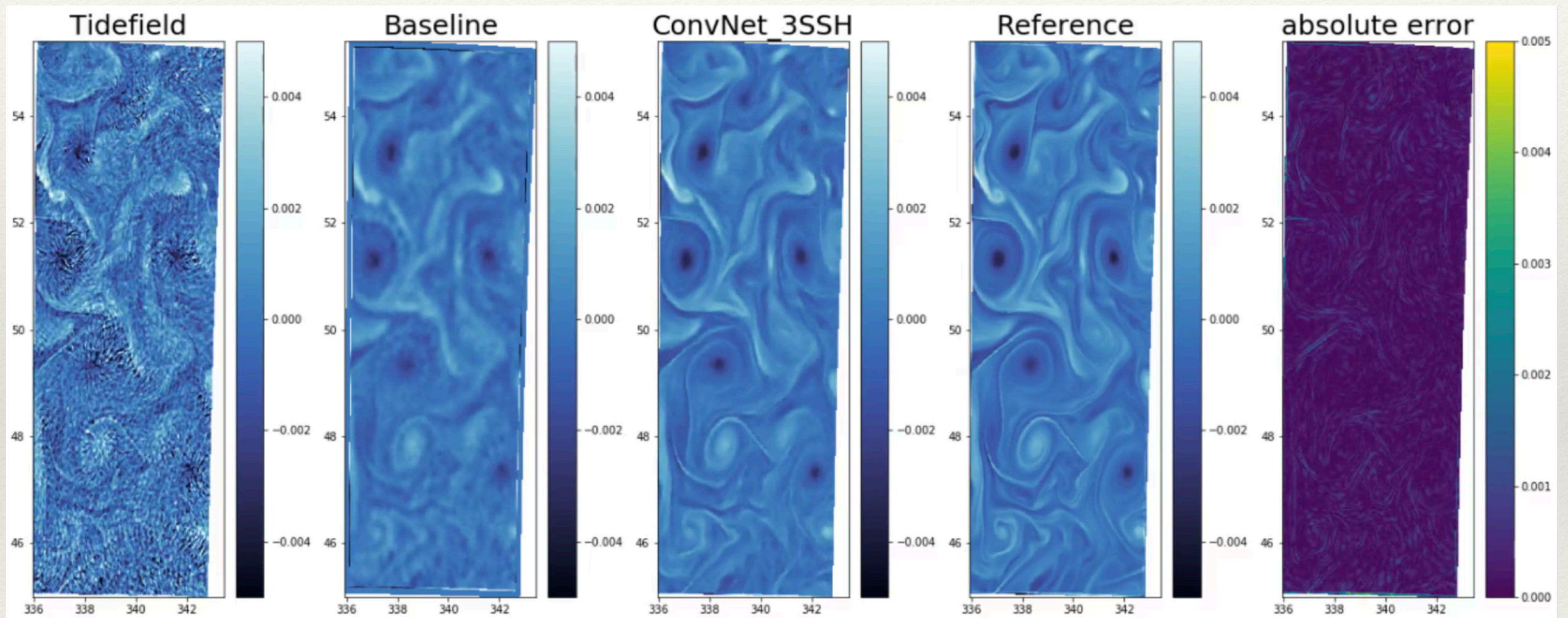
$$R = 1 - \frac{E \left[\left(PSD_y - PSD_{\hat{y}} \right)^2 \right]}{E \left[PSD_y^2 \right]}$$

Comparing powerspecs



A movie on a test dataset

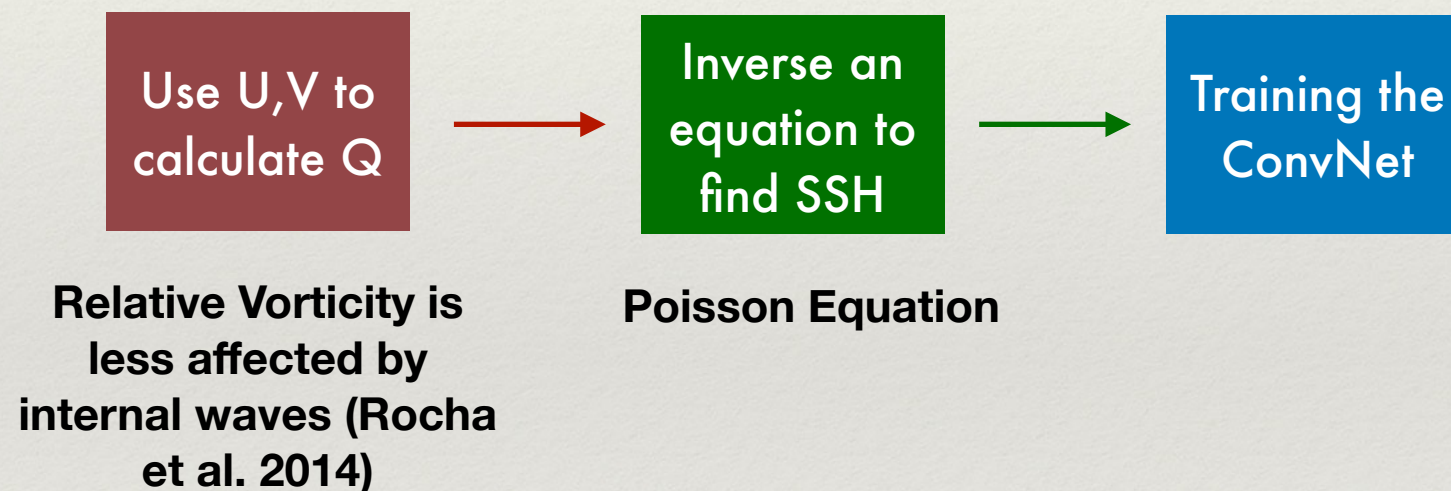
An example of tide-filtering for a test dataset from **summer**



Please click on the image

New version (paper in prep.)

- ❖ Collaboration with Florian le Guillou (MEOM, IGE Grenoble), creation of a better ground truth



- ❖ Compare with Generative Adversarial Networks

Limitations and future work

- ❖ Any supervised learning technique depends on the reference data
- ❖ Generalization on farther regions (spatially) from the training regions is hard, especially when the dynamics of waves are different. A naïve solution consists in training a big ConvNet with training data from several special regimes in the global ocean.
- ❖ This work is relevant for the fast sampling phase of SWOT, after its end SWOT cycle will be around ten days or more, techniques for interpolation will be needed before applying our ConvNets.
- ❖ From a machine learning perspective, investigating unsupervised techniques could be interesting

Keep in touch

I work on several other applications of machine learning for physical oceanography and ocean remote sensing. If you have questions or remarks about this work or have other subjects to discuss, please do not hesitate to send me an email:
redouane.lguensat@locean.ipsl.fr



@redouanelg



redouanelg



redouanelg.github.io