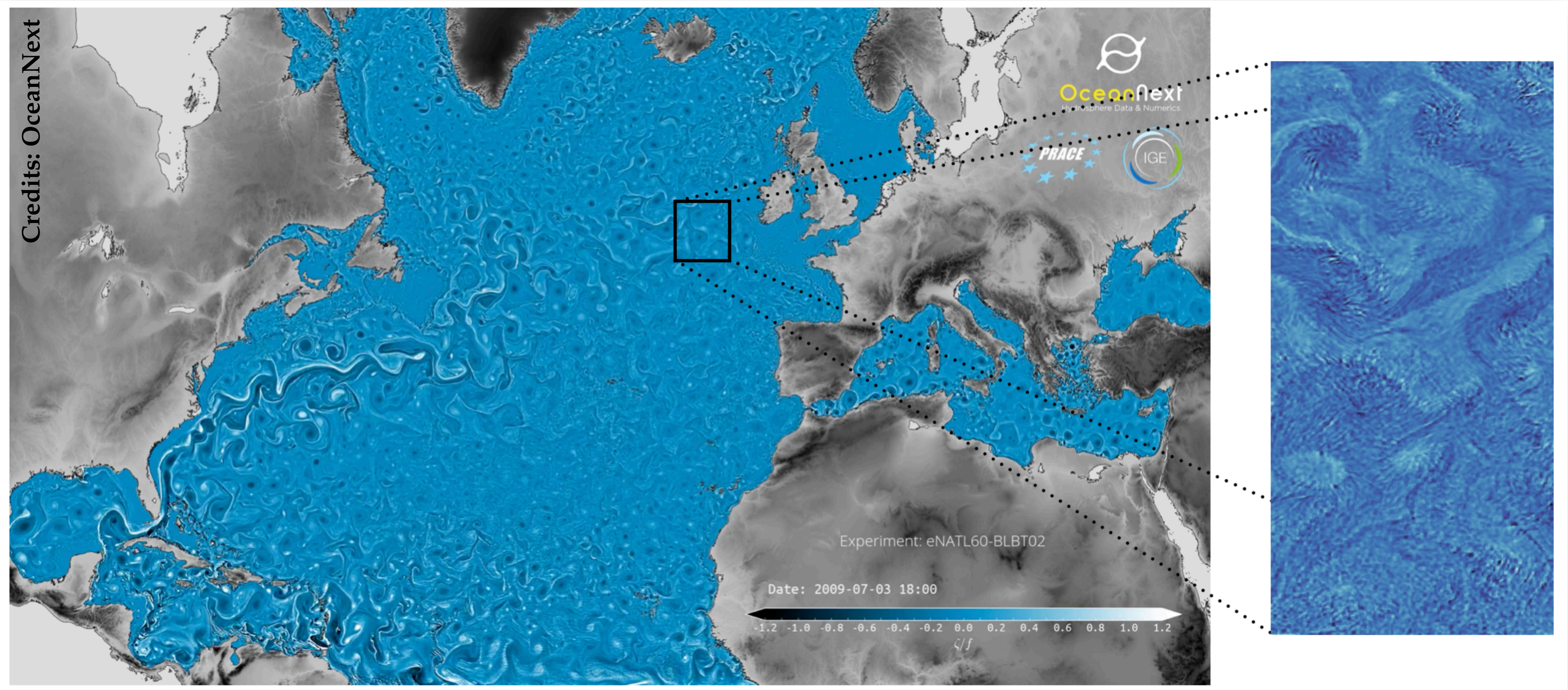

#shareEGU20, Ocean Remote Sensing session, at home, 04 May 2020

Filtering tide-generated internal waves using Convolutional Neural Networks

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Collaborators

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

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- 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

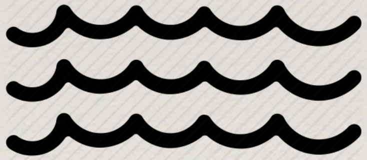
Motivation

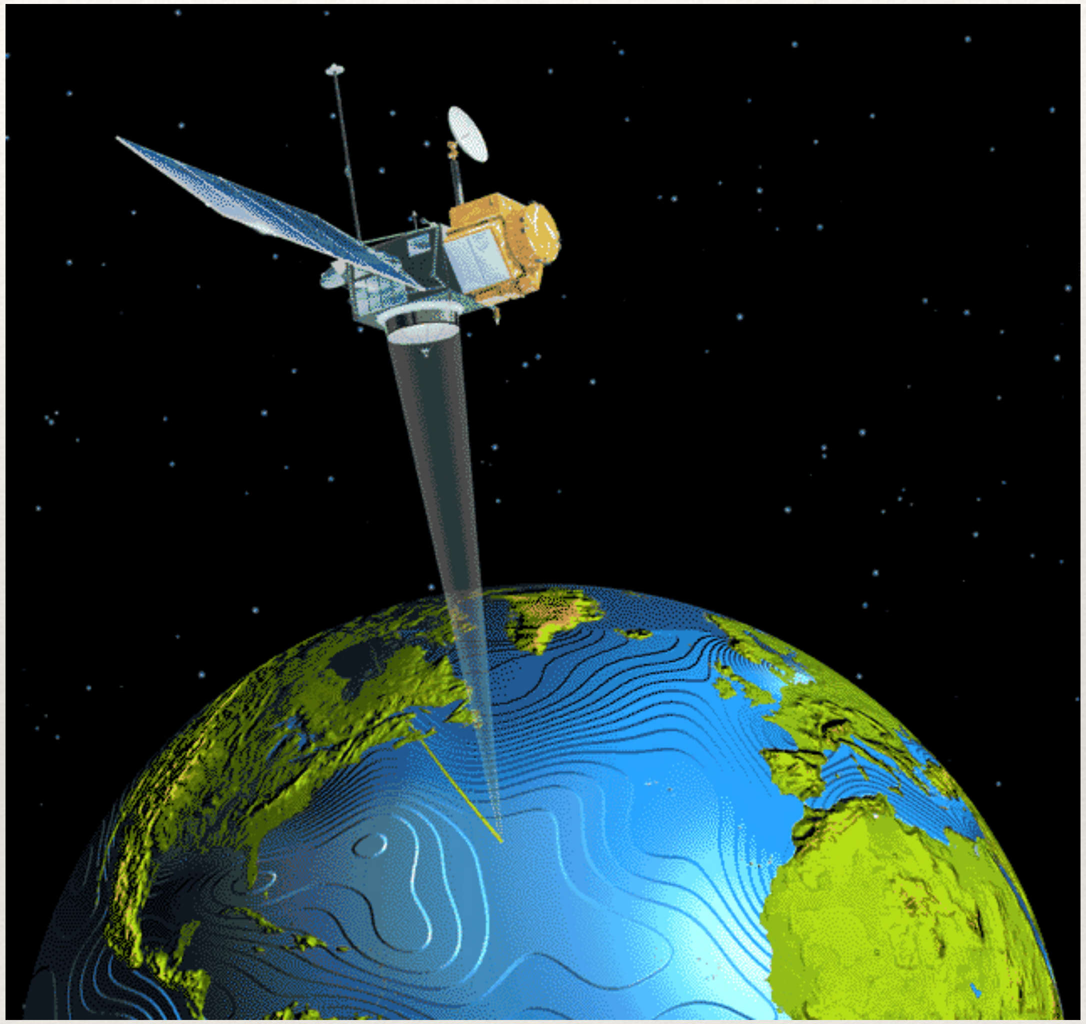
- At fine scale (<100km), ocean dynamics combine two dominant classes of motions with distinct properties: baroclinic eddies (balanced motions) and internal gravity waves (unbalanced motions)

Ocean dynamics

Balanced motions

Unbalanced motions





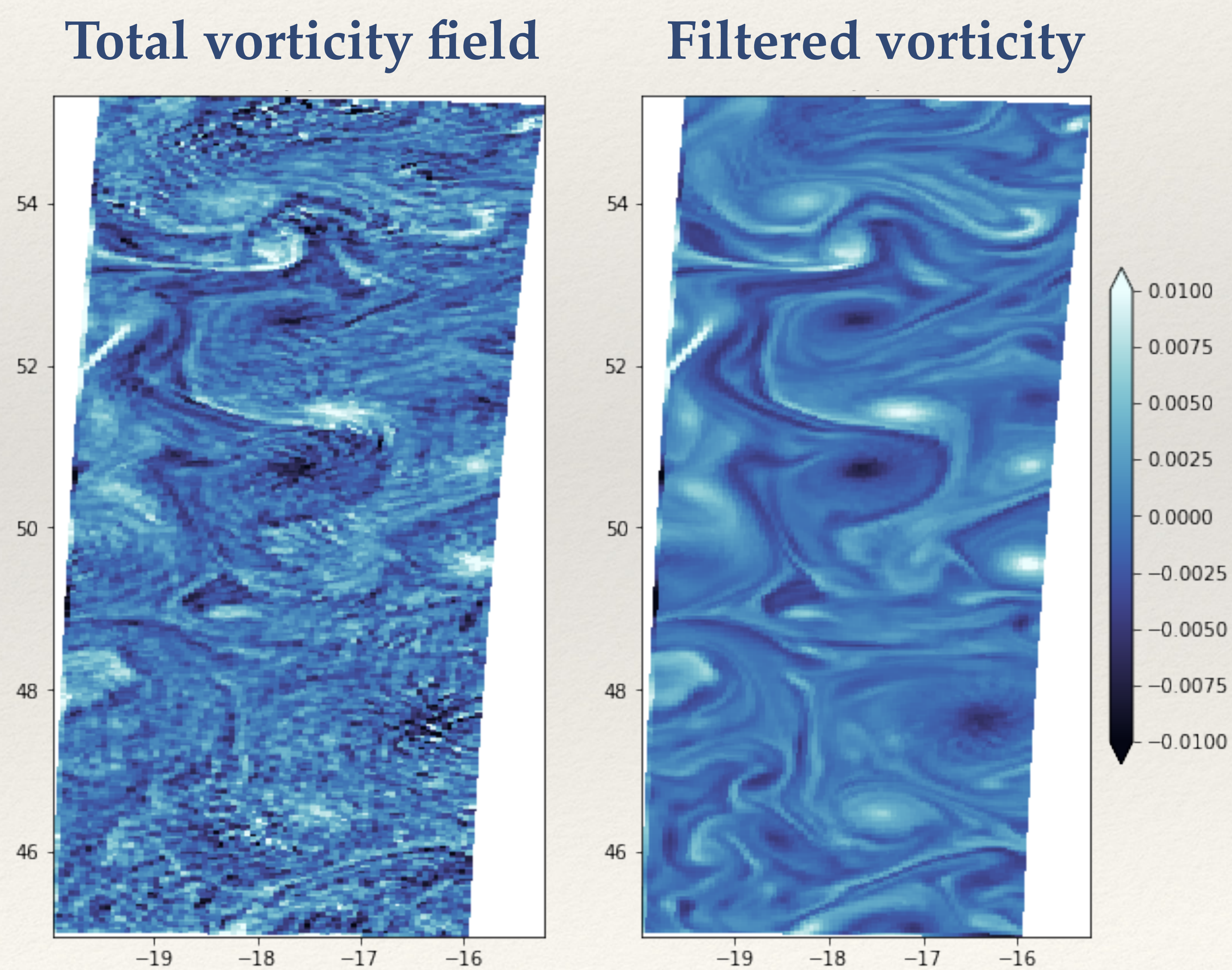
(Image: NASA)

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



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..

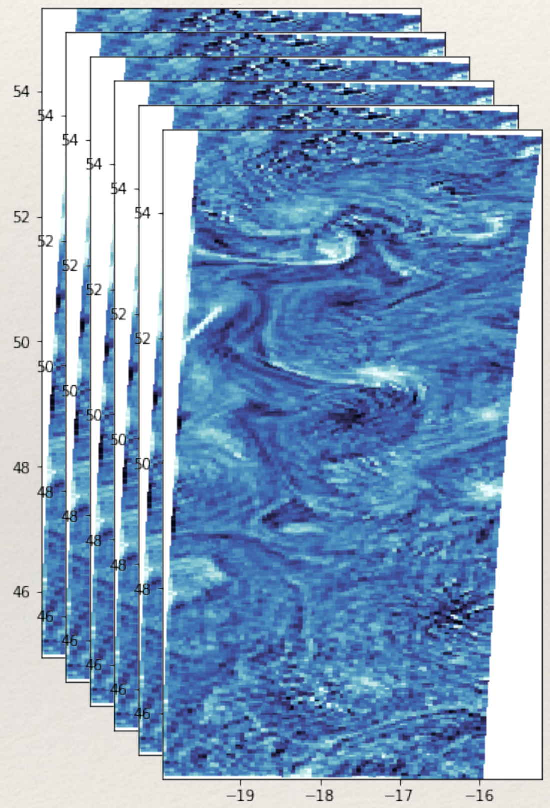
Caveat: these methods assume the availability of high temporal sampling SSH data (ex: hourly data)

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

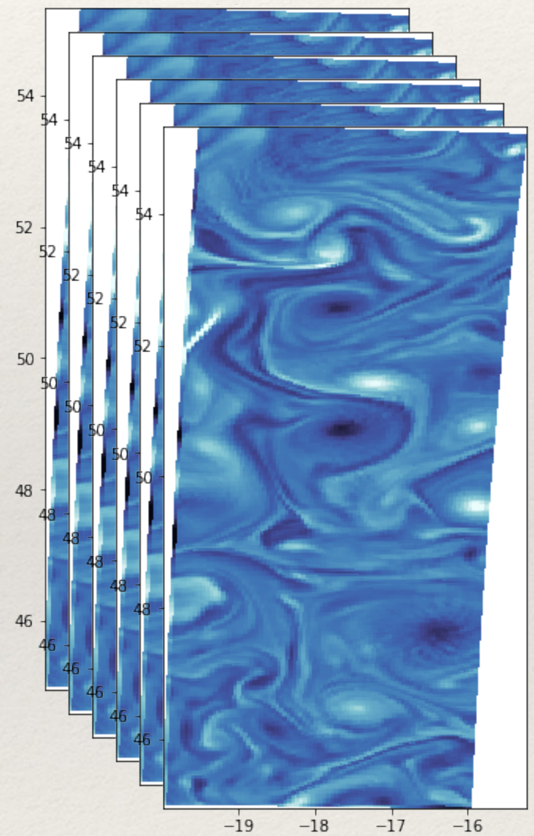
Proposed method

Given a high-resolution ocean numerical model (here NEMO-eNATL60, 1/30° 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



X_i



$Y_i = \Sigma_{j=-12}^{12} X_{i+j}$

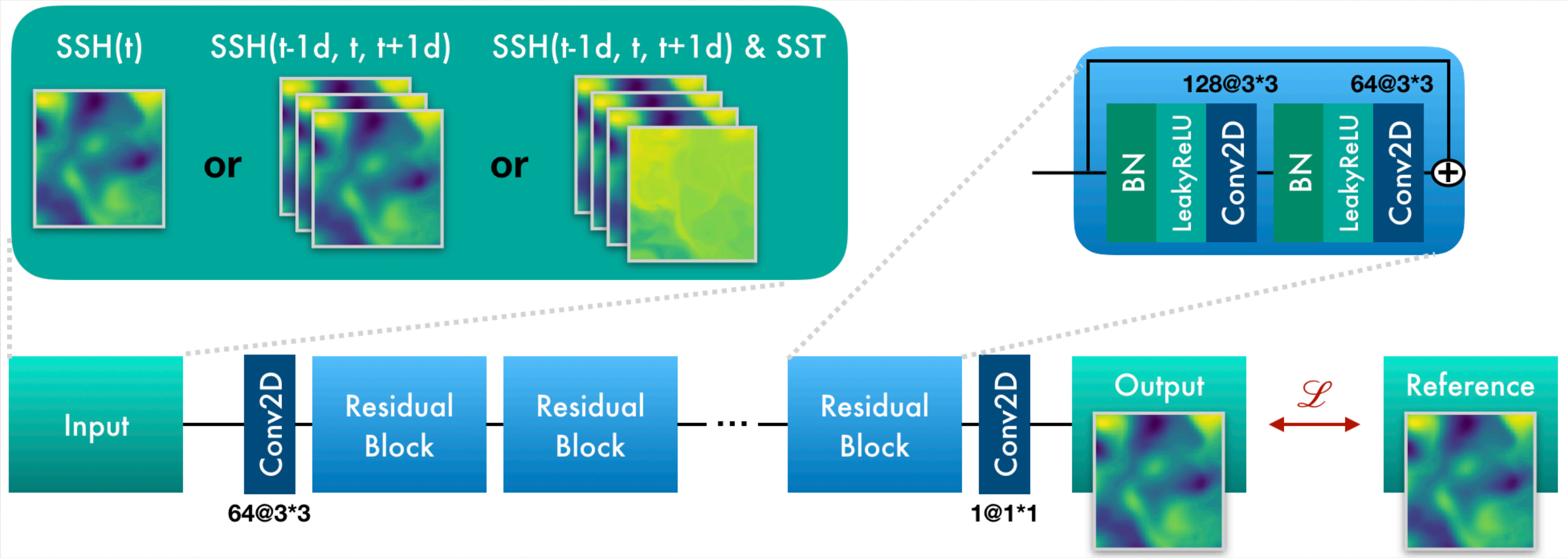
<u>Example:</u>

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:



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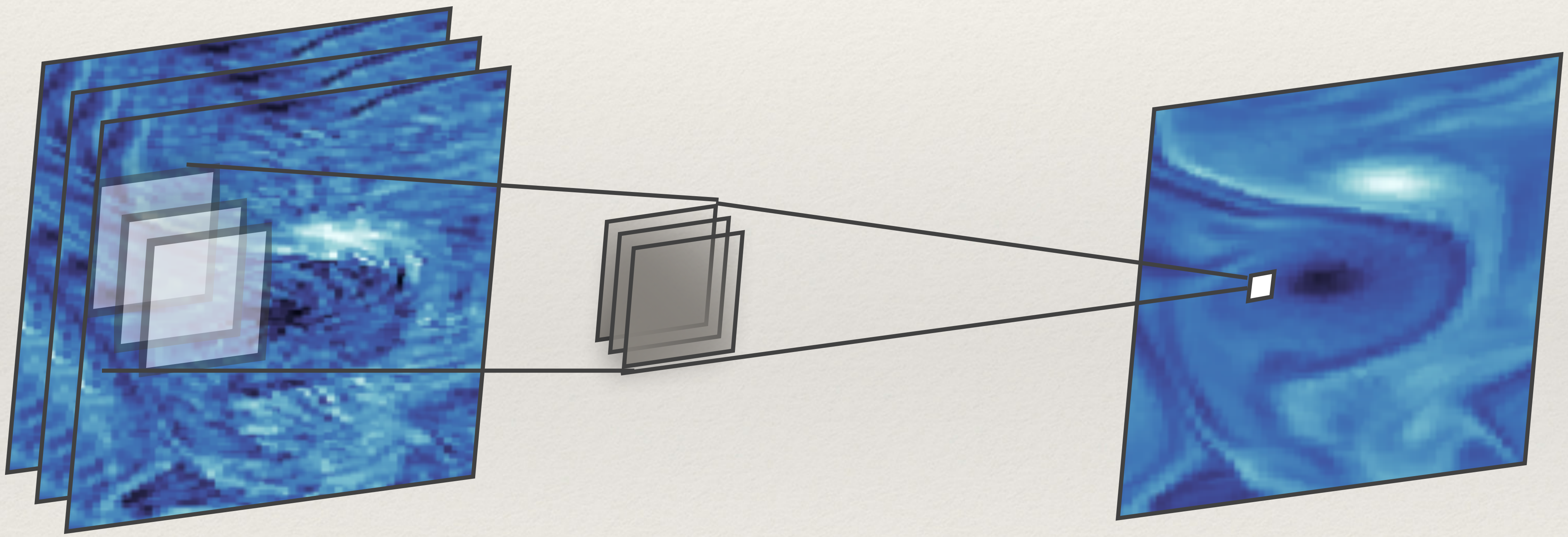
Importantly, we found that using a loss function that combines MSE(SSH) and MAE of laplacian of SSH (related to vorticity) leads to a better reconstruction

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

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

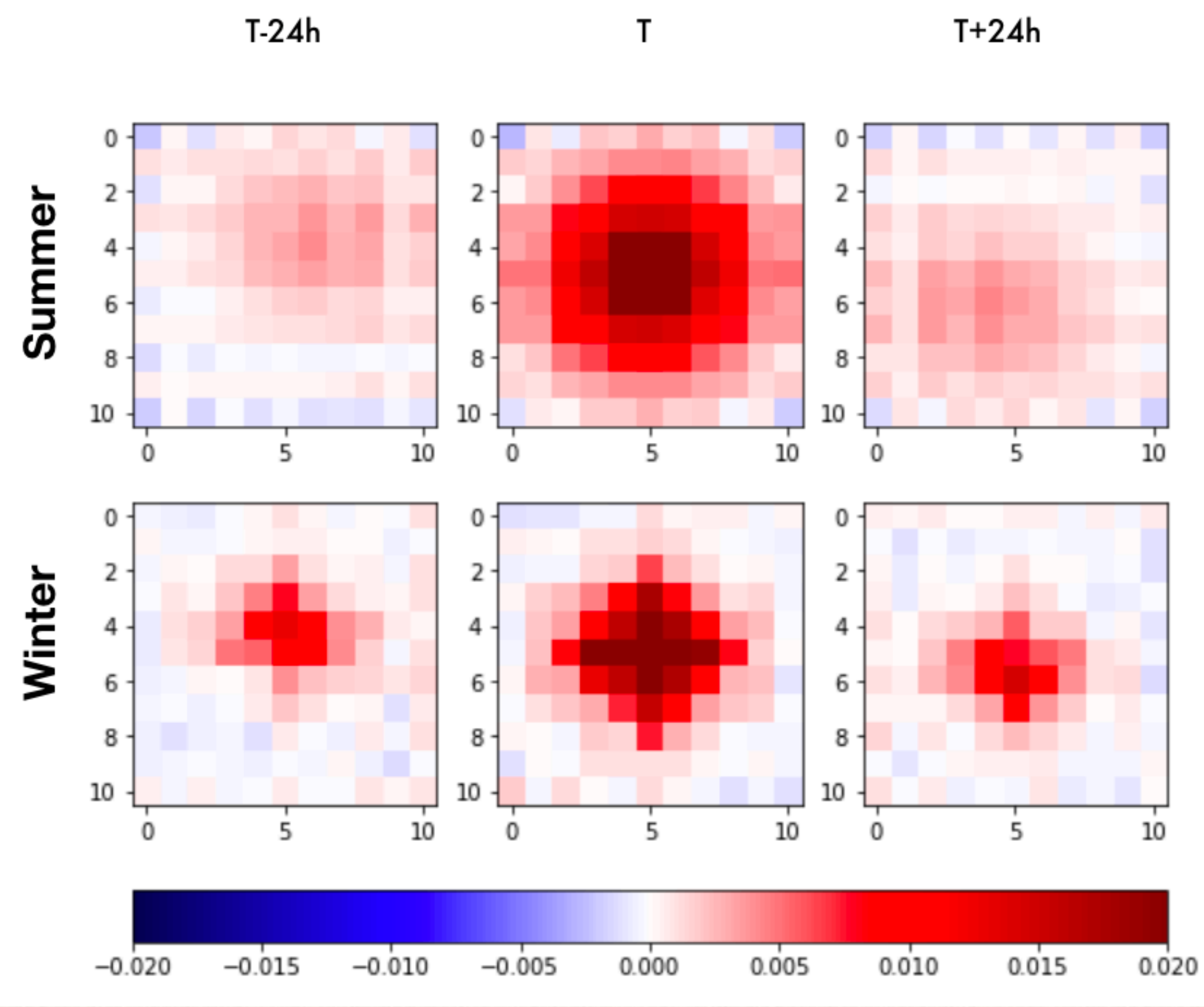


After train we can visualize the learned filters

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

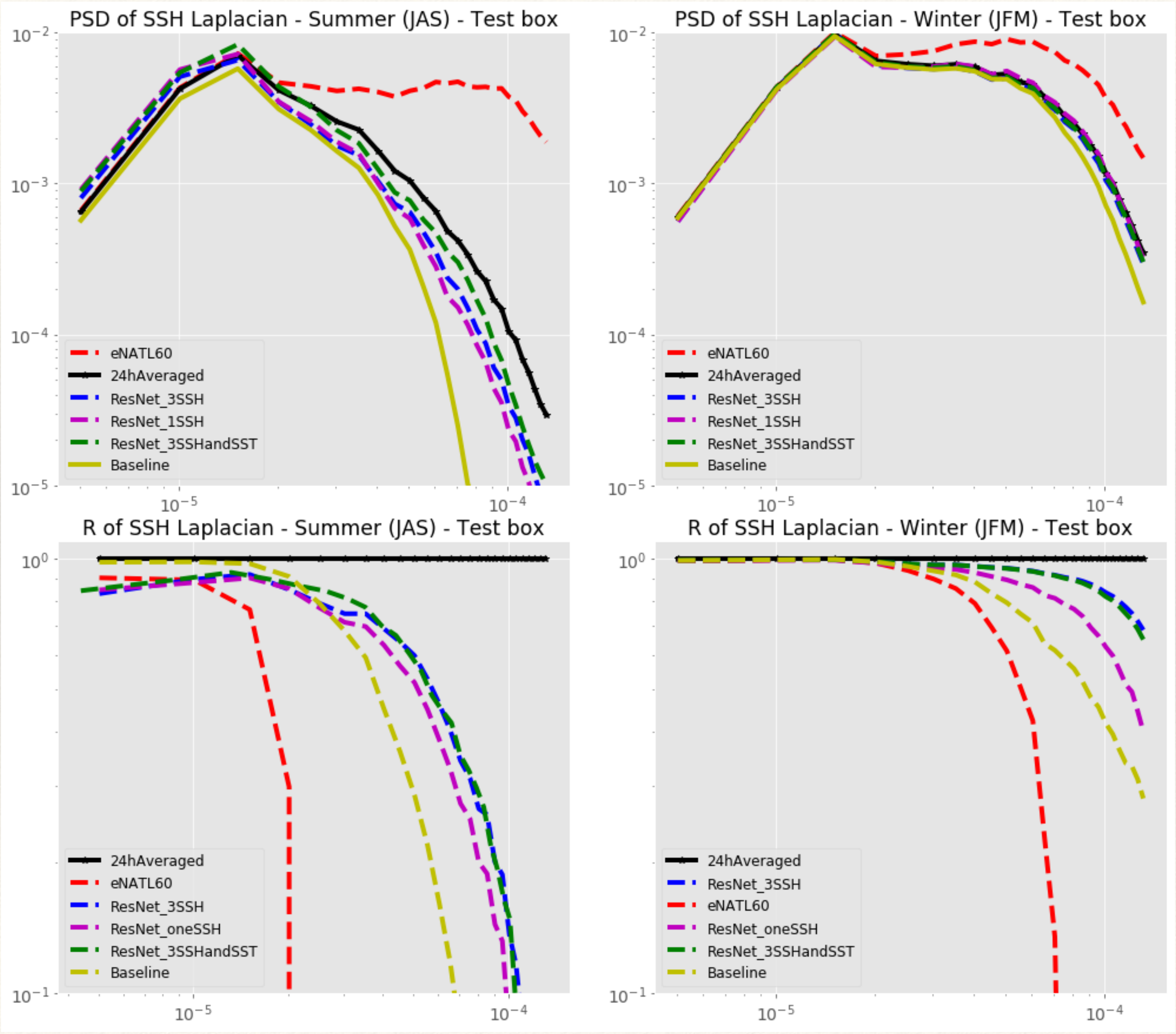
- For summer and winter. We run experiences with as an input:
- * 1 SSH: SSH at time t
- * 3 SSH: SSH at times t-24h, t, t+24h
- * 3 SSH 1SST: SSH at times t-24h, t, t+24h and SST at time t

- 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:

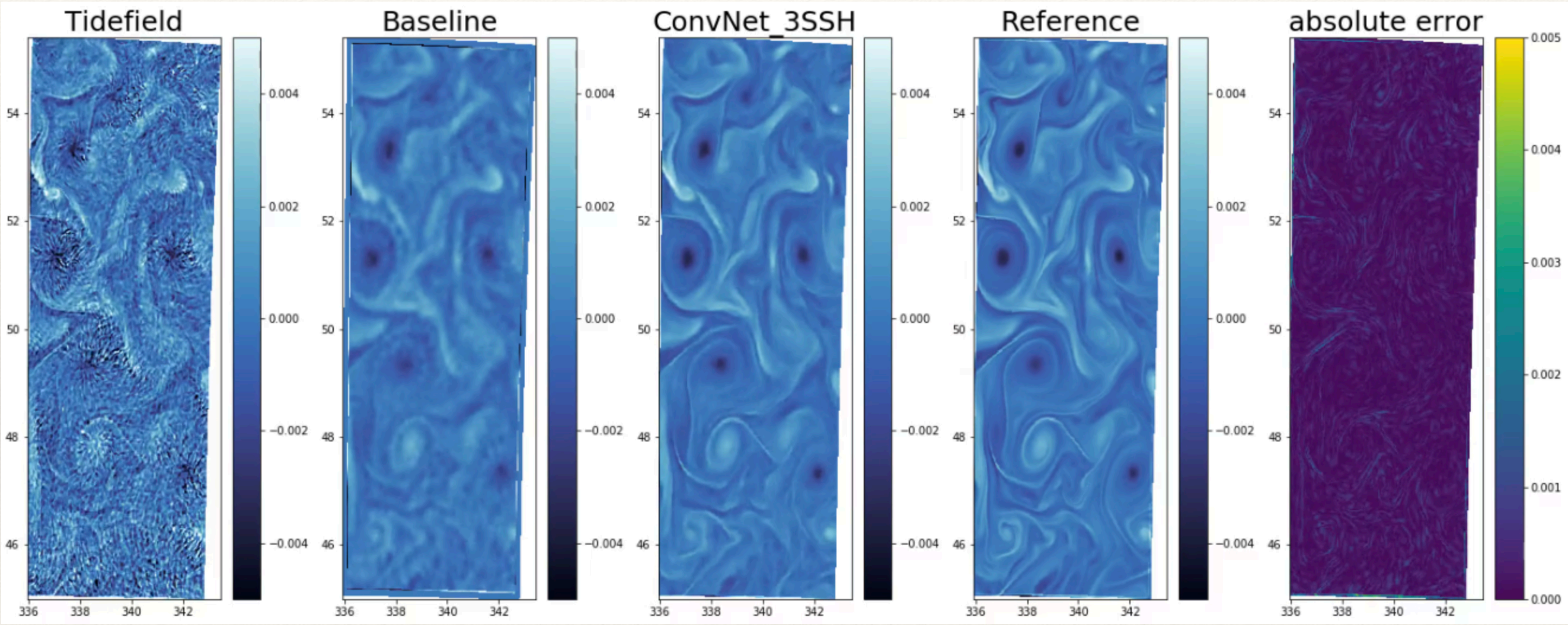
$$R = 1 - \frac{\mathrm{E}\left[\left(PSD_y - PSD_{\hat{y}}\right)^2\right]}{\mathrm{E}\left[PSD_y^2\right]}$$

Comparing powerspecs



A movie on a test dataset

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



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Limitations and future work

- Any supervised learning technique depends heavily on the reference data (here 24h average), investigating other more reliable references is one of our priorities.
- 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, the use of Generative Adversarial Networks is a promising direction

We are working on an extended version of this work.
Stay tuned !

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: rlguensat@locean-ipsl.upmc.fr

Enjoy #shareEGU20. Stay home and stay safe!