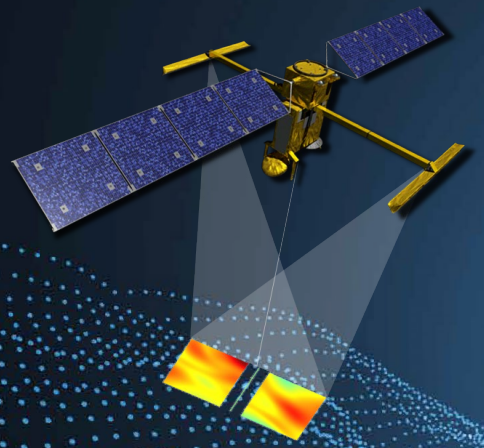
Karin noise filtering using AI techniques



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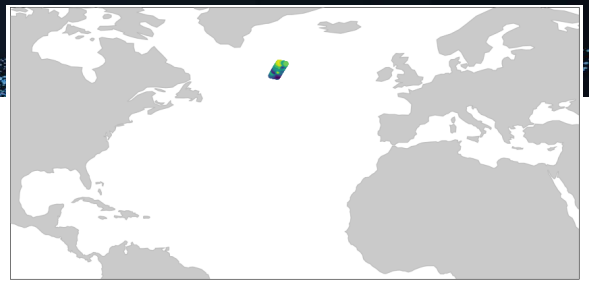
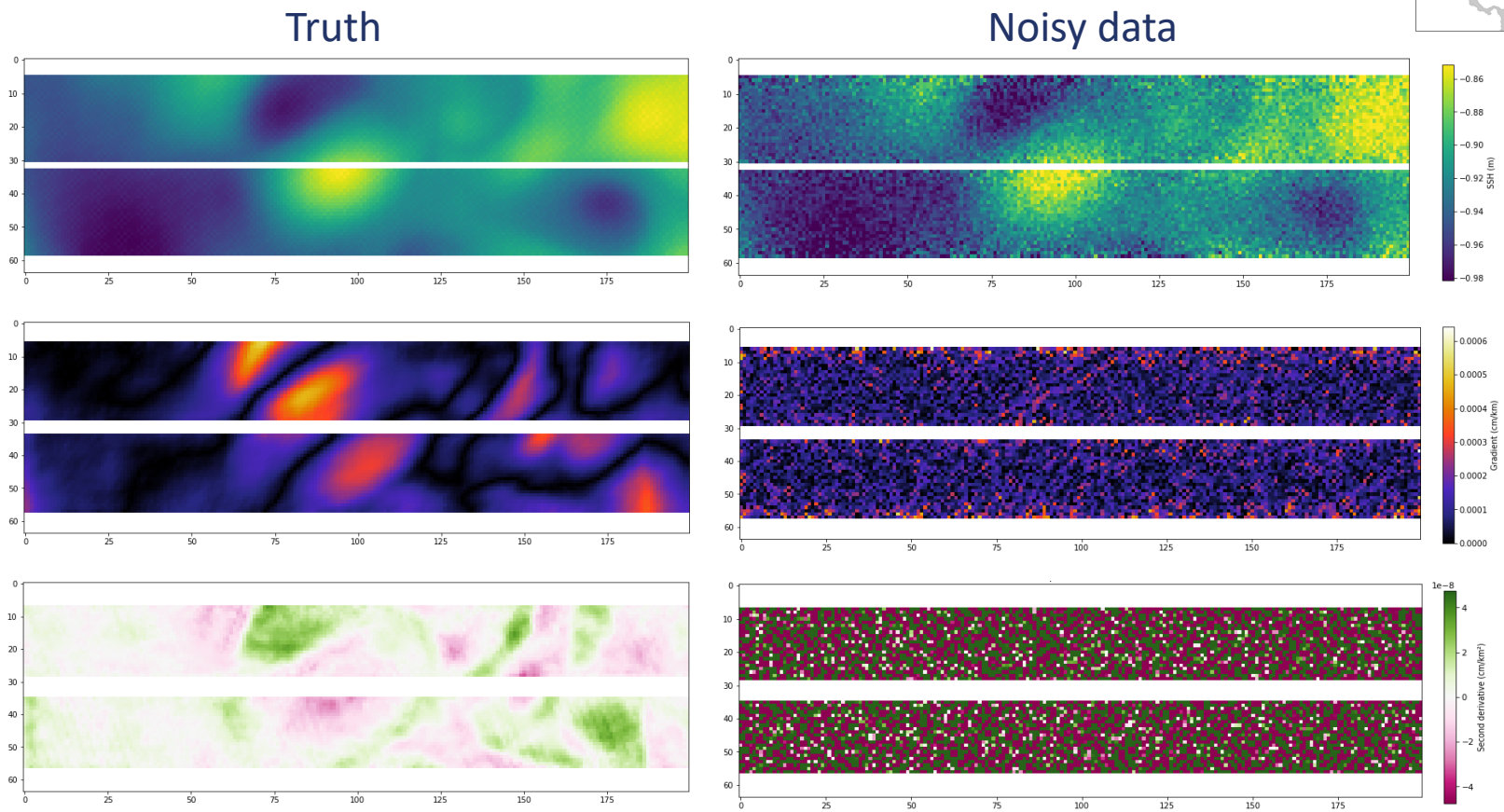
Problematic



- The SWOT products will be impacted by a Karin noise :

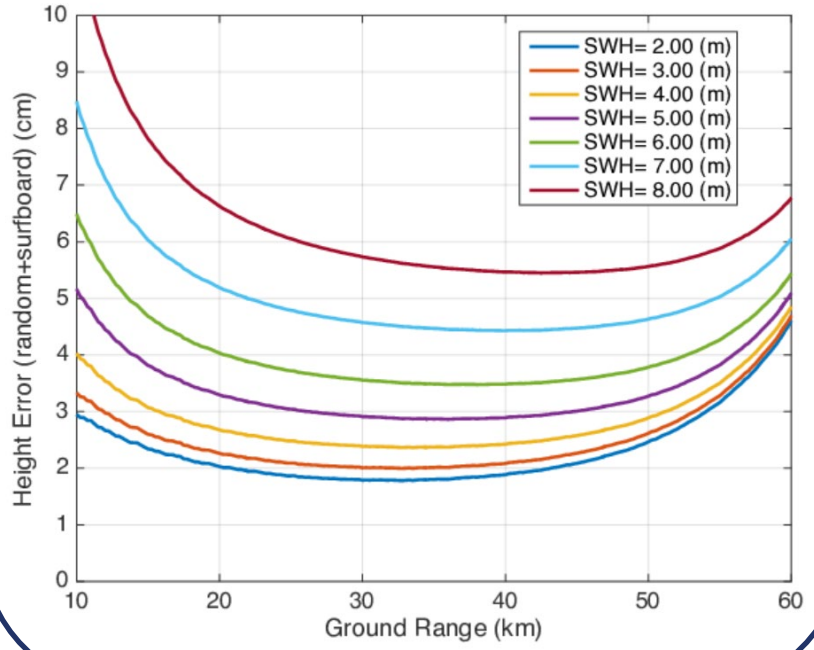


→ Need a SSH L3 product cleaned of various errors for downstream users (e.g., assimilation), especially high frequency errors related to the instrument. **A filtering step must be done**

Objectives

KaRIn Noise:

- Depend on the distance from the nadir
- Depend on the wave heights



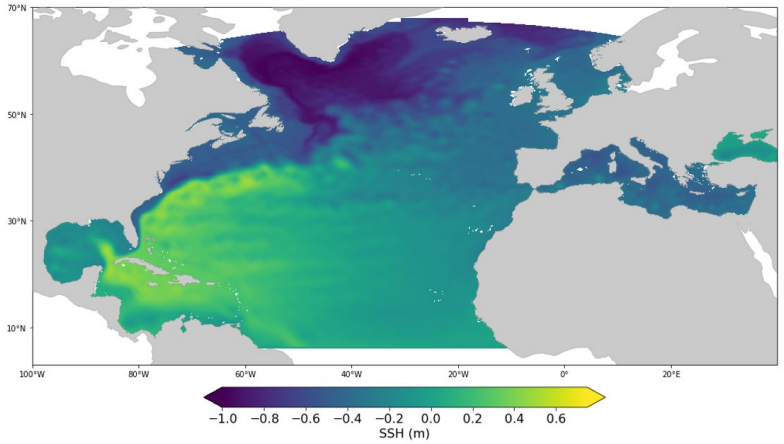
- Lots of methods exist to denoise data :
  - Classical filters (Gaussian, Lanczos, Median, …)
  - Empirical filters (filter developed by Laura Gomez)
  - Neural Network Filter usually used in image processing

In a SWOT context, the objective is to used neural network techniques to reduce the errors already analyzed by other teams, to remove the Karin noise and to compare this model to classical methods.

- Gomez-Navarro, L., Cosme, E., Sommer, J., Papadakis, N., Pascual, A., 2020. Development of an Image De-Noising Method in Preparation for the Surface Water and Ocean Topography Satellite Mission. Remote Sens. 12, 734. https://doi.org/10.3390/rs12040734
- Gómez Navarro, L., 2020. Image de-noising techniques to improve the observability of oceanic fine-scale dynamics by the SWOT mission. (Theses). Universite Grenoble Alpes; Universitat de les Illes Balears.

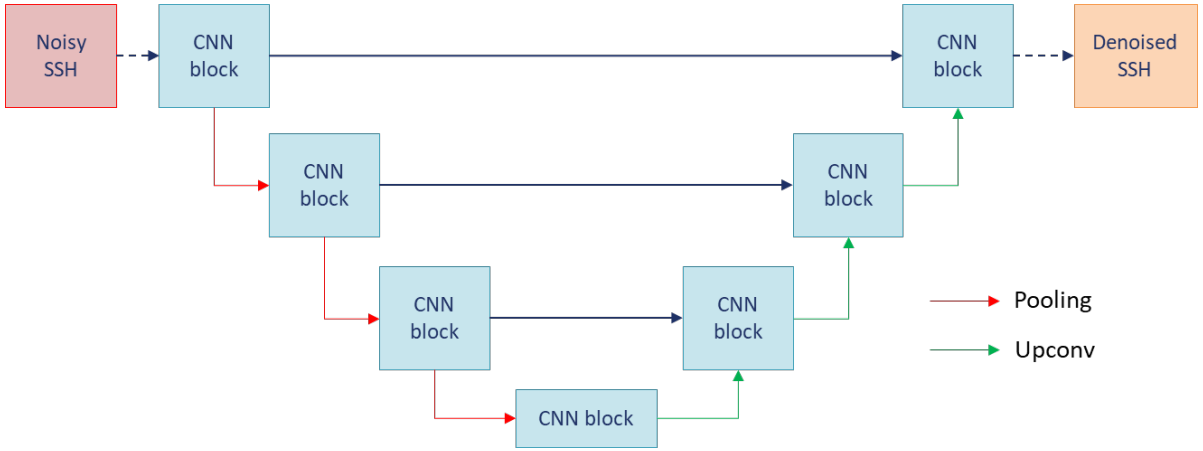
Data and model

- **Simulated SWOT Data (eNATL60 model)** : Noisy SSH = true SSH + Karin noise modulated by the waves
- **Waves model** : global ocean reanalysis wave system of Météo-France (WAVERYS) with a resolution of 1/5° degree*
- **Division of the dataset** :
  - Year 2009 : training dataset (train : 75 %, validating : 25 %)
  - Year 2010 : dataset for the calculation of scores
- **Data preprocessing :**
  - used of anomalies of SSH
  - used of data normalization
  - used of data augmentation : Vertical and/or Horizontal Flip
- **Division of the swaths :** 512 km along-track



Example of SSH on eNATL60 domain

- **U-Net architecture (231 000 parameters)**



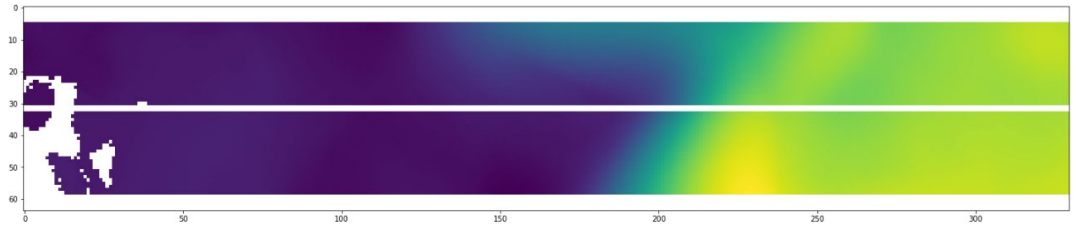
Inspired by Ronneberger, O., Fischer, P., Brox, T., 2015. U-Net: Convolutional Networks for Biomedical Image Segmentation. ArXiv150504597 Cs.

* https://catalogue.marine.copernicus.eu/documents/PUM/CMEMS-GLO-PUM-001-032.pdf

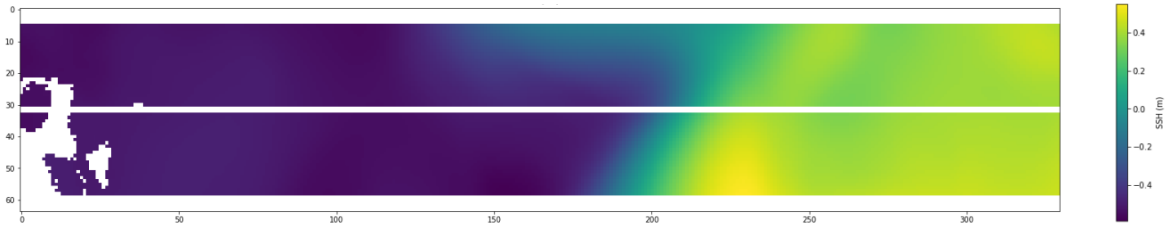
U-Net – Results

- **Swath example**:

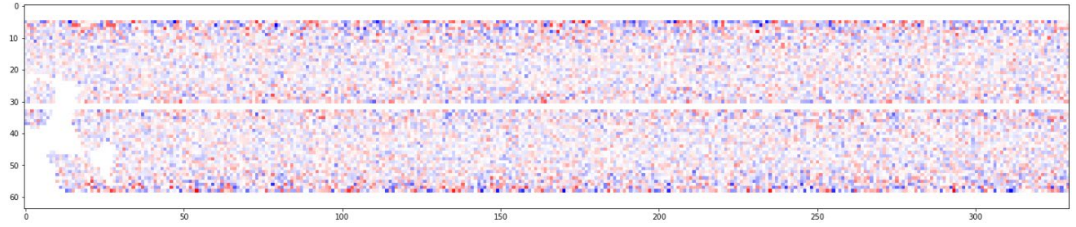
1. True SSH



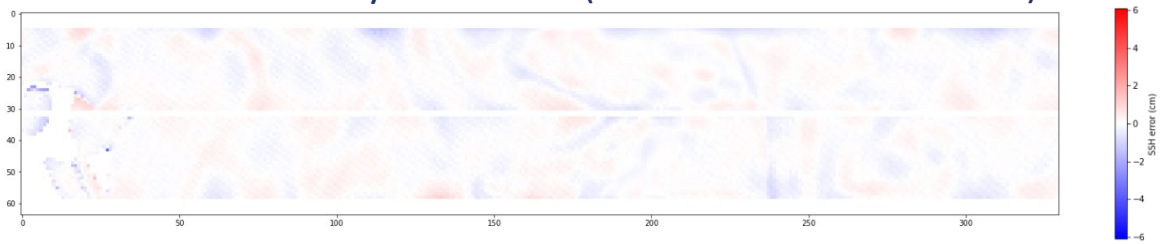
3. Denoised SSH



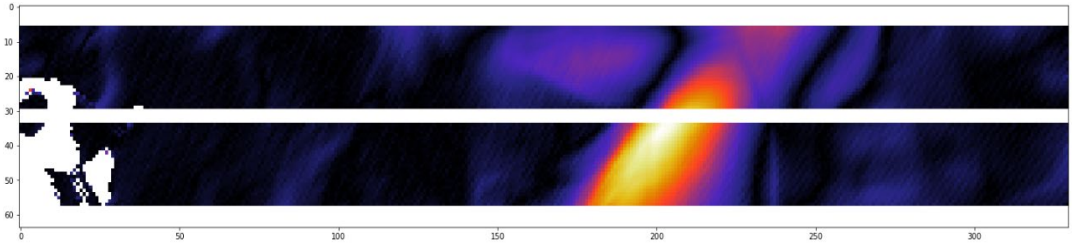
2. Noise



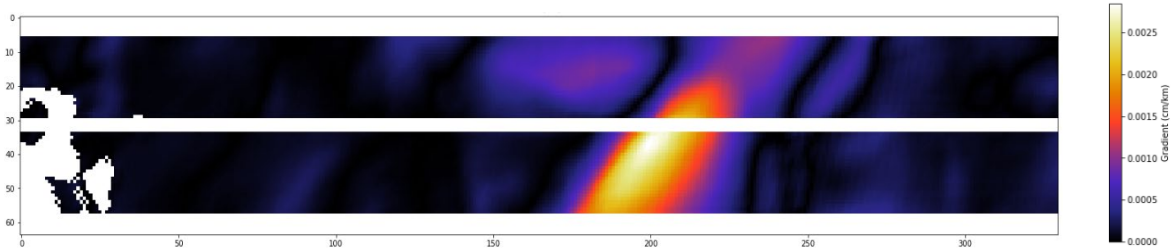
4. Errors made by the model (True SSH – Denoised SSH)



5. First derivative of the True SSH



6. First derivative of the Denoised SSH



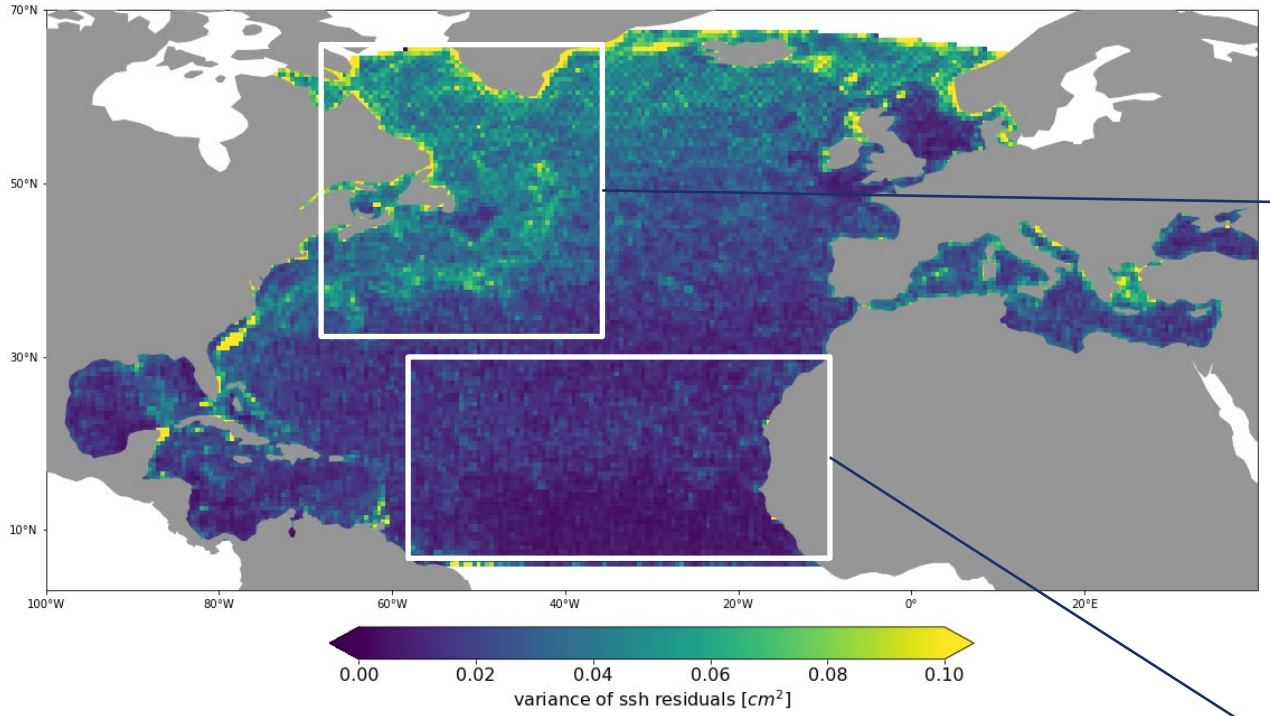
→ Noise is correctly removed : the error made by the U-Net is around 1 cm

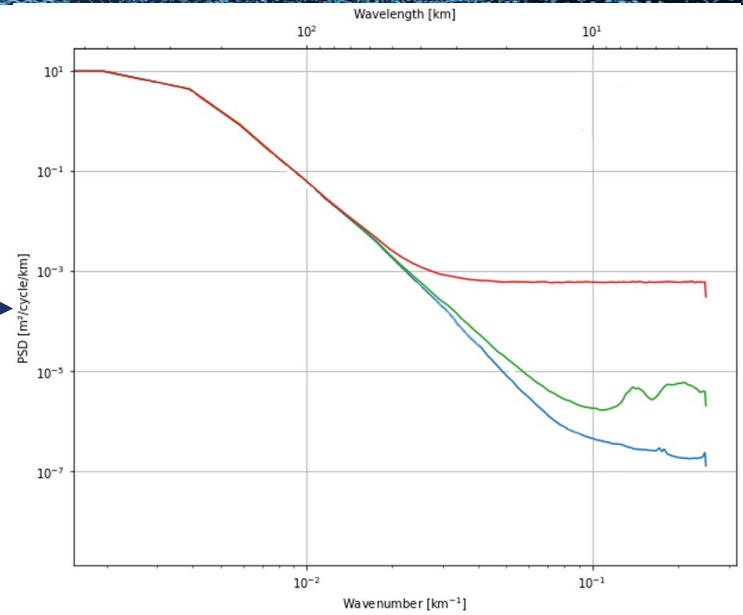
→ No artefacts on the coastline

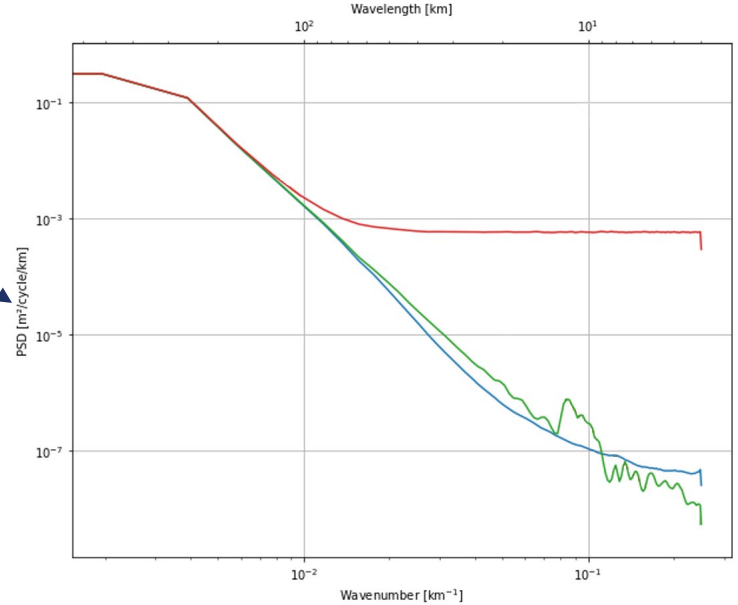
→ The first derivative is correctly restored

U-Net – Results

- **Variance of SSH residuals**







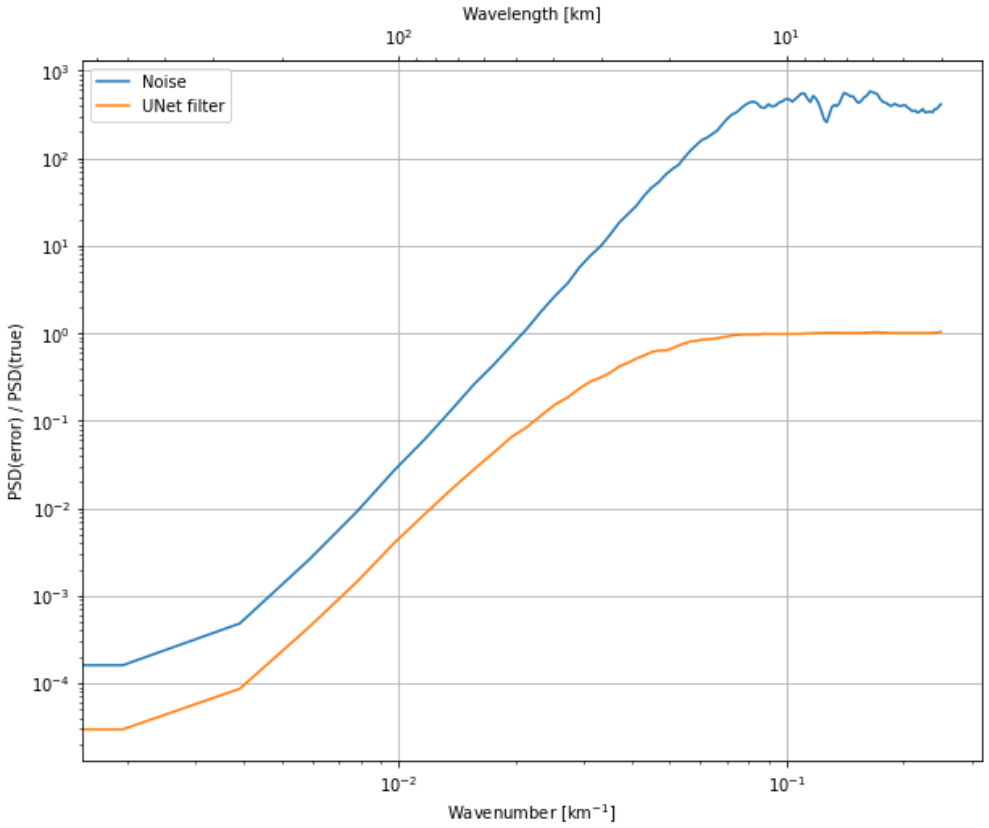
Red : Noisy SSH
Green : True SSH
Blue : Denoised SSH

→ RMSE = 0.17 cm
→ The variance of SSH residuals is lower than 0.1 cm²
→ The model can be adapted to different variability areas

U-Net – Results

- **Spectral analysis**

PSD(denoised SSH – true SSH) / PSD(true SSH)



	Wavelength corresponding to SNR = 1
No filter	47 km
U-Net	**~ 10 km**

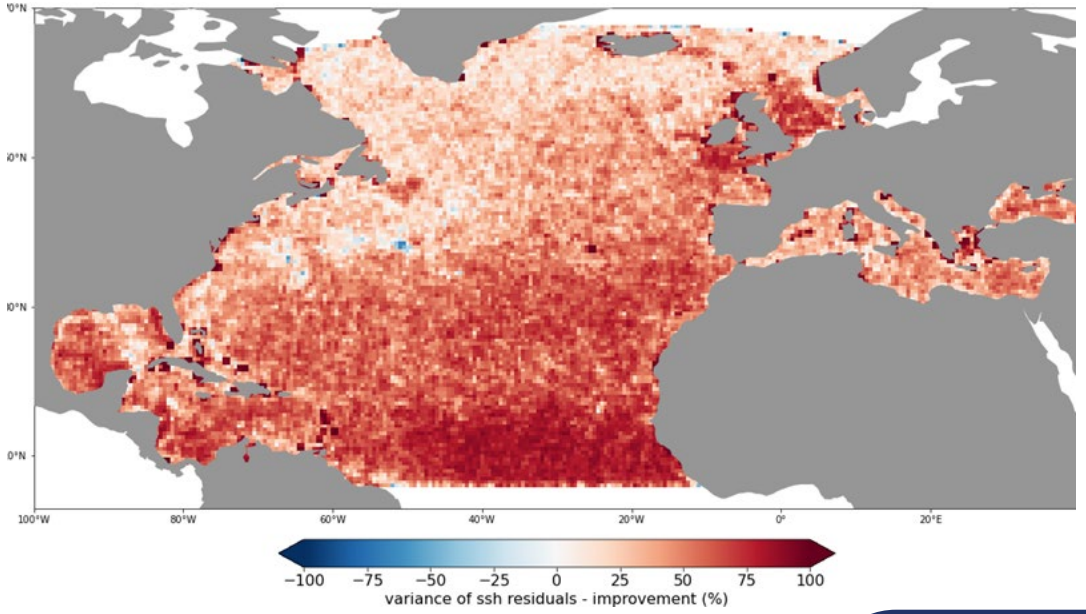
→ All the wavelengths are denoised by U-Net model. It is due to its architecture : phenomena at several scales are taken in account.

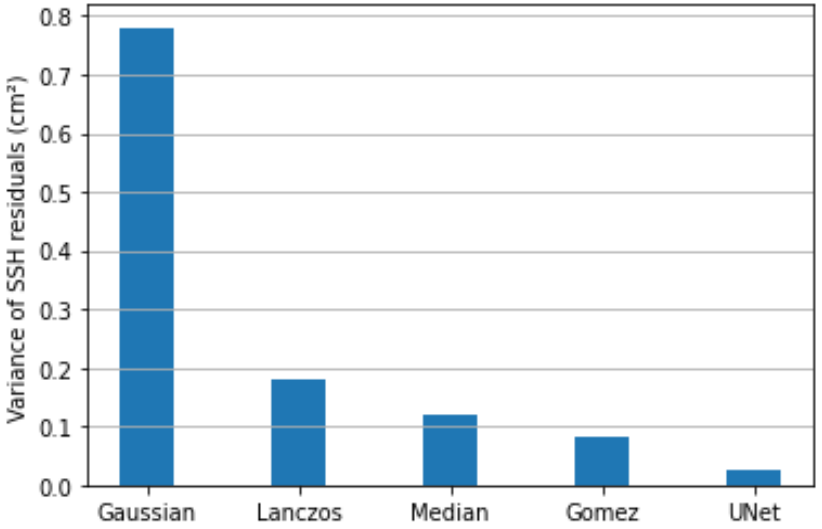
→ Achievement of the objectives of the Scientific Requirement (15 km resolution) without the hypothesis of the requirement (SWH of 2 m, mean over 7.5 km x 7.5 km areas and 68% quantile spectrum)

U-Net – Comparison with classical filters

- **Variance of SSH residuals**

U-Net vs Gomez filter ($\lambda_2 = 10$)





$$\frac{Var(UNet_{NATL60}) - Var(Gomez_{NATL60})}{Var(Gomez_{NATL60})}$$

Red : The Unet is the best

Blue : The Gomez filter is the best

→ U-Net model has better results than classical filters (Gaussian, Lanczos, Median filters)

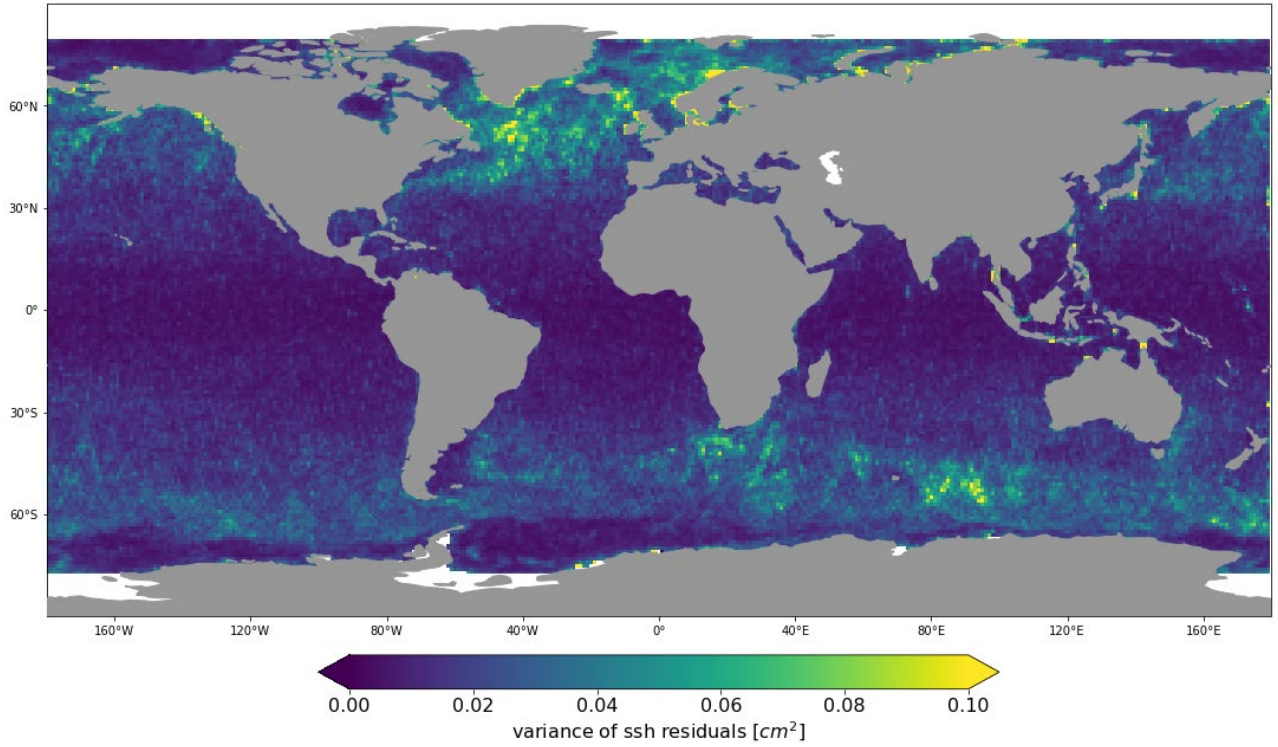
→ U-Net model has similar performance as Gomez filter if λ_2 is correctly adjusted

→ Only one training of the U-Net denoise all domain

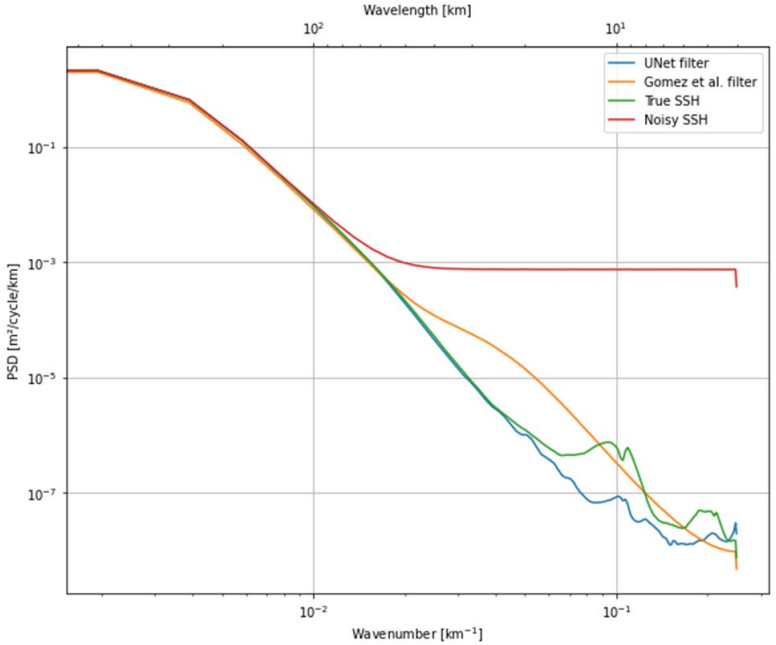
Generalization of U-Net model

- **Method** :
  - Used of the U-Net model trained on NATL60 data
  - Application of the model on GLORYS data without training
  - Calculation of the scores with the benchmark

- **Variance of SSH residuals:**



- **PSD (SSH)**



→ U-Net model can be adapted to new oceans and to a new ocean model.

→ RMSE (Unet) = 0.13 cm

Conclusion

- Used of a neural network model : **U-Net**
- Denoising up to **10 km** wavelength
- U-Net model **adaptable to different ocean areas**
- U-Net model can be **easily used for new data**

- **Next step :** Apply on real SWOT data and comparison to other methods via a data challenge