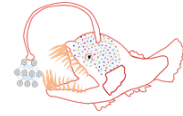


# R&T DeepSee



**SRoll** : an algorithm based on data inversion and scattering transform to reduce systematic effects and foregrounds on satellite data.



Théo Foulquier  
Jean-Marc Delouis

# Context



Data from space observations have instrumental effects or foregrounds that degrade the signal of interest recovery.

This problem is common to **astrophysical and oceanographic** data as with CFOSAT, but the geophysical signal evolves over time on the scale of the measurement, unlike astrophysical processes.

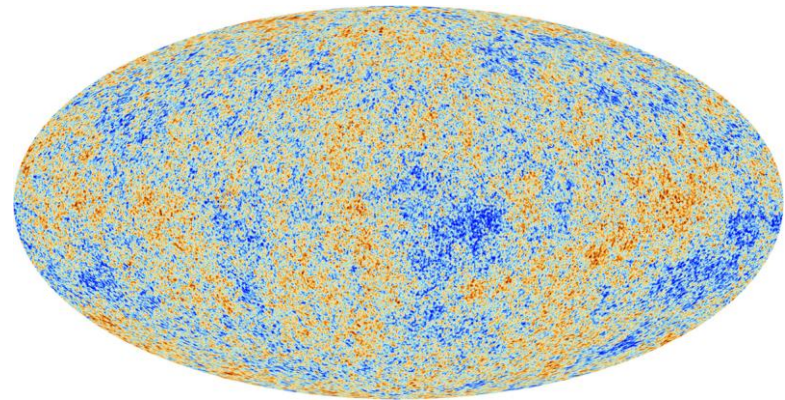
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**Planck** - European Spatial Agency (2009-2013)



**Cosmic Microwave Background (CMB)**: 380,000 after the Big Bang

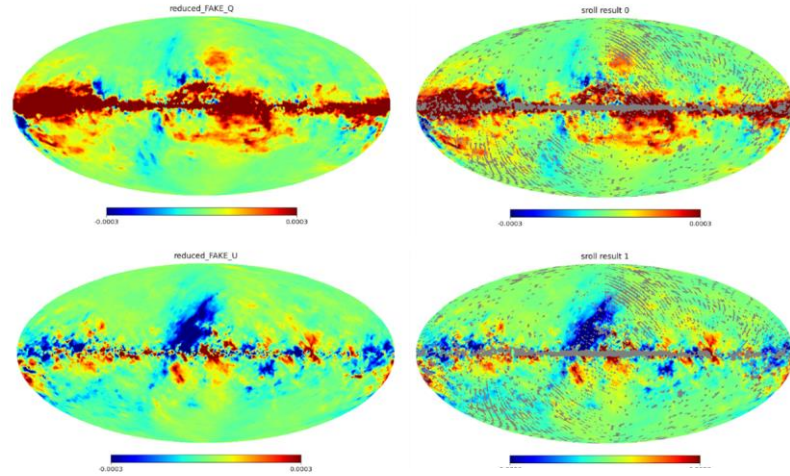
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Planck - European Spatial Agency (2009-2013)



Use of SRoll to denoise Planck HFI data



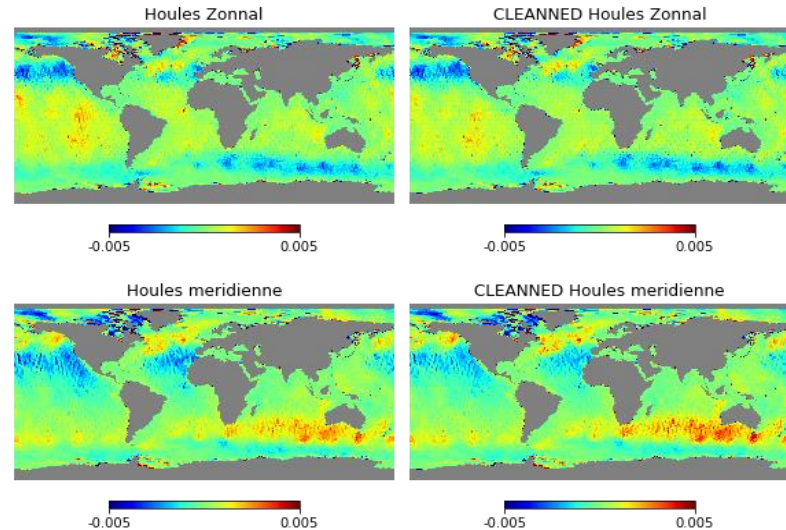
# Context

Data from space observations have instrumental effects or foregrounds that degrade the signal of interest recovery.

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CFOSAT – CNES / CNSA



# Context : SRoll ,an algorithm of denosing for planck HFI

The SRoll software developed initially for cosmology (Planck Project) simultaneously inverts this signal and the instrumental effects including noises.

Therefore, SRoll uses the all available dataset to minimise the variance of the measured calibration parameters.

2014

**SRoll1** became the official Planck-HFI data processing pipeline.

2018

**SRoll2\*** Post Planck consortium work that improves the handling of certain instrumental effects:

- *Reionization optical depth determination from Planck HFI data with ten percent accuracy (Astronomy & Astrophysics)*
- *Improved large scales interstellar dust foreground model and CMB solar dipole measurement (Astronomy & Astrophysics).*

2020

**SRoll3** uses the dimensionality drop modelled by generative neural networks to extract instrumental systematics.

. *SRoll3: A neural network approach to reduce large-scale systematic effects in the Planck High Frequency Instrument maps. M. Lopez-Radcenco, J.-M. Delouis, and L. Vibert, Astronomy & Astrophysics (Accepted 02/2021)*

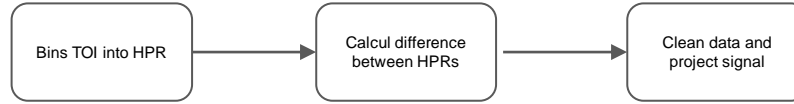
2021/22

**SRoll4** uses dimensionality reduction for instrumental effects and for the signal. Also incorporates Scattering Transform approaches. Stabilisation of the code to make it a cross-cutting tool.

\*SRoll2: an improved mapmaking approach to reduce large-scale systematic effects in the Planck High Frequency Instrument legacy maps. *J.-M. Delouis, L. Pagano, S. Mottet, J.-L. Puget and L. Vibert*

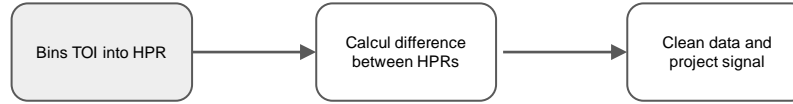
# SRoll : Global solution (0/3)

\*  
TOI = Time ordered Information  
HPR = HealPix Rings

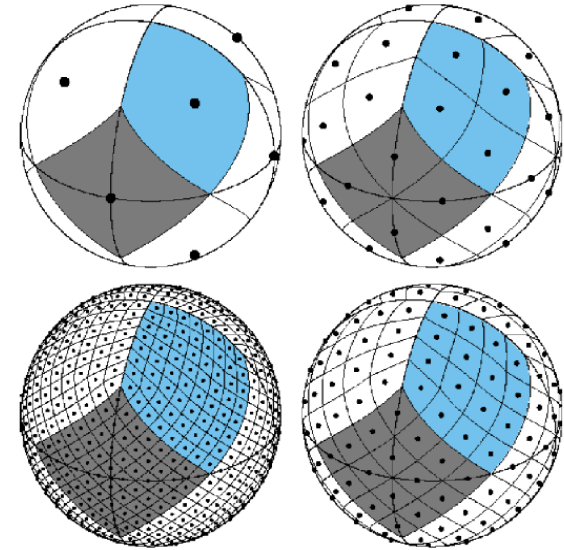
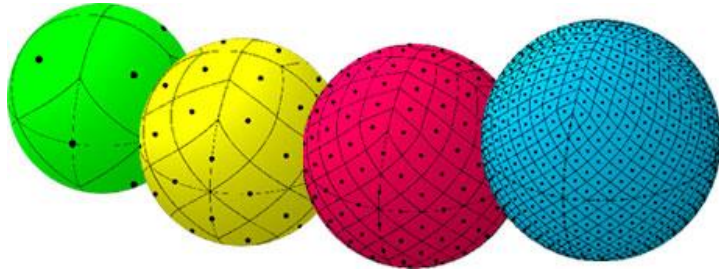


# SRoll : Global solution (1/3)

TOI = Time ordered Information  
HPR = HealPix Rings



Bins the Time Ordered Information (TOI) into **HEALPIX** pixels per periods of stable satellite pointing to reduce the amount of data.

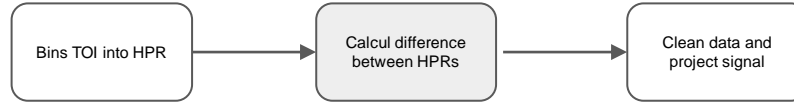


**Healpix** - Hierarchical Equal Area isoLatitude  
Pixelation of a sphere



# SRoll : Global solution (2/3)

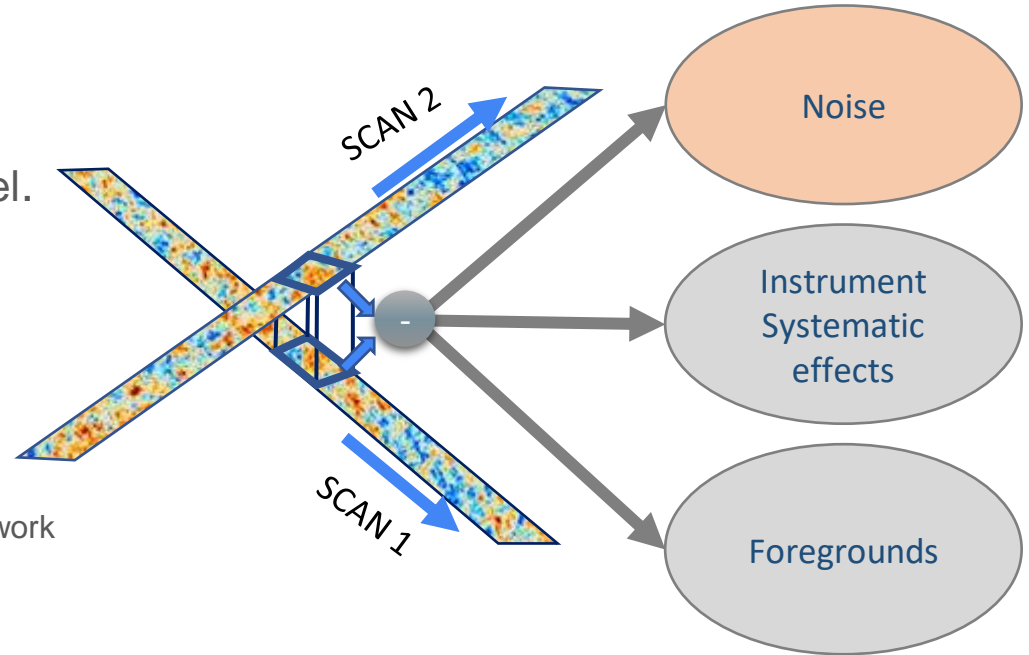
TOI = Time ordered Information  
HPR = HealPix Rings



Fits systematics effects,  $1/f$  noise and calibration using differences between measurements in the same HEALPIX pixel.

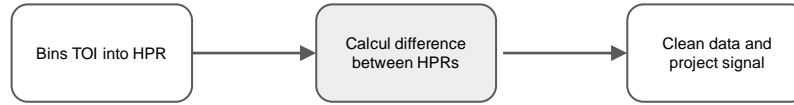
The algorithm :

- **Learns** the most suitable form to represent the difference between two measurements.
- **Synthesises** structures with small generative neural networks(SRoll3)
- **Finds the laws** constraining the structure, does not work on white noise.



# SRoll : Global solution (2/3)

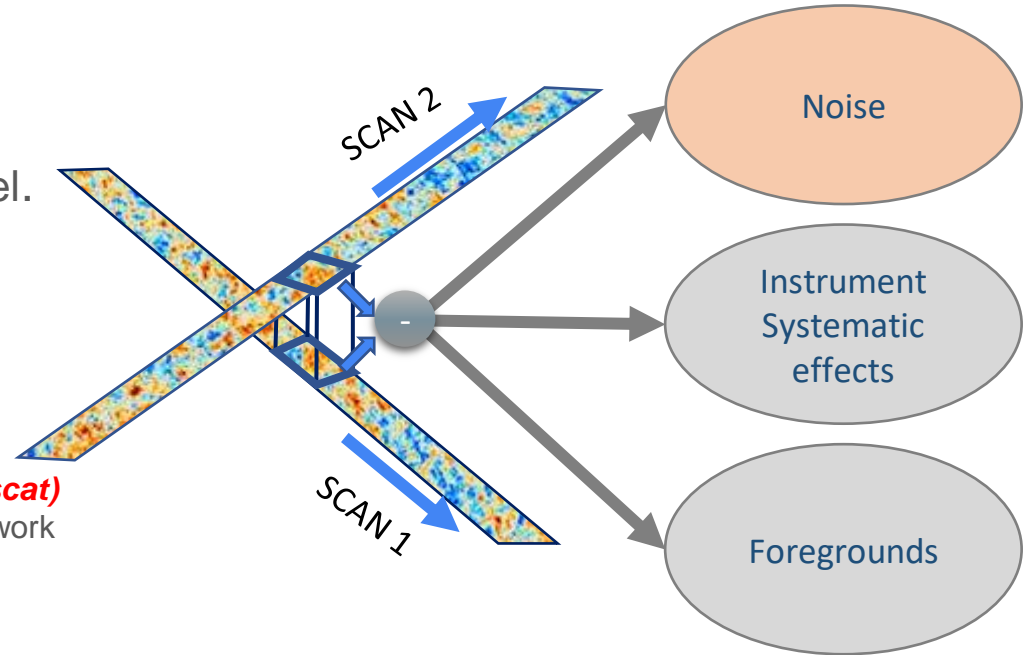
TOI = Time ordered Information  
HPR = HealPix Rings



Fits systematics effects,  $1/f$  noise and calibration using differences between measurements in the same HEALPIX pixel.

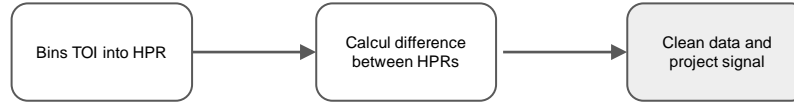
The algorithm :

- **Learns** the most suitable form to represent the difference between two measurements.
- **Synthesises** structures with small generative neural networks(SRoll3) => **use scattering transform ( foscat)**
- **Finds the laws** constraining the structure, does not work on white noise.

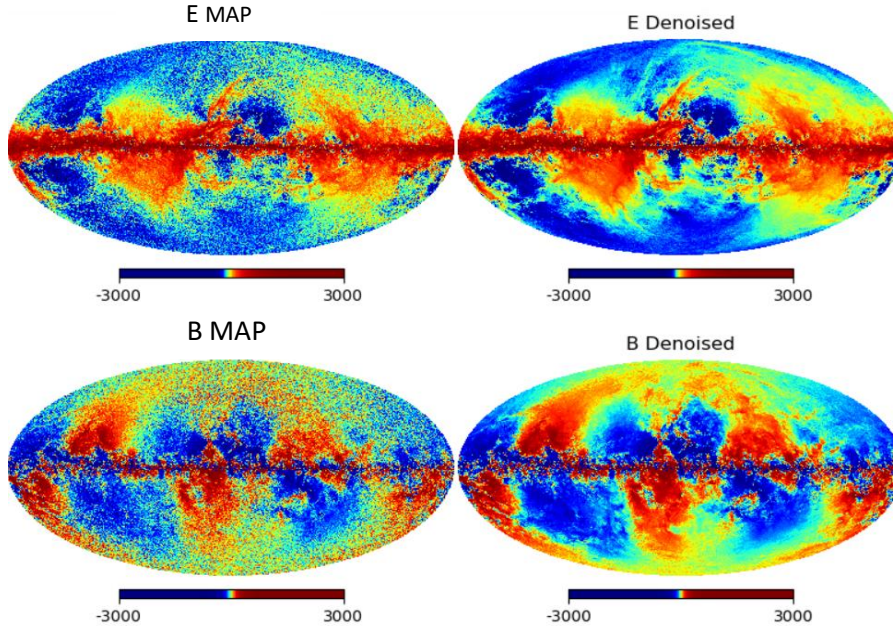


# SRoll : Global solution (3/3)

TOI = Time ordered Information  
HPR = HealPix Rings

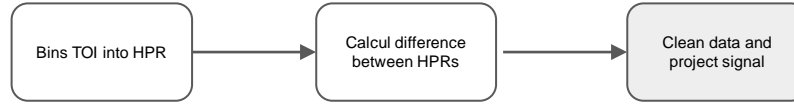


Clean the data using fitted parameters and projects the signal to make maps.

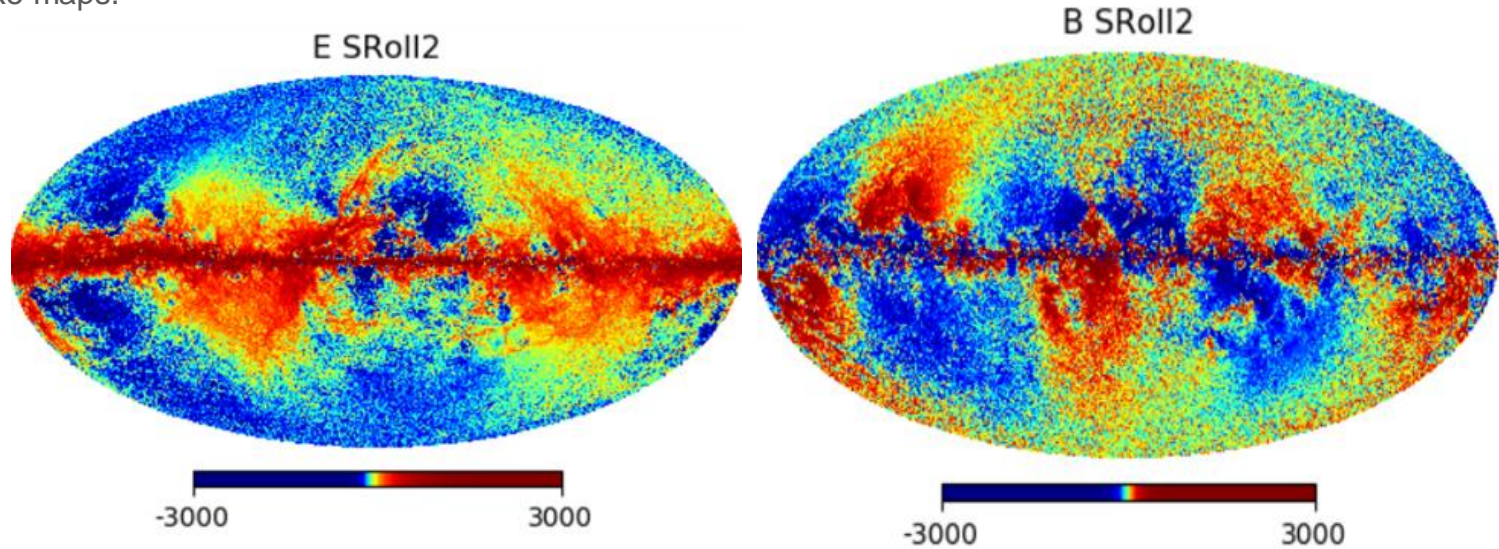


# SRoll : Global solution (3/3)

TOI = Time ordered Information  
HPR = HealPix Rings

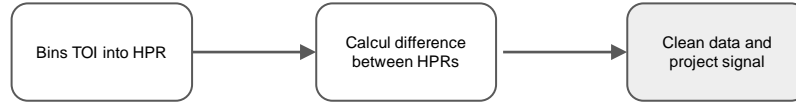


Clean the data using fitted parameters and projects the signal to make maps.

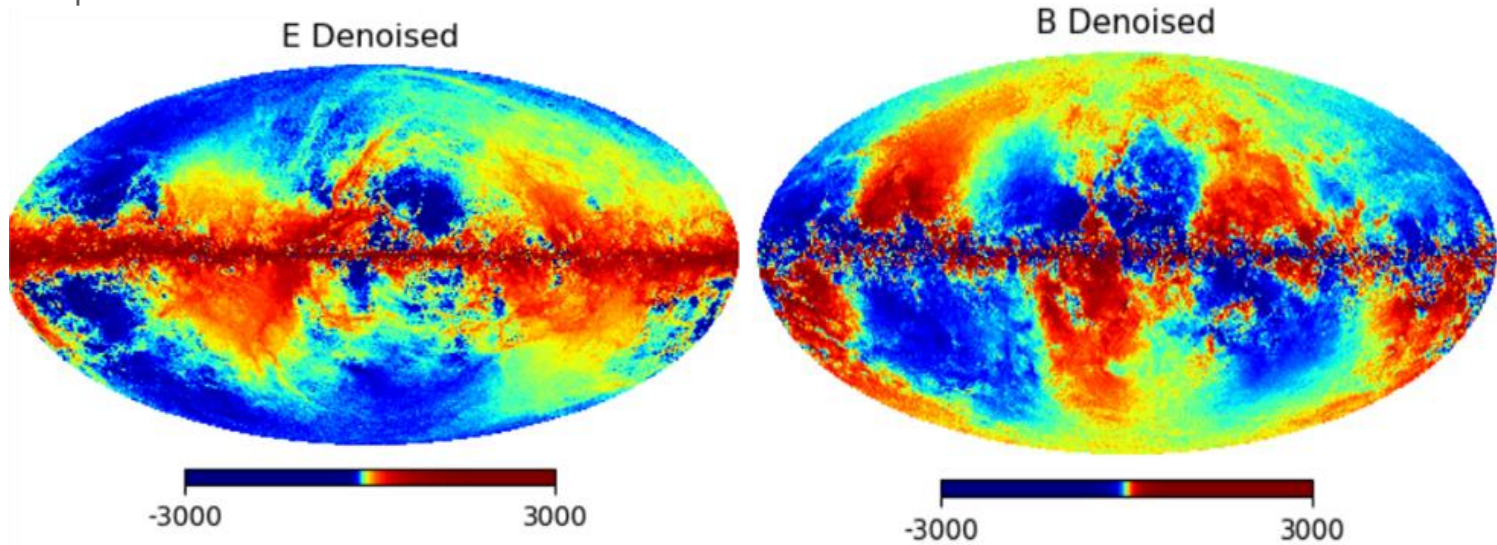


# SRoll : Global solution (3/3)

TOI = Time ordered Information  
HPR = HealPix Rings



Clean the data using fitted parameters and projects the signal to make maps.



# SRoll : Calibration

- Relative calibration instead of global calibration
  - Calibration between detectors M1,M2 (Determine  $\Delta g$ = gain error)

$$gM = Ax + N + n$$
$$\Delta gM = A(\Delta gX + \Delta X) + \Delta N + \tilde{n}$$

*g = gain*  
*A = data*  
*N = noise*

Where  $x = X + \Delta X$

For **SWIM** :

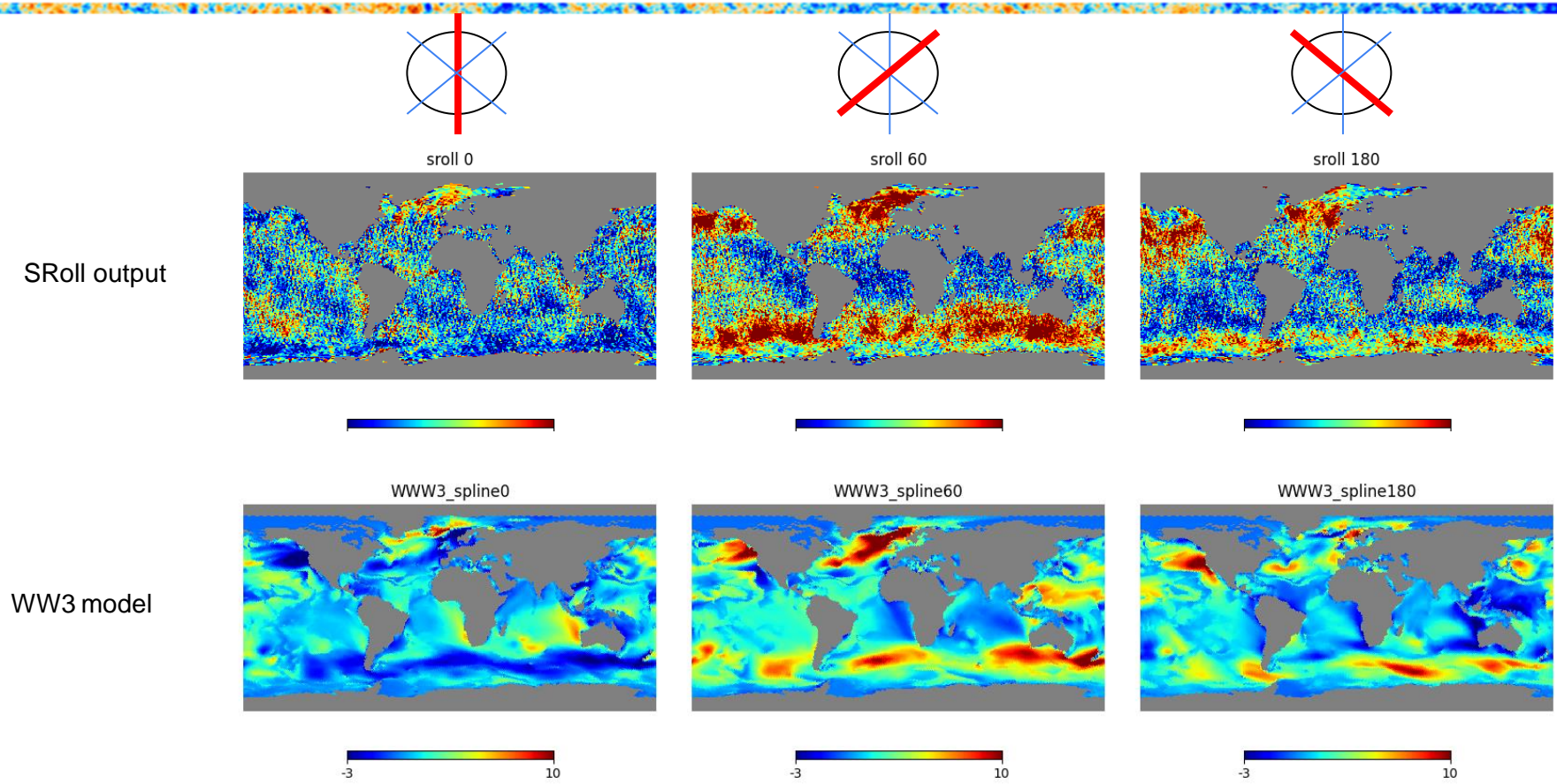
x = wave spectrum

X = WW3

$\Delta X$  = difference between the model and the signal to be determined

This SROLL data model has the advantage that after a certain number of iterations there is no more residual of the model (here WW3) so it is very efficient for relative calibration.

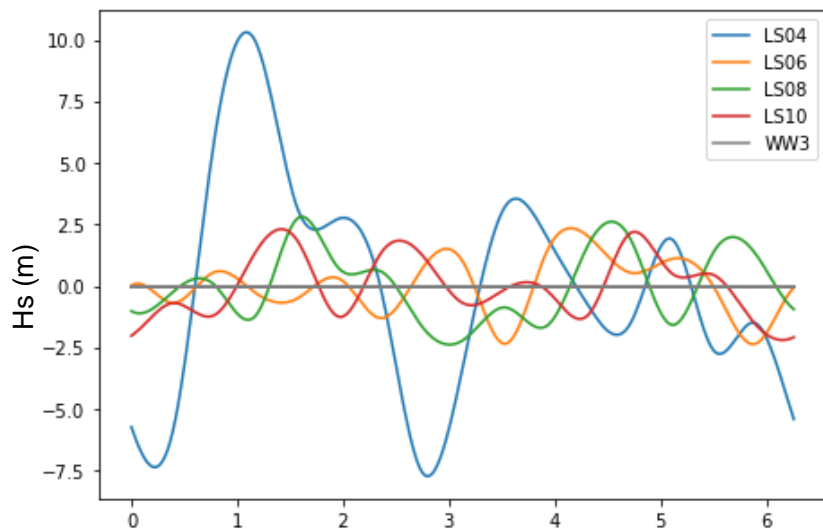
# First results with CFOSAT data :



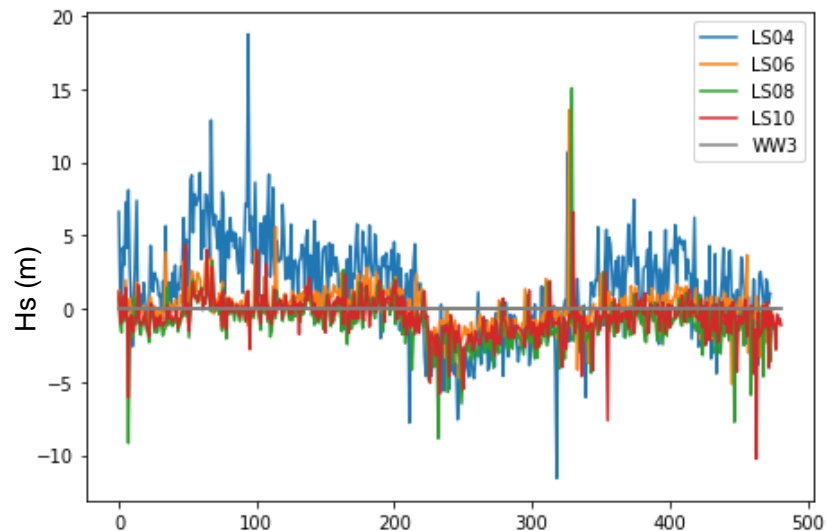
# N values retrieved by SRoll (one month of data)

N values retrieved by SRoll (one month of data)

The data used are the ODL L2



Along track azimuth angle [rad]

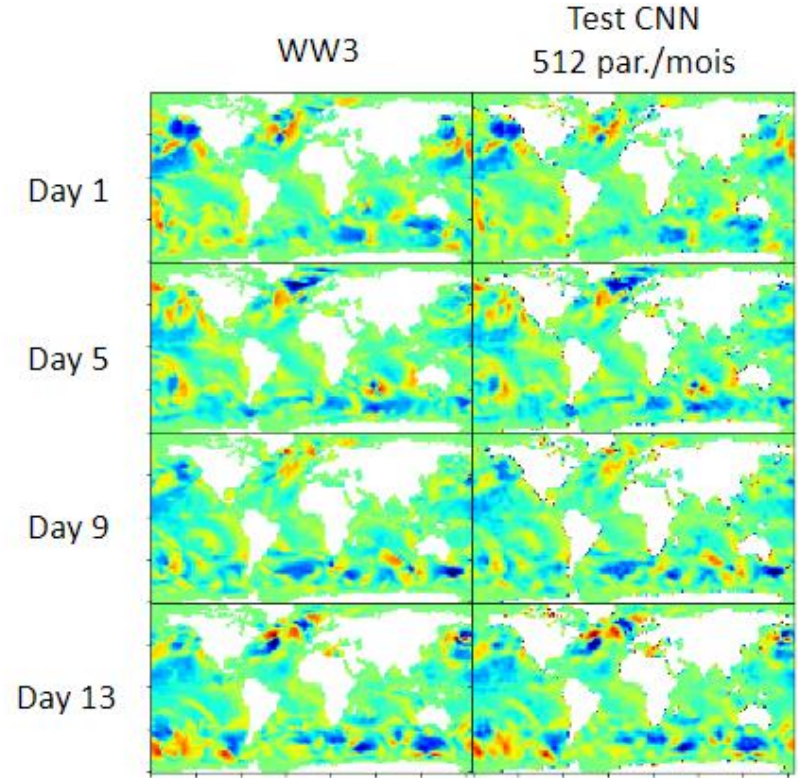


#orbit



# SRoll : Use of IA

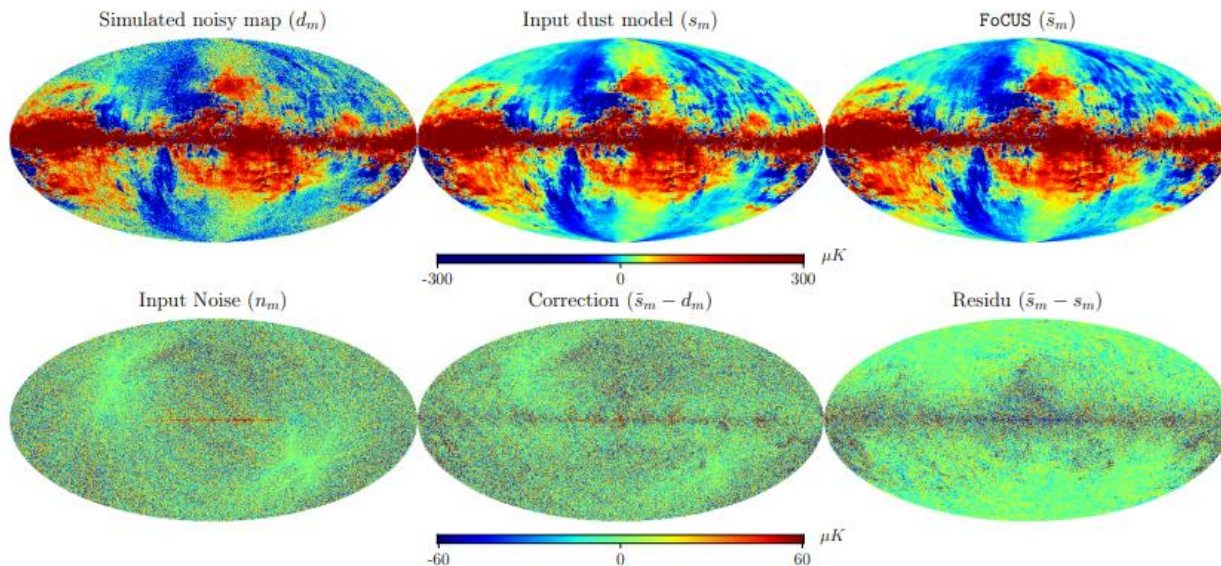
- 3 versions:
  - 1) Use Sroll without NN to find difference between the model and the signal to be determined with precalculated templates or spline base
  - 2) Neural networks not very satisfying because need to know the solution to be able to invert.
  - 3) Implementation of scattering transform



# New implementation : Scattering transform

Therefore, we present a new version of SRoll based on **Scattering Transforms** (ST) to model the signal dynamics.

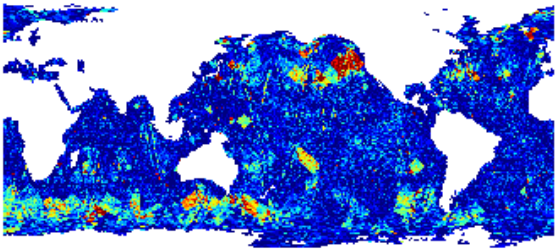
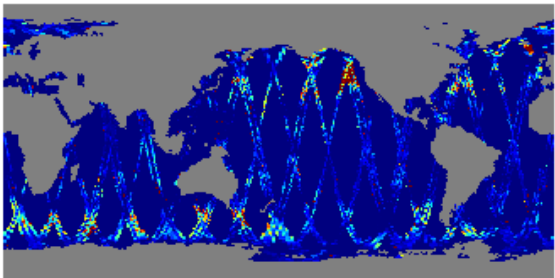
- STs have been used successfully on interstellar medium thanks to the intermittent structure of its turbulent processes. By using these statistical constraints measured on the data itself there is no learning phase as with usual neural networks.



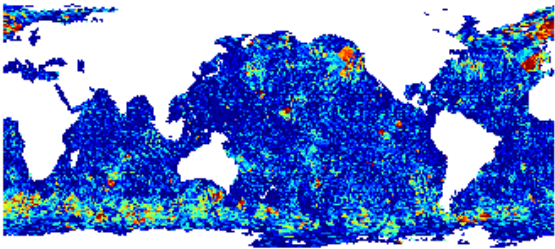
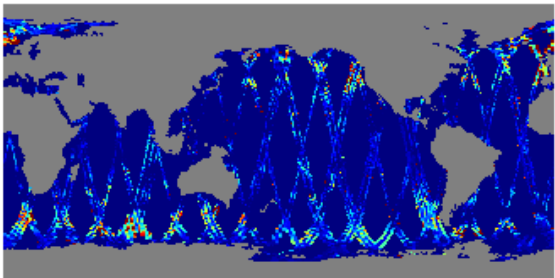
**Non-Gaussian modelling and statistical denoising of Planck dust polarization full-sky maps using scattering transforms** : J.-M. Delouis, E. Allys, E. Gauvrit, and F. Boulanger.

# Results cross stat

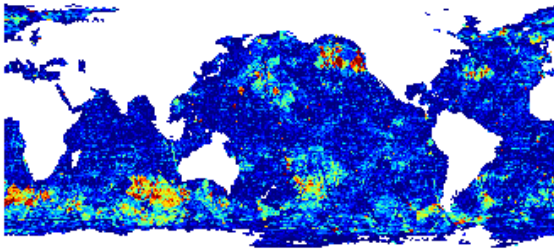
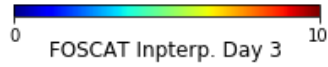
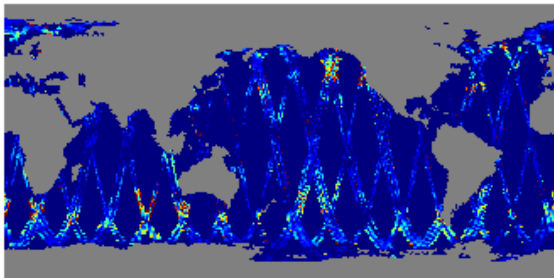
CFOSAT Day 1



CFOSAT Day 2



CFOSAT Day 3



# Conclusion

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This work presents the encouraging results obtained with this type of method on one month of CFOSAT data to correct the calibration of the SWIM instrument. Already prove it efficiency with comsologic data.

Possibility to work on other domain/projects : SKA, SWOT, LITEBIRD..

**Thanks for your attention.**