Deep learning methods for ocean observation

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Intro

Theory

- Satellite observation
- Inverse Problem
- Deep Learning and Data assimilation
- Real-world scenario

Application

- Sea Surface Height and Temperature
- Downscaling or interpolation?
- RESAC method
- Along tracks interpolation

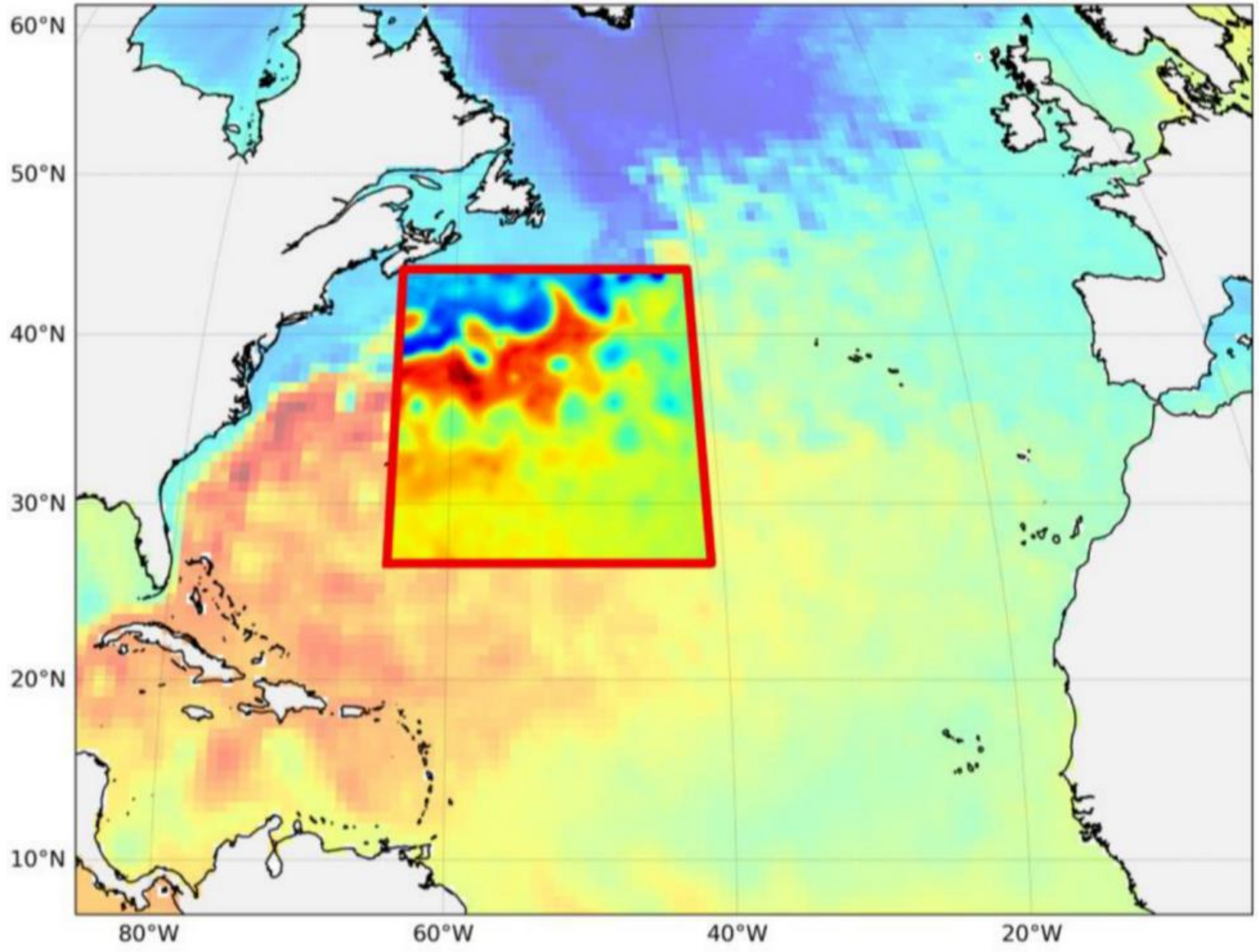
Ocean Remote sensing with satellites

Ocean Observation

- Ocean plays an important role in climate regulation
- Heat stockage

- Oceanic fields are observed with satellites
- Sea Surface Temperature (SST)
- Sea Surface Height (SSH)
- Salinity

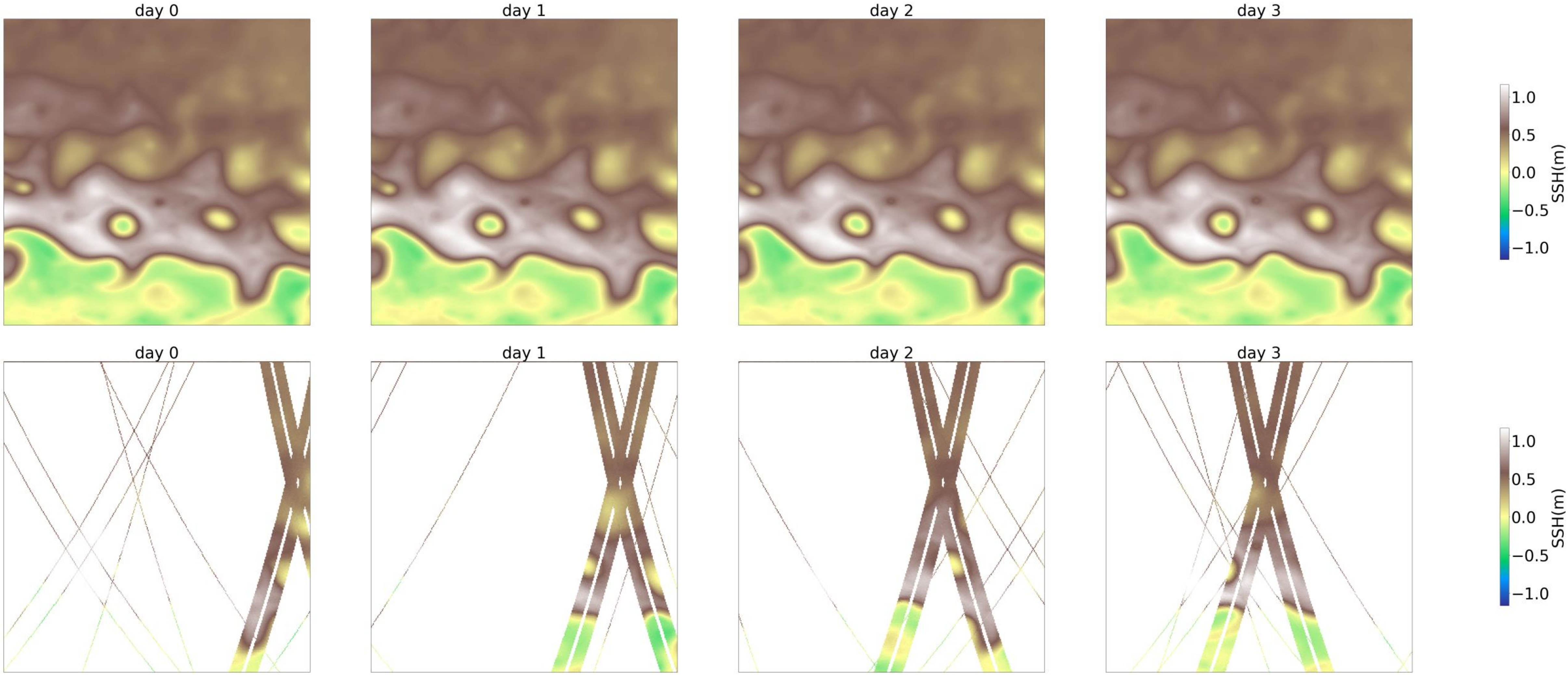
Sea Surface Height



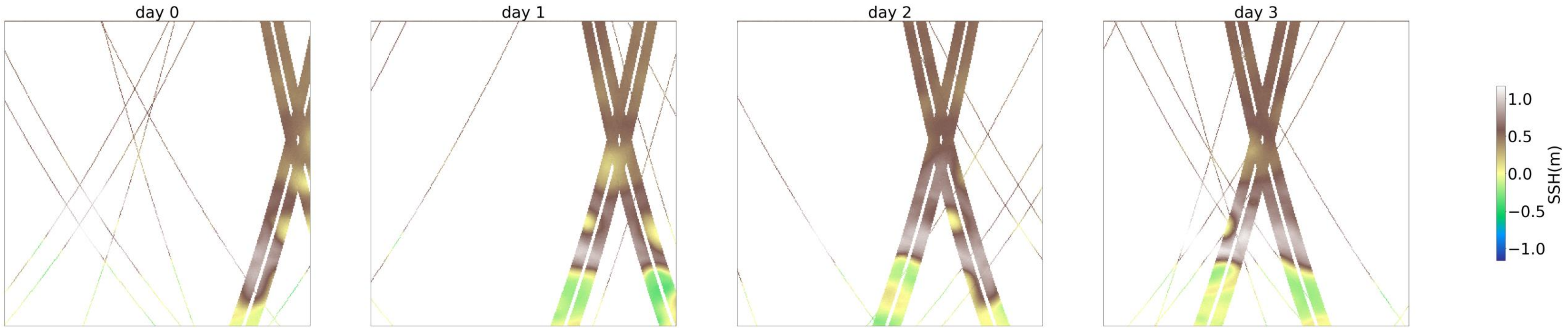
- An altimetry measure
- Useful to measure geostrophic currents

- Low resolution
  - Missing small structures

Sea Surface Height



Sea Surface Height

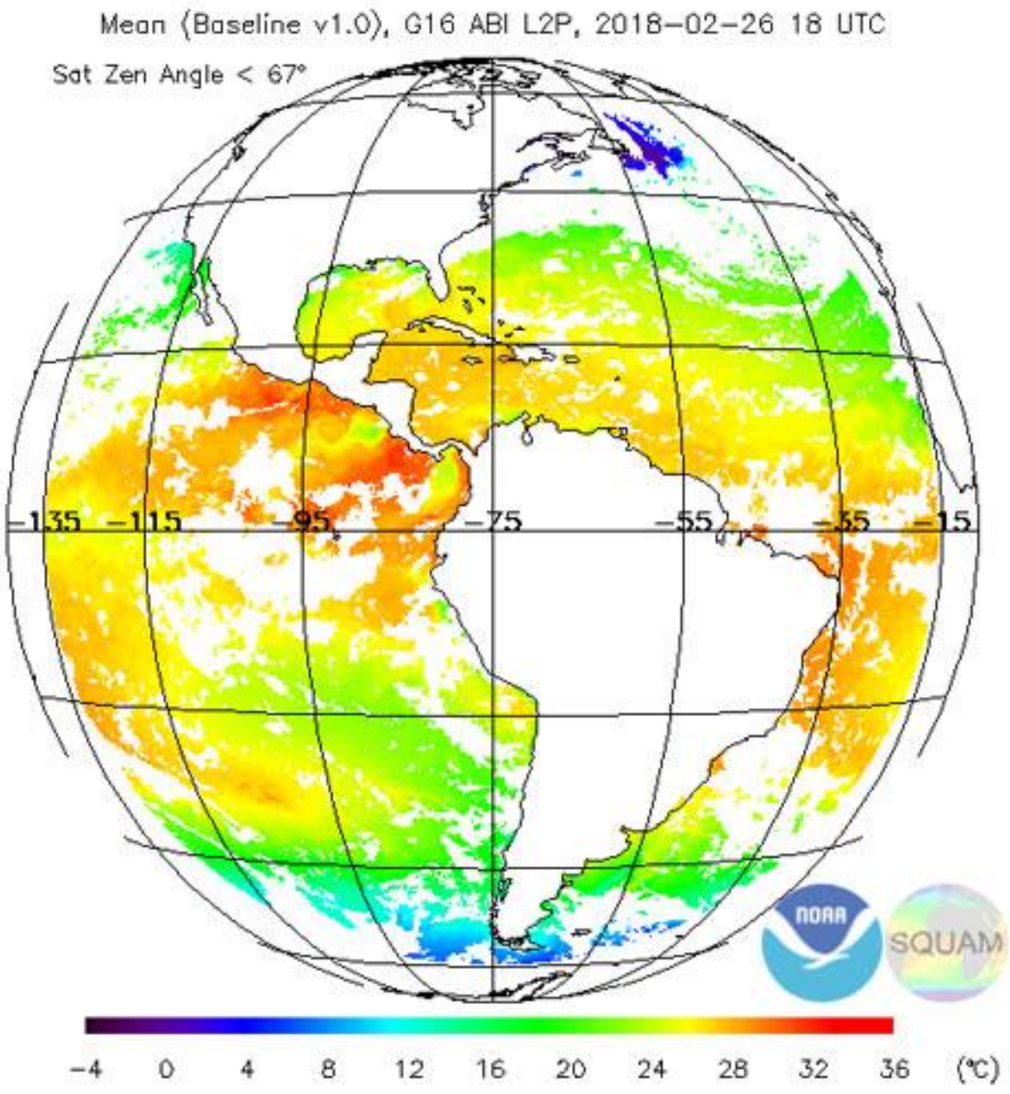


- Measured along satellite tracks
  - Nadir (working)
  - Swot (Still to launch)

- Linear Optimal Interpolation
  - Mapping at res 1/4°

- Problems
  - A small percentage of coverage
  - 10 days of return time
  - Smaller eddies have a short life expectancy
  - OI is biased

Sea Surface Temperature



- Infra red measure
- High resolution (1/25°)
- Measure daily everywhere on earth

- Cloud issues
  - Wait a few days for the cloud to getaway

Inverse Problem

Inverse Problem

$$y = d(X)$$

$$X \in \mathbb{R}^n \quad y \in \mathbb{R}^m$$

- d is the decimation operator
- X is the system state vector
- Y is the observation vector

Downscaling /Super-Resolution

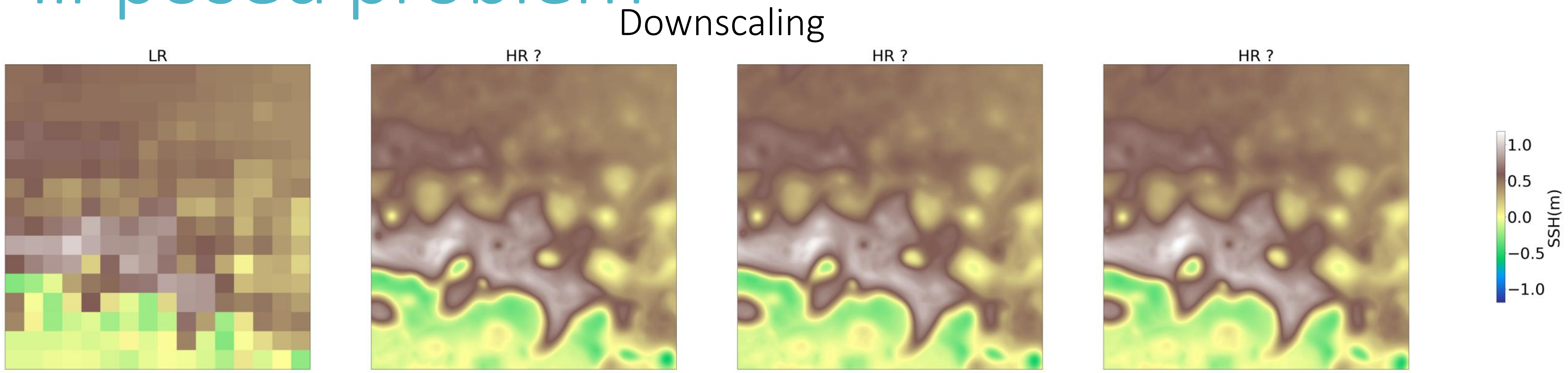
- d is a average off pixels

Interpolation / Inpainting

- d is a mask along the satellite tracks

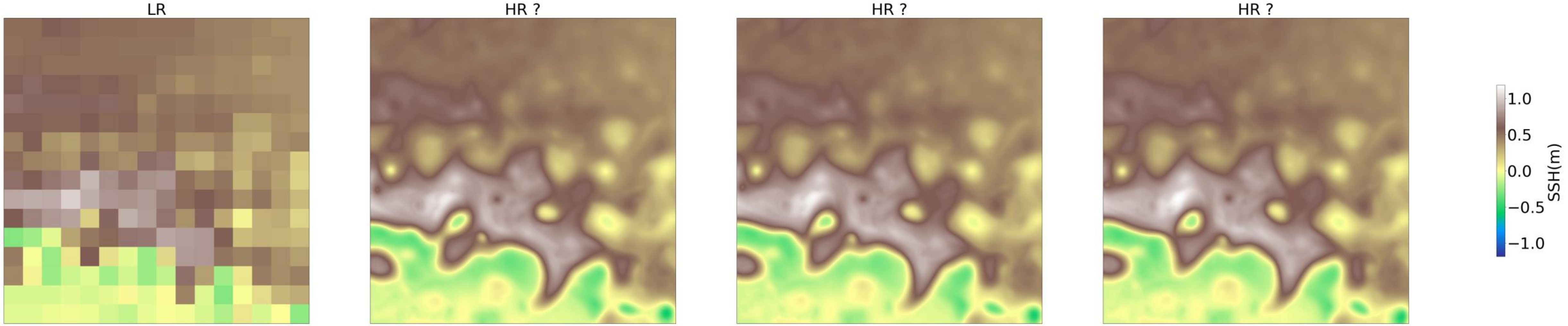
<u>**In both problems : how to find a pseudo inverse of the decimation operator d?**</u>

Ill-posed problem

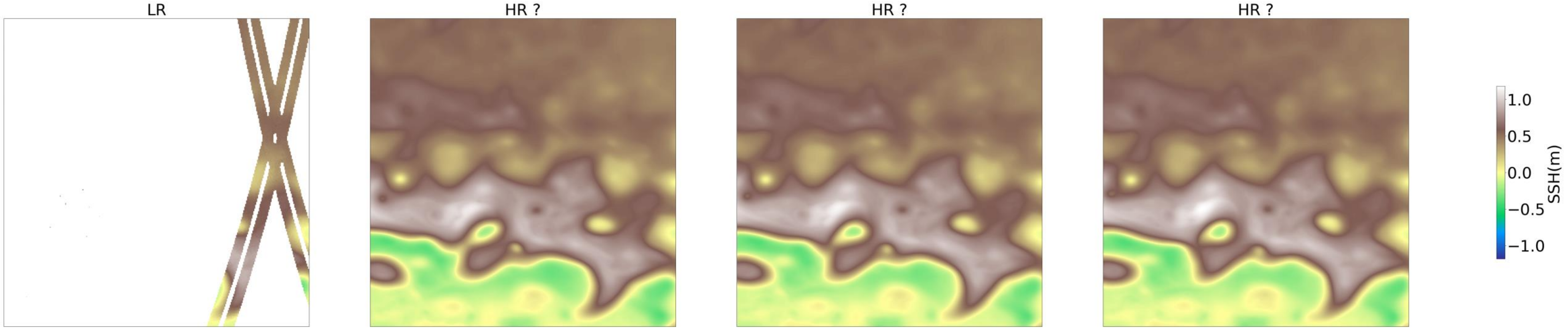


Ill-posed problem

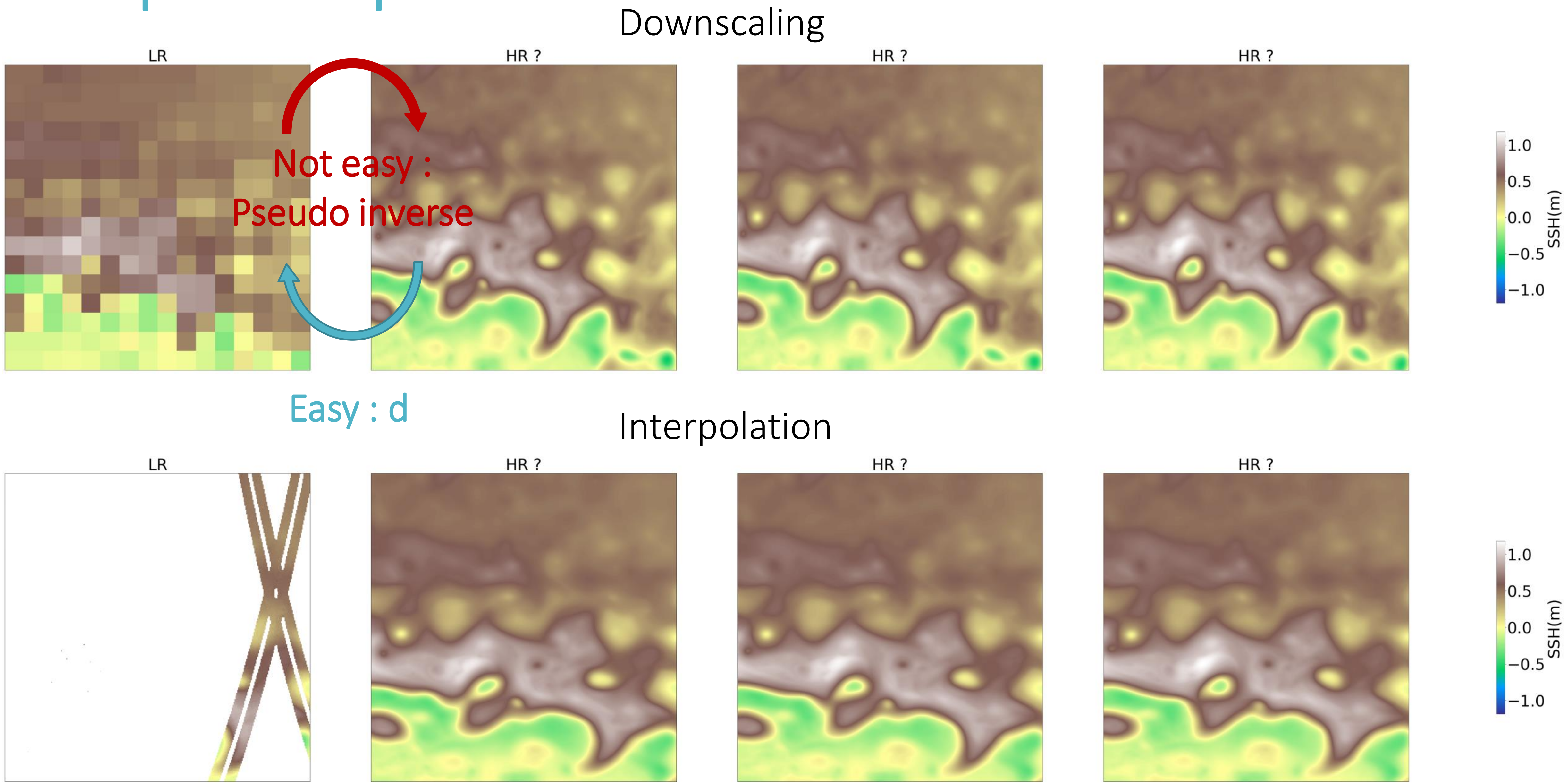
Downscaling



Interpolation



Ill-posed problem



Ill-posed problem

How to constrain our solution?

- Contextual information :
  - Data base
  - Other measured fields
- Physic :
  - Physic based model using measured data: data assimilation

Deep learning methods

Two ways to constrain the problem

Statistics :

- Machine learning

Physics

- Data Assimilation

Data assimilation :

- Physic model of evolution of the system M such as $X_{t+1} = M(X_t)$ + error
- Observation model of the system H such as $Y_t = H(X_t)$ +error

We have access to observations on a time window :

$$Y_t\ , Y_{t+1}\ , Y_{t+2}\ , \dots , Y_{t+W}$$

And we try to recover the hidden state of the system by minimizing a distance between the observations and a trajectory

Data assimilation :

Issues :

- Gridded models
- Rely on a physic model
- Very computationally intensive

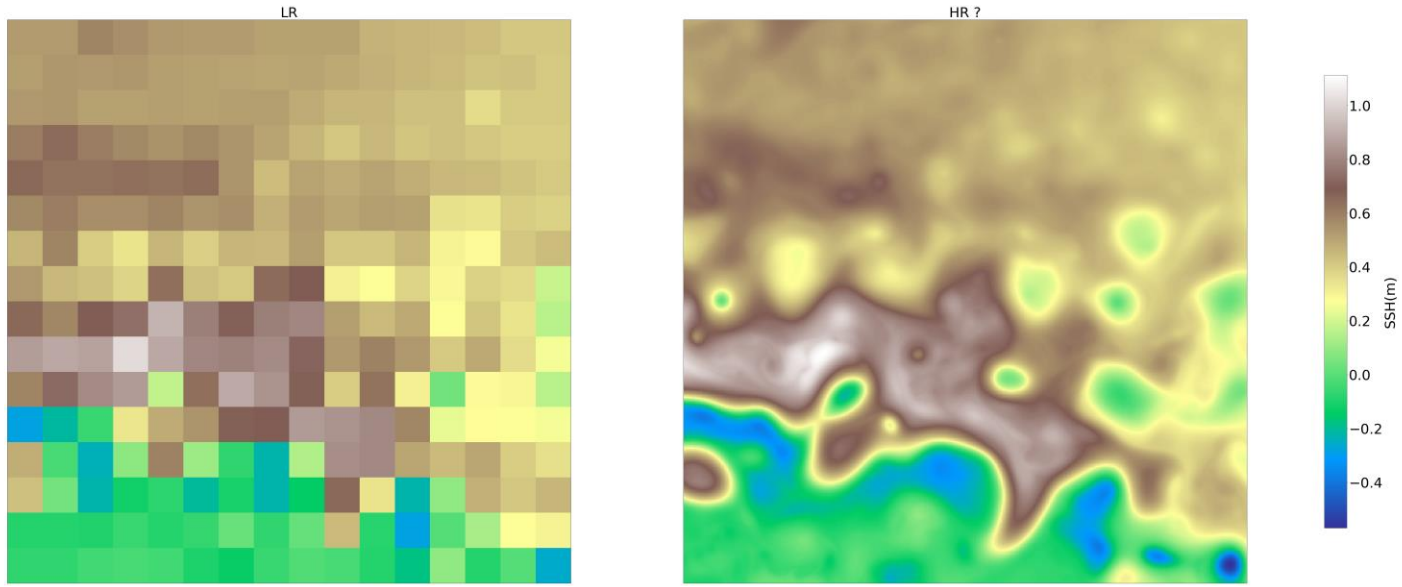
Deep learning

- Feeds on large datasets to determine statistical links
- Well suited for image applications

- In a supervised framework needs to have access to a ground truth
- We use simulated data (natl60)

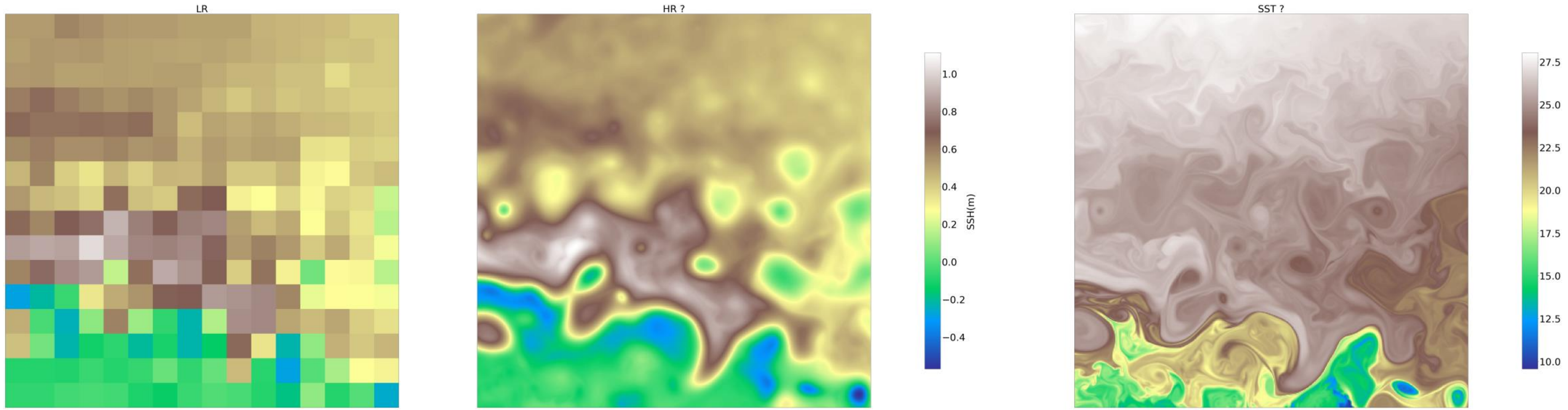
Case study : downscaling SSH with DL and High resolution SST

- How to increase the resolution of a coarse SSH?



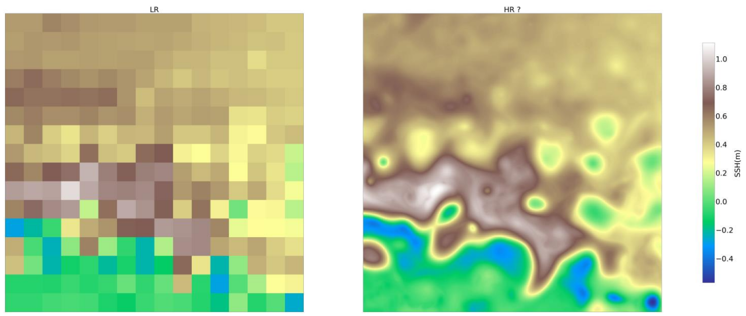
Case study : downscaling SSH with DL and High resolution SST

- How to increase the resolution of a coarse SSH?
- SST : contextual information to constrain the problem

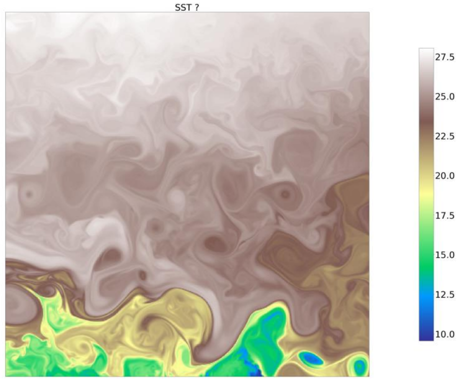


RESAC method

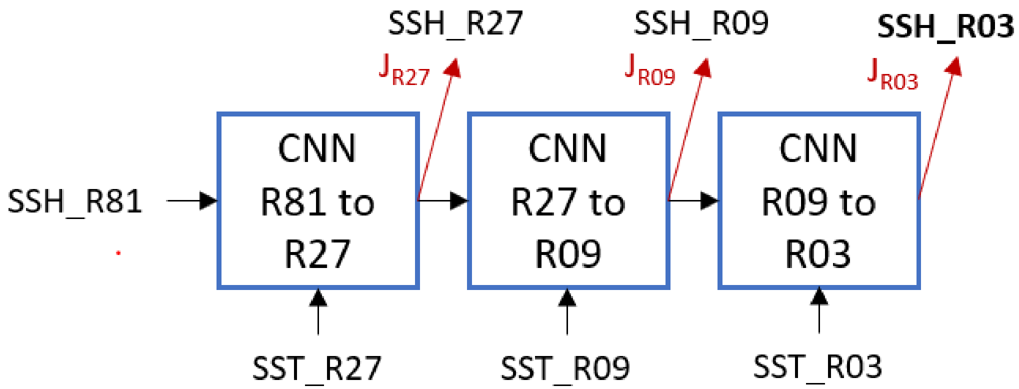
- A CNN that performs a very high upsampling



- SST information

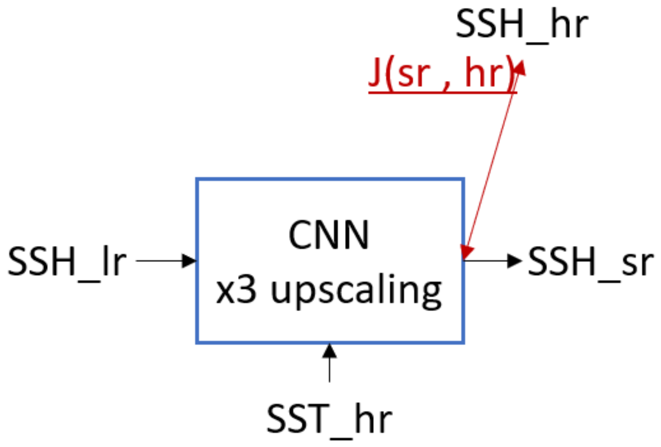


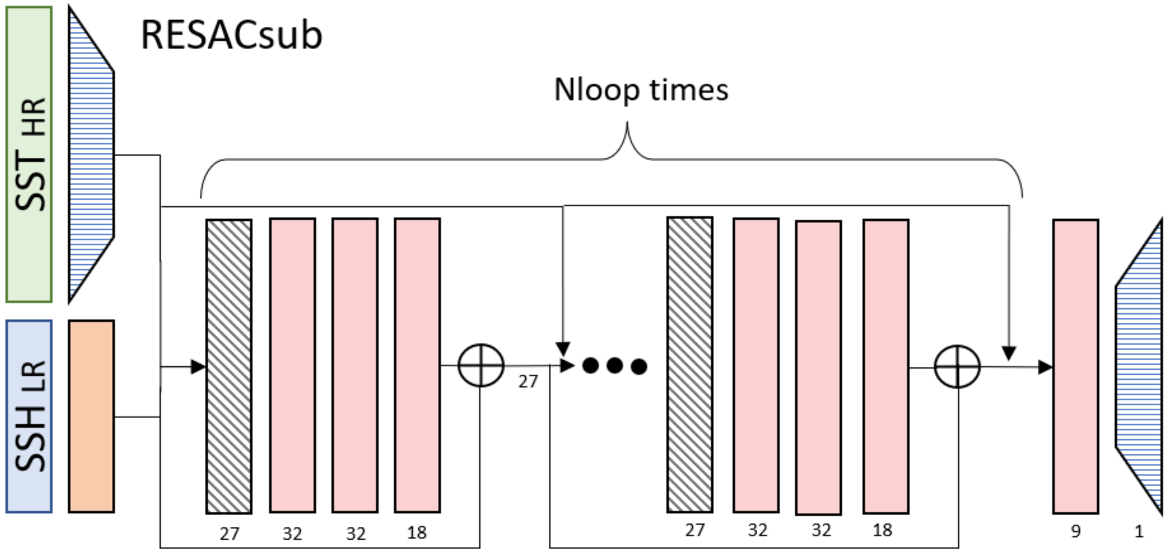
- Multi-resolution control



RESAC method

RESAC method





<u>Residual network</u> : $SSH_{l+1} = SSH_l + f_\theta^l(SSH_l)$

- Stack more layer
- Brings stability during learning

<u>Subpixel convolution :</u> subspcace

<u>Adapted Batch Normalization</u>

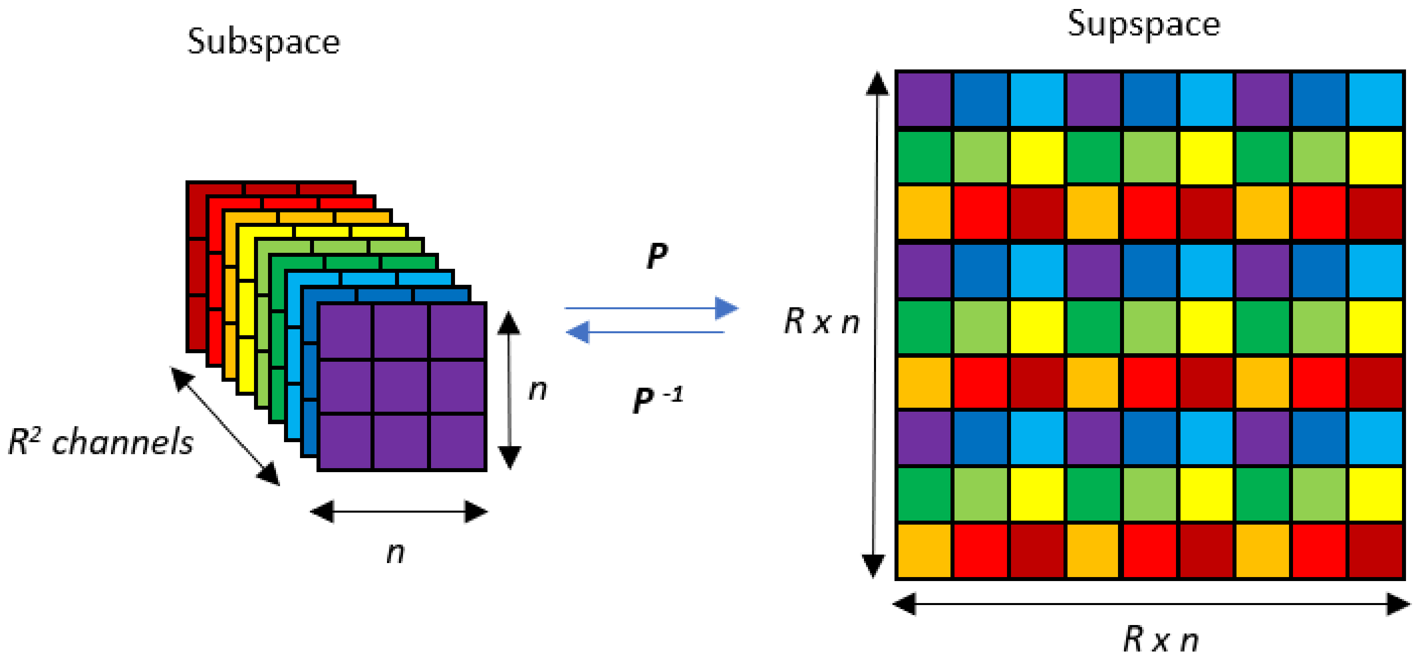
RESAC method

Subpixel convolution :

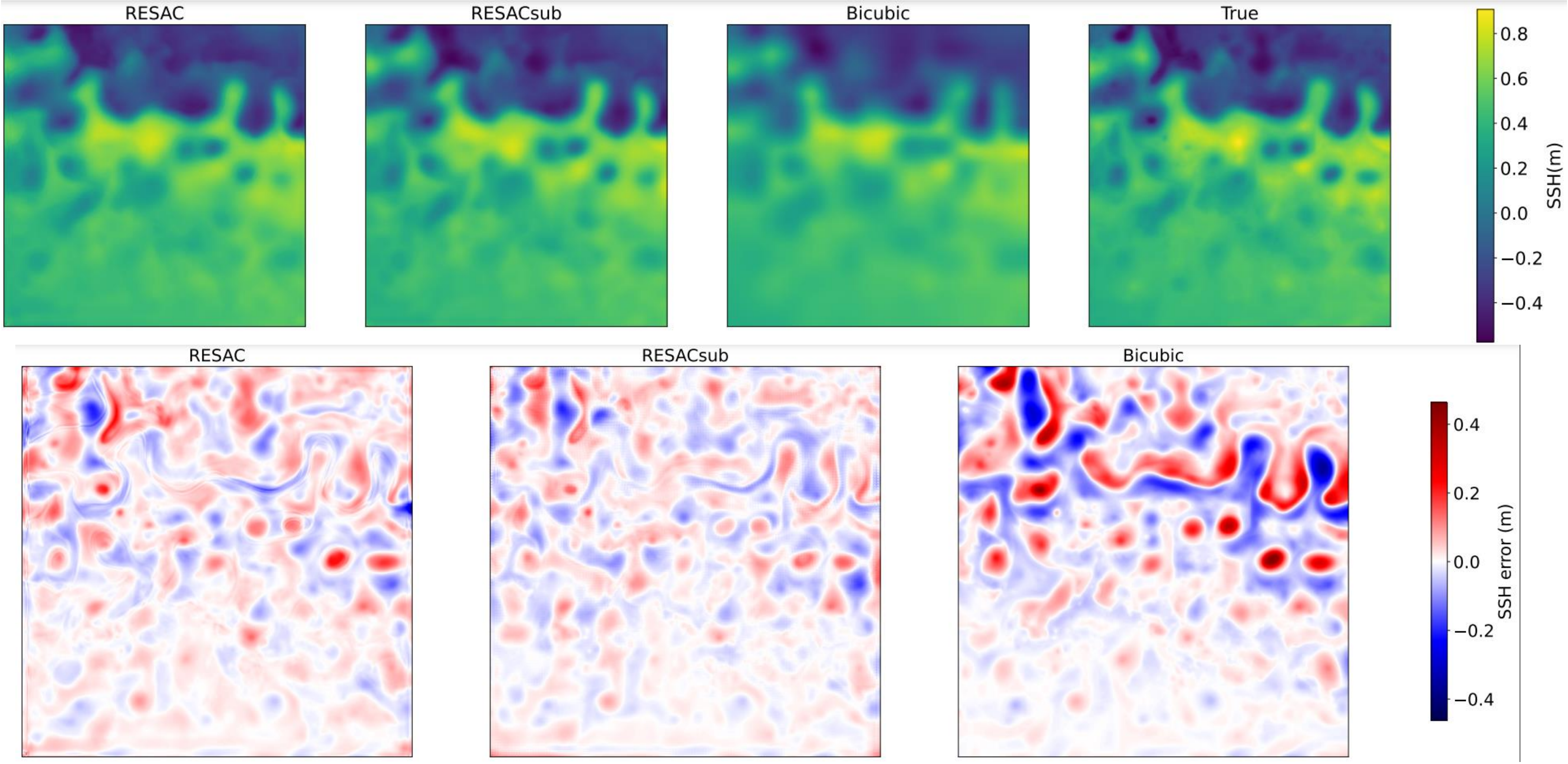
- Convolution in a subspace
- Pixel shuffle operator P
- Higher perceptive field
- Less training time

Adapted Batch Normalization

- Normalization by channels
- Neighbors pixels normalized with different values

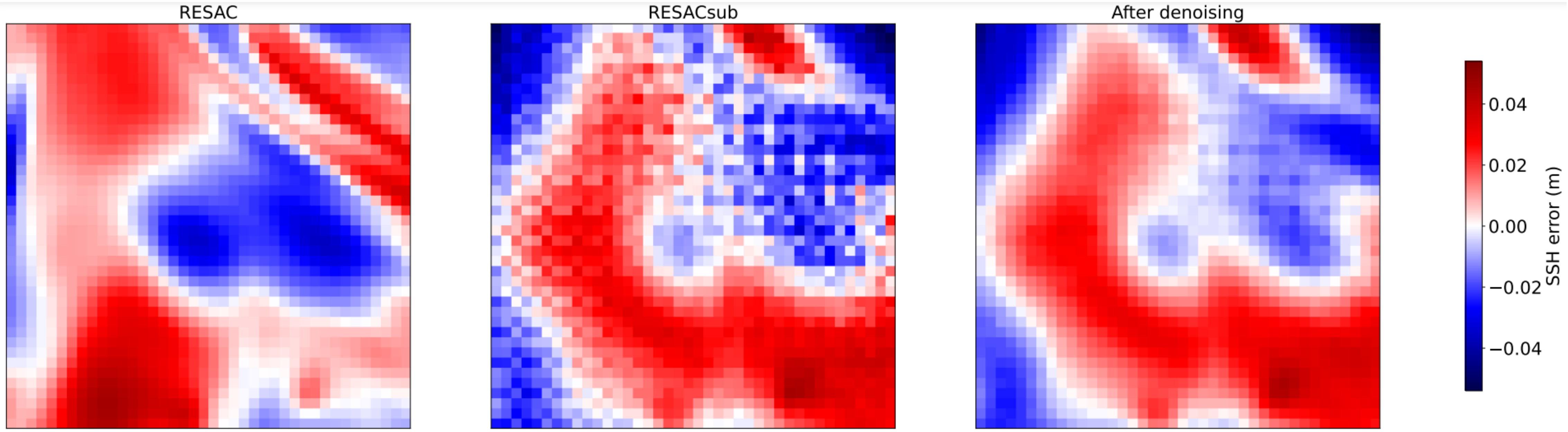


RESAC results



RESAC results

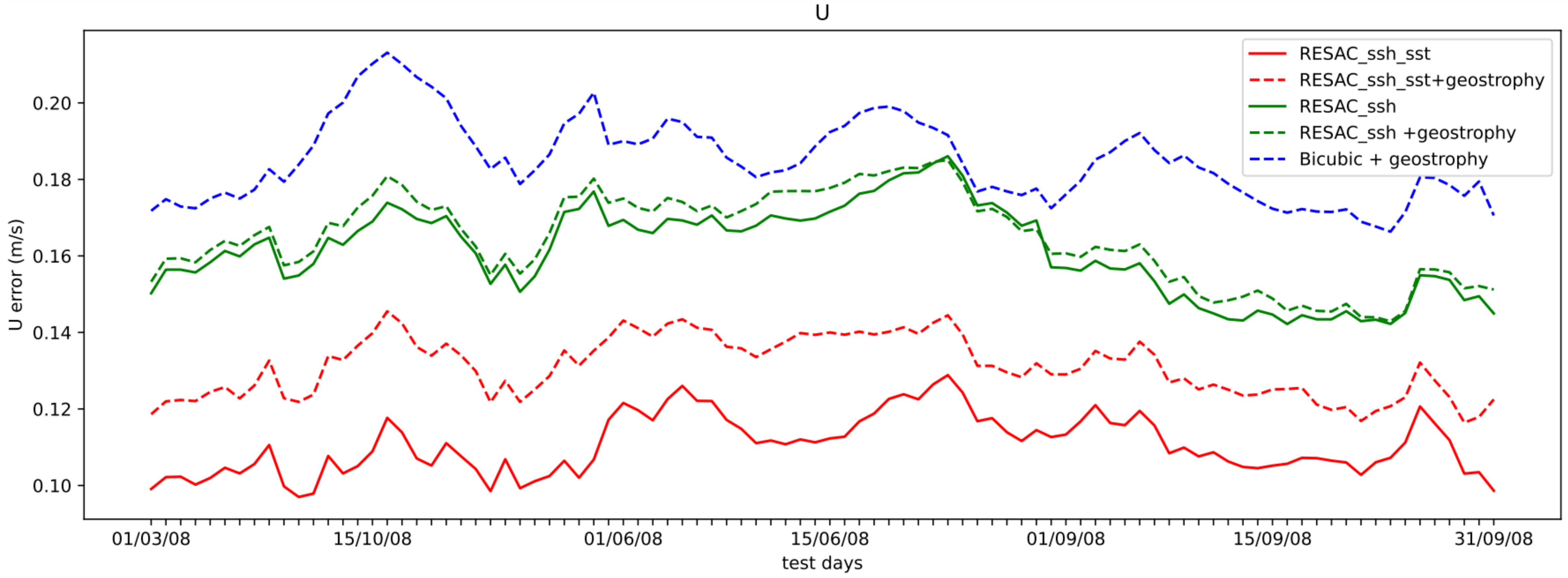
Checkerboard artifacts



RESAC results

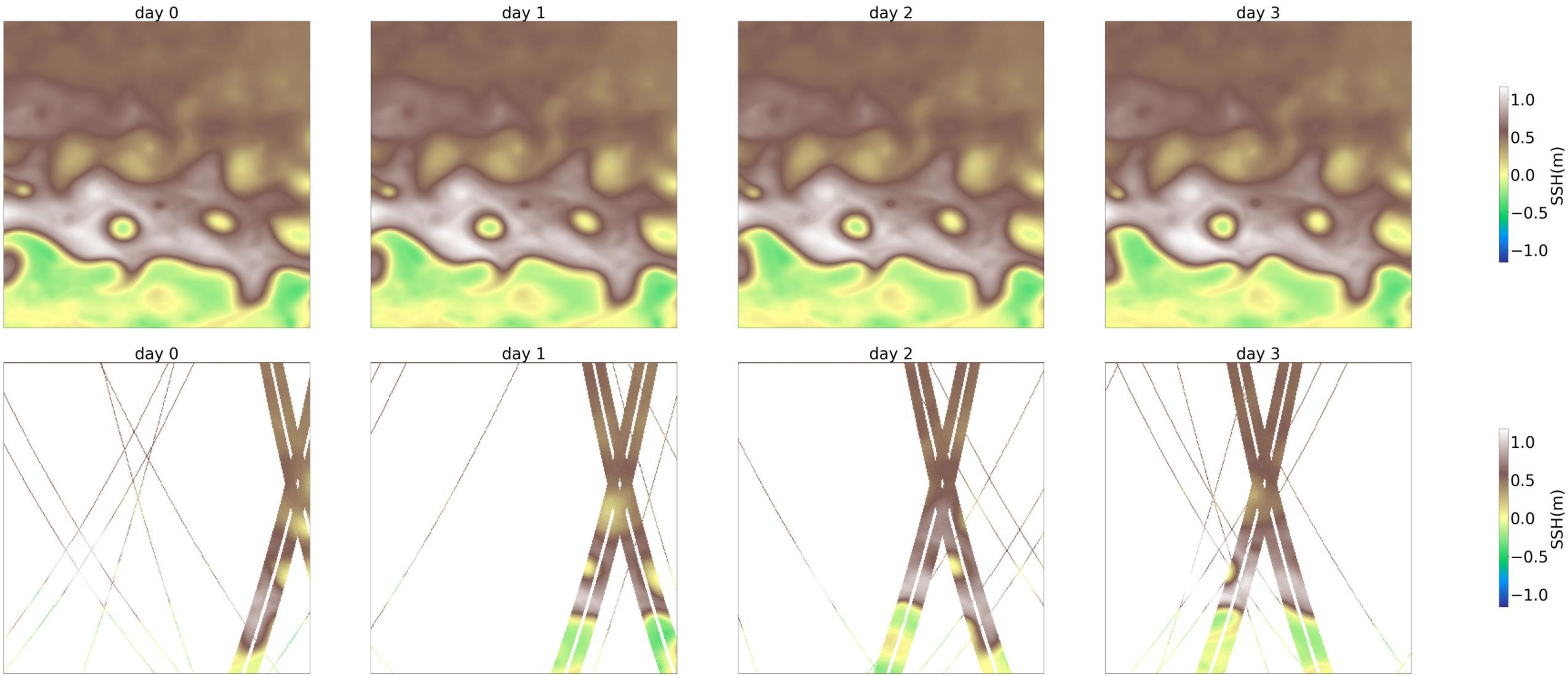
<u>Geostrophic reconstruction</u>

$$f_0 V = \frac{\partial SSH}{\partial x} \qquad f_0 U = -\frac{\partial SSH}{\partial y}$$



Real-world scenario

OSSE (Observing system simulation experiment)



State of the art : OI

Optimal linear interpolation :

- Misses a lot of small scales structures
- Can’t use SST

Noise :

- Along the tracks
- Clouds in the sst

A deep learning network could be trained to replace this linear interpolation.

- GAN

Thank you