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► **To cite this version:**

Clément Dorffer, F. Jourdin, D. Mouillot, Rodolphe Devillers, Ronan Fablet, et al.. Data-Driven Reconstruction of Sea Surface Turbidity Dynamics with 4dVarNet Neural Scheme Applied To Gappy Satellite Images. IGARSS 2023: IEEE International Geoscience and Remote Sensing Symposium, Jul 2023, Pasadena, CA, United States. IEEE, pp.4025-4027, 2023, IGARSS 2023 - 2023 IEEE International Geoscience and Remote Sensing Symposium. 10.1109/IGARSS52108.2023.10281712 . hal-04363492

**HAL Id: hal-04363492**

**<https://hal.science/hal-04363492>**

Submitted on 15 Mar 2024

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# DATA-DRIVEN RECONSTRUCTION OF SEA SURFACE TURBIDITY DYNAMICS WITH 4DVARNET NEURAL SCHEME APPLIED TO GAPPY SATELLITE IMAGES

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## 1. Objective

**Turbidity:** the measurement of the amount of suspended matter in a liquid or solution.  
 ⇒ **A Key parameter that influences coastal and marine ecosystems.**

### How to get turbidity values?

- ▶ In-situ measurement techniques:



Figure: Secchi Disk

→ **Good data reliability, but poor time and/or space coverage.**

- ▶ Remote sensing measurements:

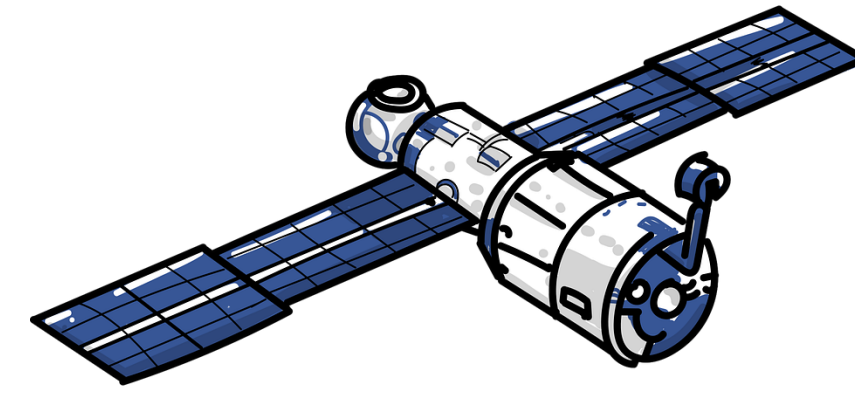


Figure: Satellite multispectral imaging.

→ **Perennial but missing values may occur due to e.g., a cloud coverage..**

- ▶ **Our objective:** fill in the missing data of satellite images and provide complete turbidity maps.

## 2. Proposed approach

### Data assimilation problem to be solve

$$\tilde{x} = \arg \min_x \mathcal{U}(x, y, \Omega) = \arg \min_x \lambda_1 \underbrace{\|x - y\|_{\Omega}^2}_{\text{data fidelity term}} + \lambda_2 \underbrace{\|x - \phi(x)\|^2}_{\text{dynamical prior}}, \quad \text{with} \quad (1)$$

$x$  the completed field,  
 $y$  the observations (uncomplete),  
 $\Omega$  the observation mask,  
 $\phi(\cdot)$  the dynamical model.

Problem (1) solved by gradient descent, i.e., by successive updates:

$$x^{k+1} = x^k - \alpha \nabla_x \mathcal{U}(x^k, y, \Omega). \quad (2)$$

### 4DVarNet-architecture

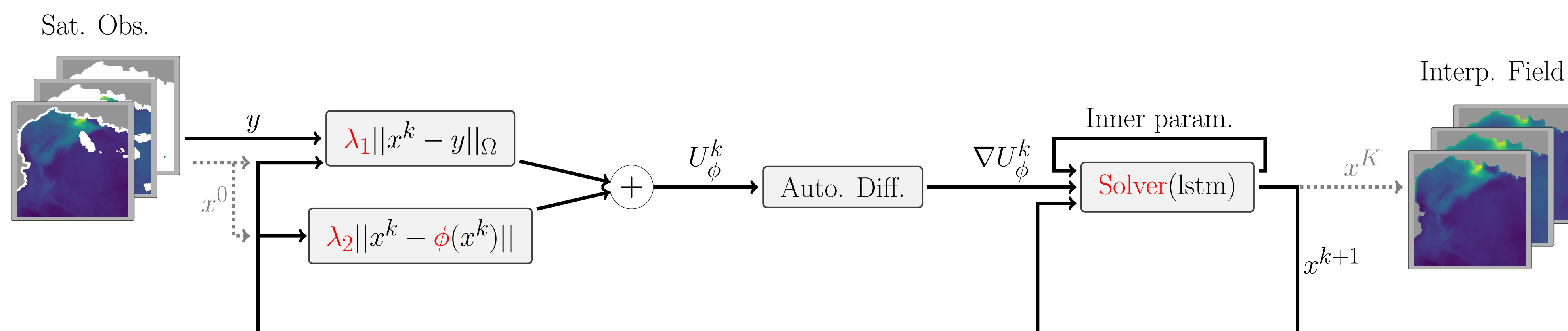
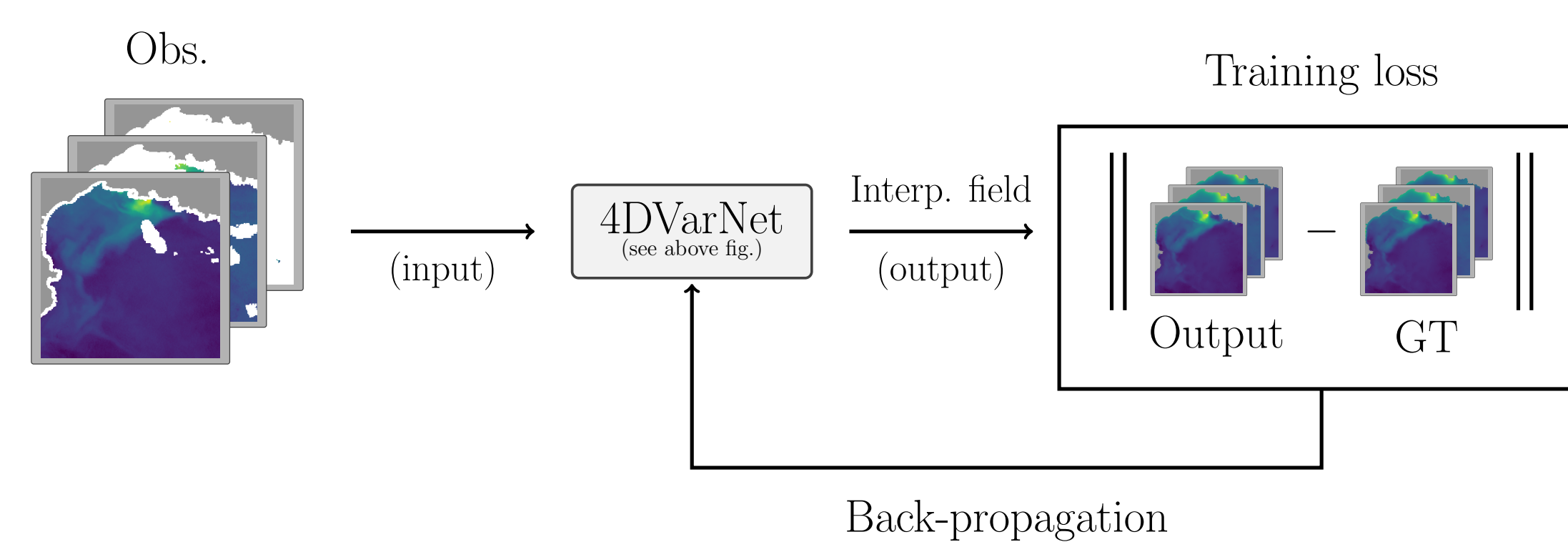


Figure: Graphical representation of 4DVarNet algorithm. Parameters to be trained appear in red.

Produces a smoothed gradient descent of (1).

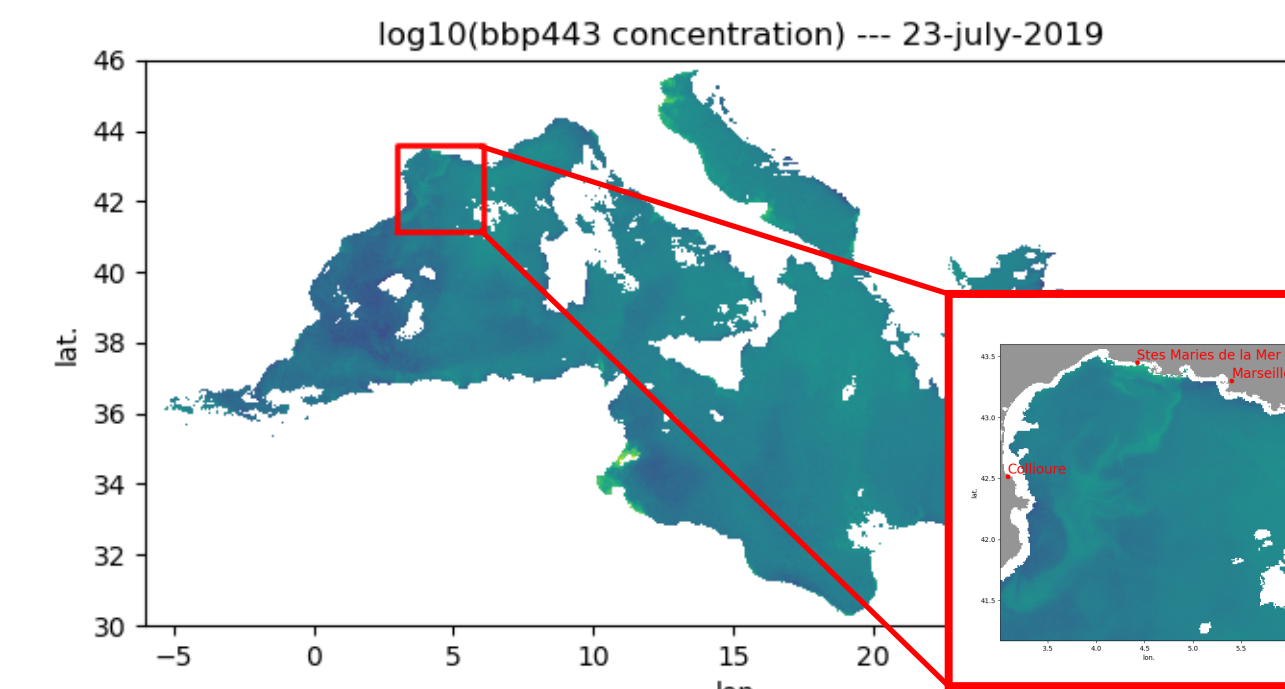
### 4DVarNet training step:

- ▶ Minimizes defined training loss *i.e.*, the reconstruction error.
- ▶ Adjusts both "model" and solver parameters.



## 3. Considered Data

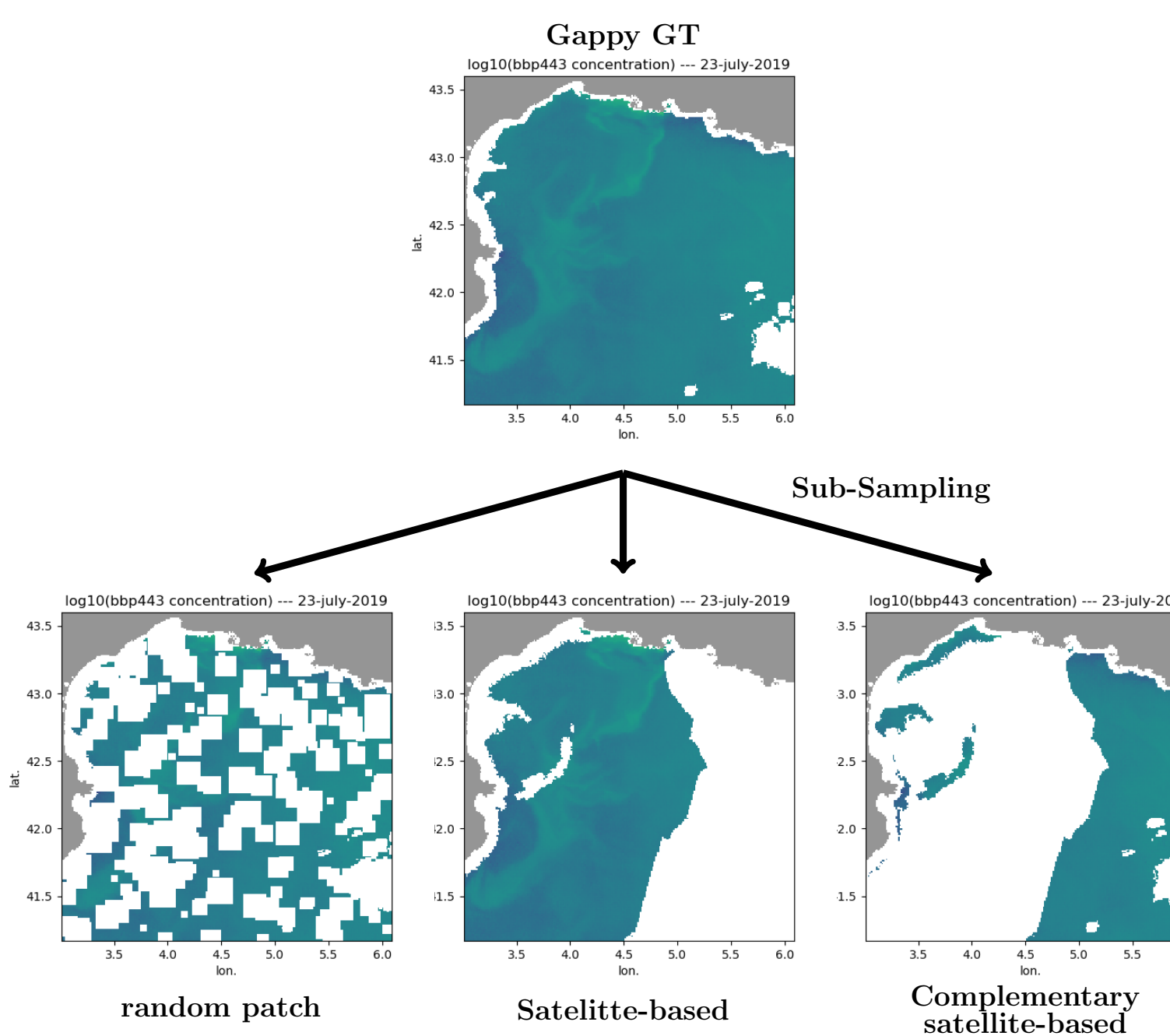
Mediterranean Sea with focus along the French coast:



**CMEMS product:**  
**OCEANCOLOUR\_MED\_BGC\_L3\_MY\_009\_143**

- ▶ Multi-sensor product.
- ▶ L3 data (preprocessed data).
- ▶ Daily mean turbidity values.
- ▶ **Problem:** No ground truth available for training.

**Idea:** No gap-free GT? ⇒ **Data subsampling for artificial obs. generation!**



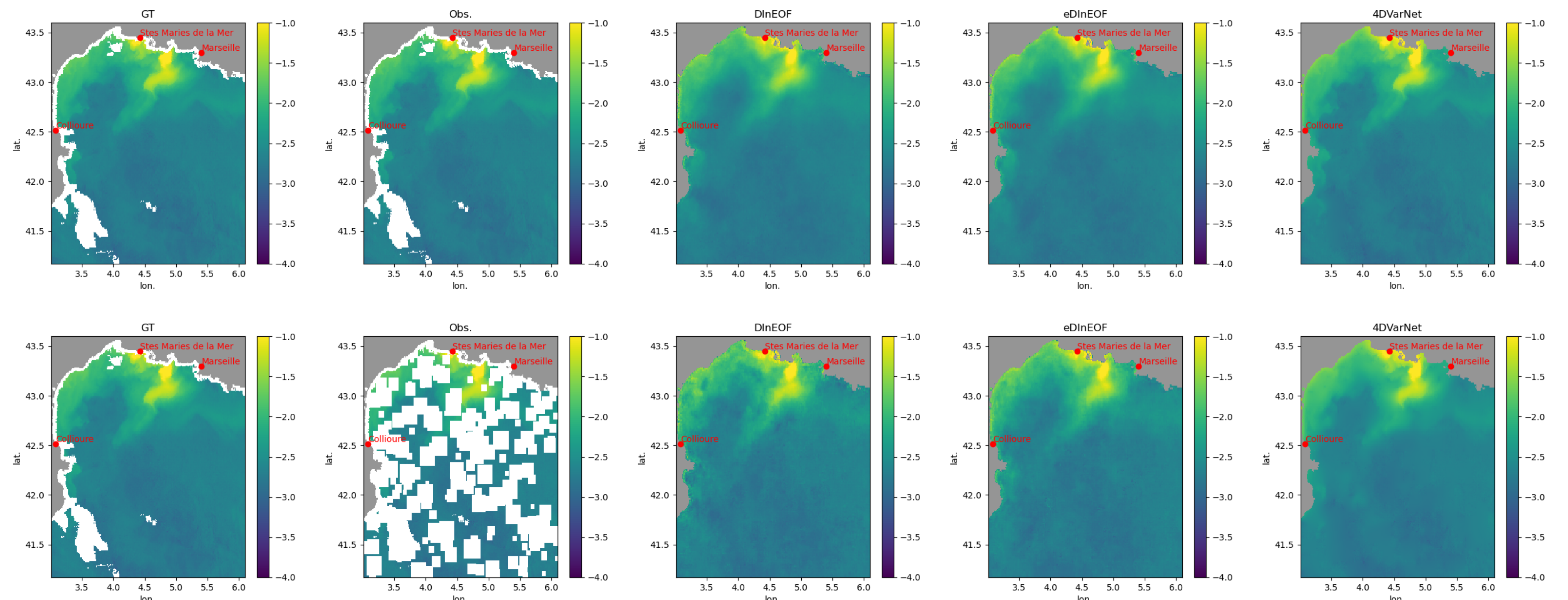
### Reconstruction results

	Patch-based	Sat.-masks	Comp.-Sat.-mask
Patch-based	0.044	0.088	0.085
Satellite-masks	0.084	0.09	0.098
Comp.-satellite-masks	0.08	0.093	0.087
DInEOF	0.081	0.12	0.095
eDInEOF	0.078	0.098	0.085

Table: RMSLE reached w.r.t. the subsampling strategies used for learning (lines) and testing (columns).

The lower the better: **4DVarNet provides up to 43% of relative gain compare to eDInEOF.**

### Reconstruction examples (log10 bbp443 the particulate backscattering coefficient at 443nm)



### Acknowledgements

This work was funded by the french ANR, as part of the AI-biodiv Challenge: fish-predict.

This work was performed using HPC resources from GENCI-IDRIS.

This study has been conducted using E.U. Copernicus Marine Service Information: <https://doi.org/10.48670/moi-00299>

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