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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:

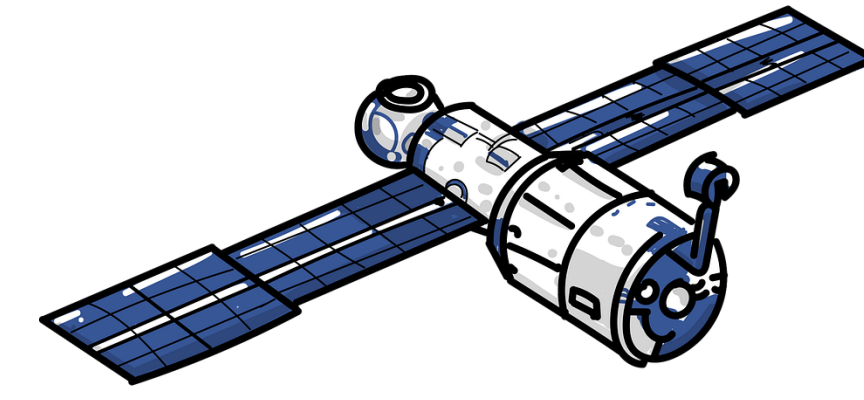


Figure: Satellite multispectral imaging.

→ **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),
 Ω 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

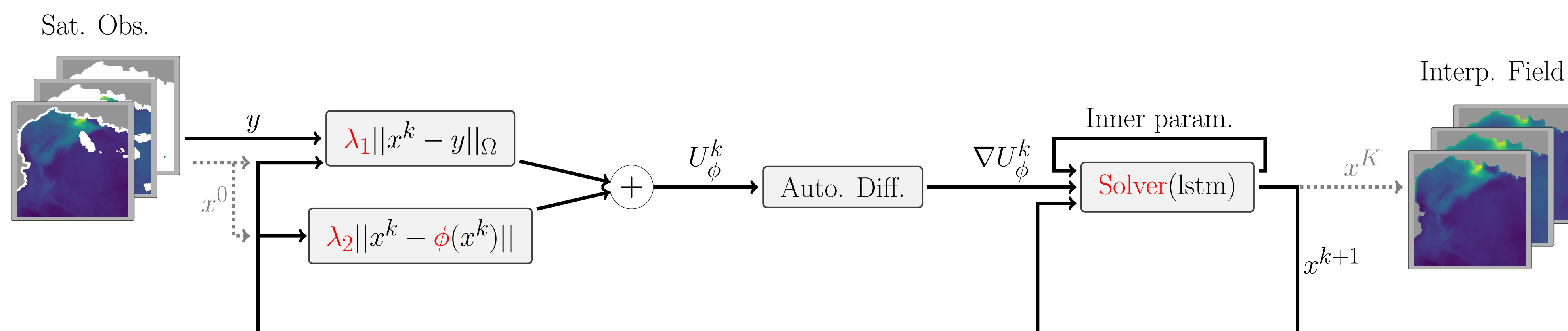
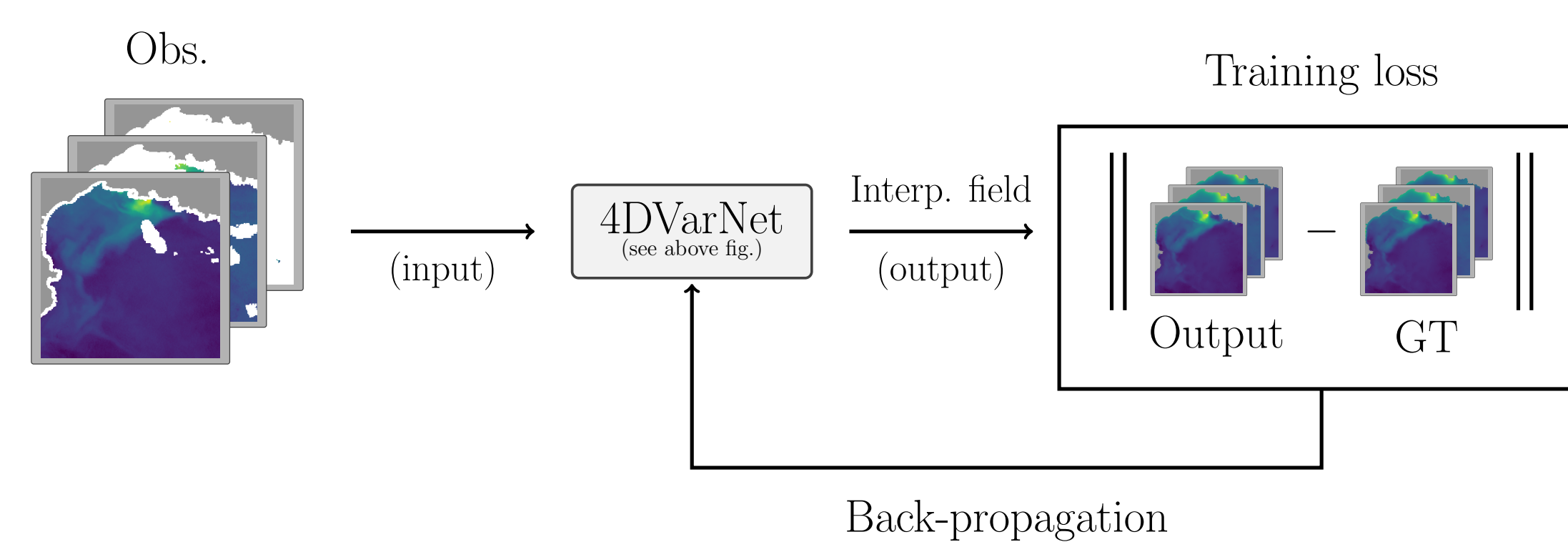


Figure: Graphical representation of 4DVarNet algorithm. Parameters to be trained appear in red.

Produces a smoothed gradient descent of (1).

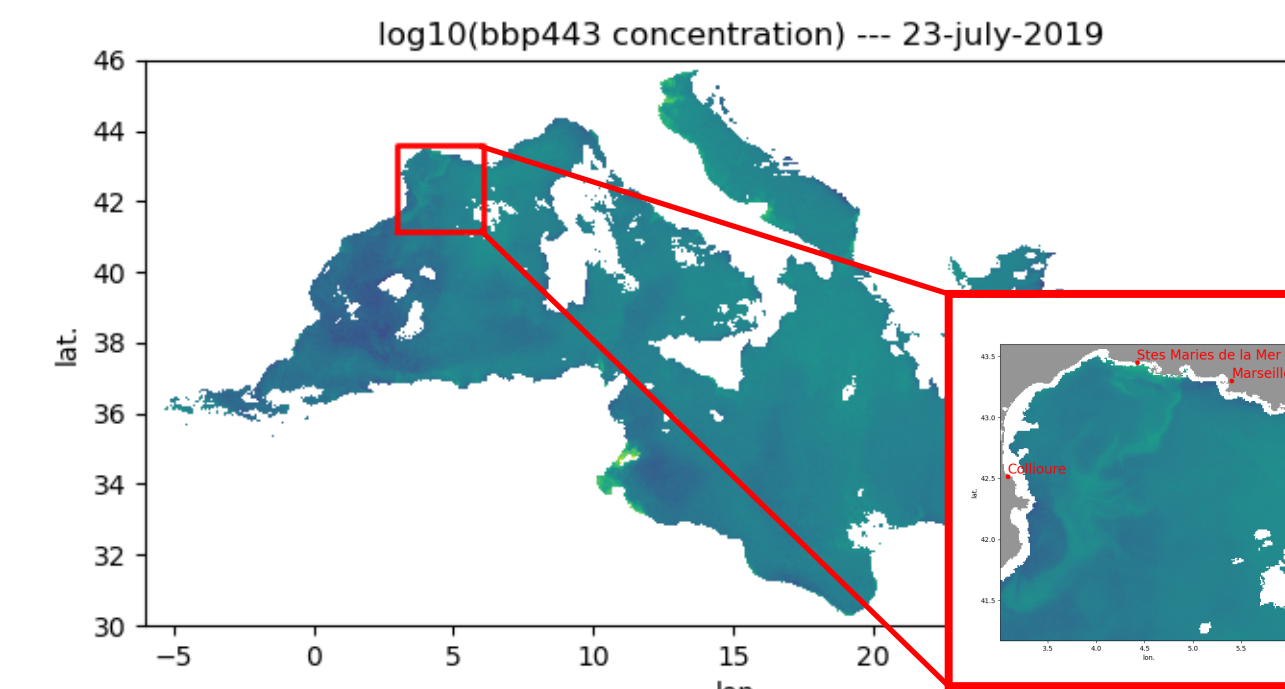
4DVarNet training step:

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



3. Considered Data

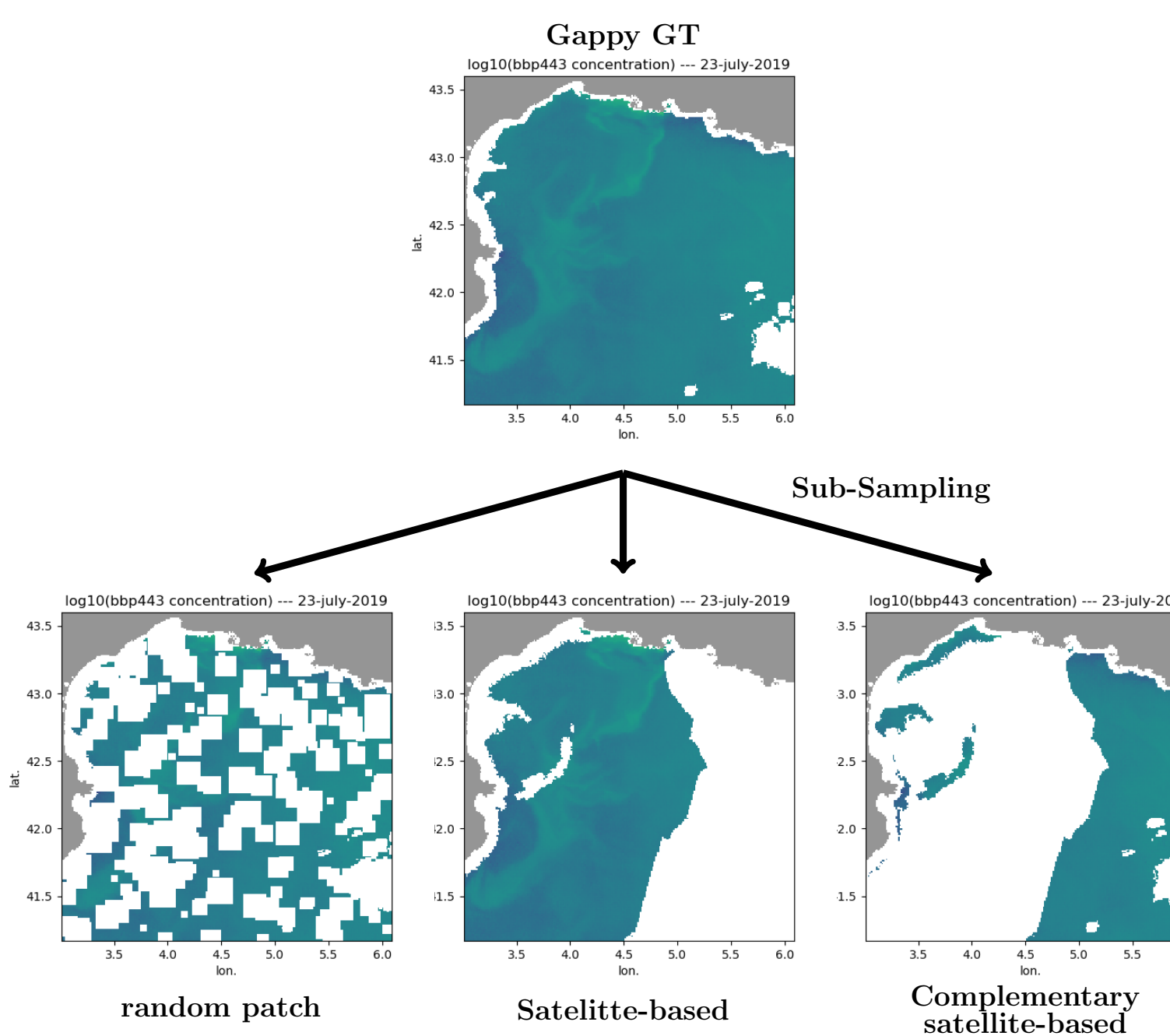
Mediterranean Sea with focus along the French coast:



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!**



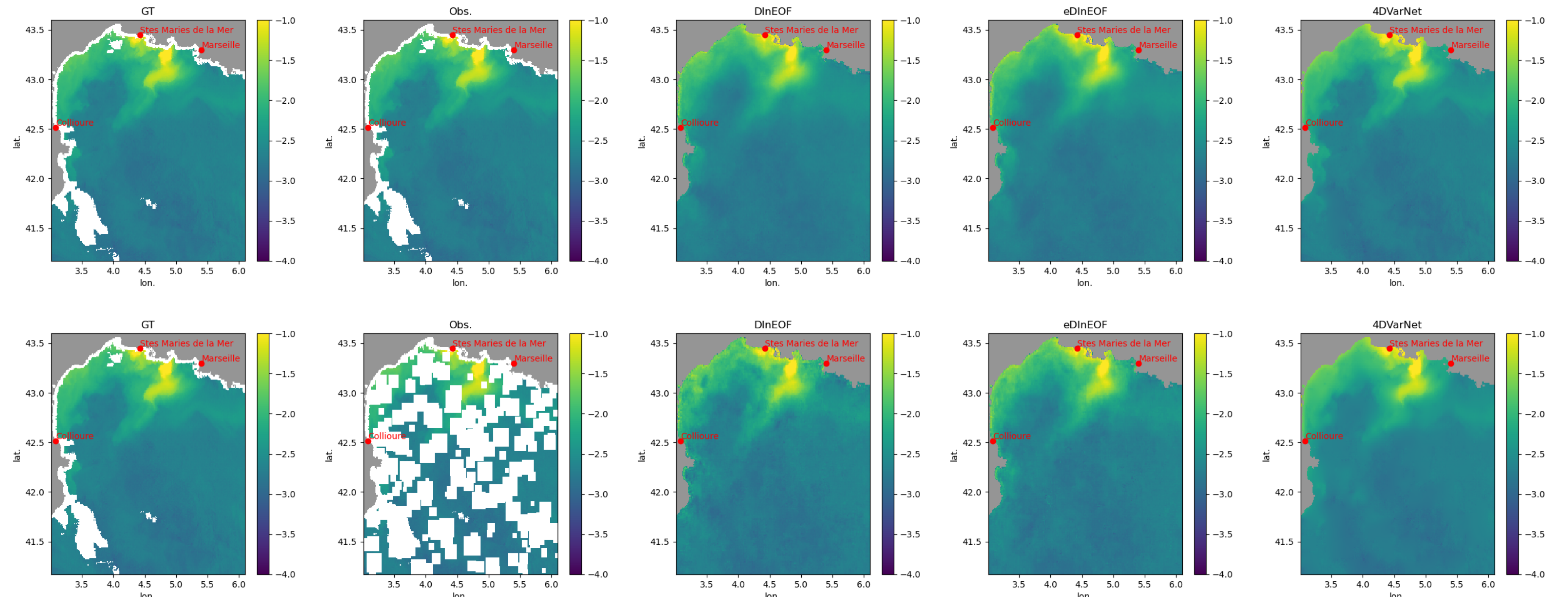
Reconstruction results

	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)



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[1] Fablet, R., et al. "Learning variational data assimilation models and solvers." *Journal of Advances in Modeling Earth Systems* 13.10 (2021).

[2] Beekers, J.-M., et al. "EOF calculations and data filling from incomplete oceanographic datasets." *Journal of Atmospheric and oceanic technology* 20.12 (2003).