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Data-driven Approaches for Ocean Remote Sensing:

from the Non-negative Decomposition of Operators to the Reconstruction of Satellite-derived Sea Surface Dynamics

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CONTEXT AND MOTIVATION

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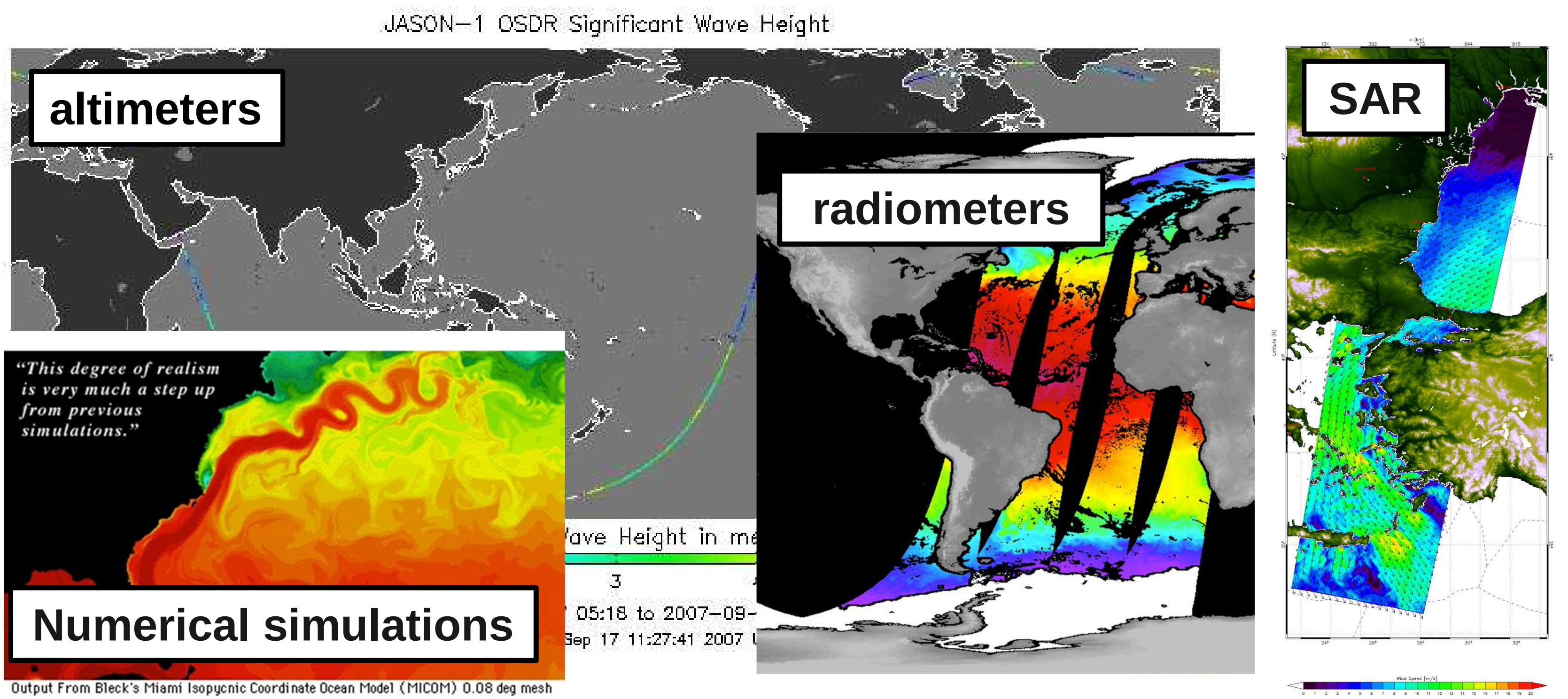
Data sources: A great variety of heterogeneous sensors and models



Key issue: Exploit these data sources to improve our understanding of geophysical processes

Operational:
Monitoring and forecasting of ocean dynamics
- High socio-economical impact
- Management of ocean resources
- Environmental protection

Scientific:
Better understanding of ocean processes
- Model calibration and validation
- Estimation of geophysical quantities and parameters
- Improve model prediction/reconstruction

However:
- Strong reliance on physical models
- *Datasets: under-exploited potential?*

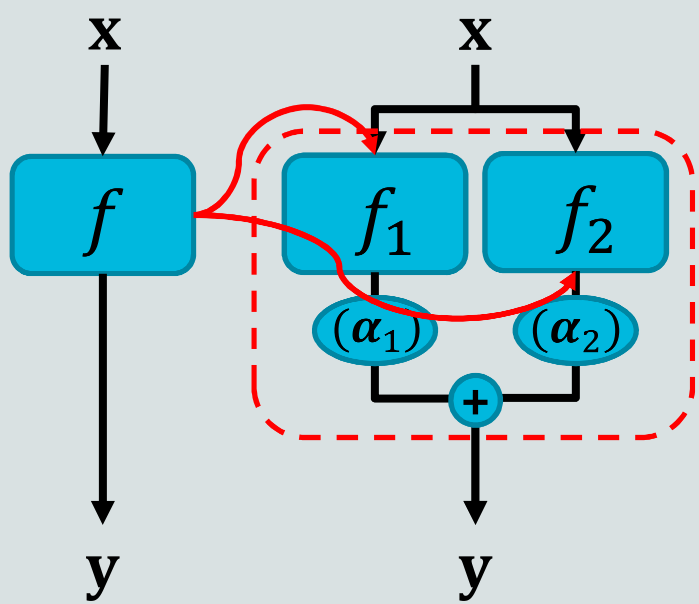
FIGURE 1: Remote sensing satellites

BETTER EXPLOIT DATA

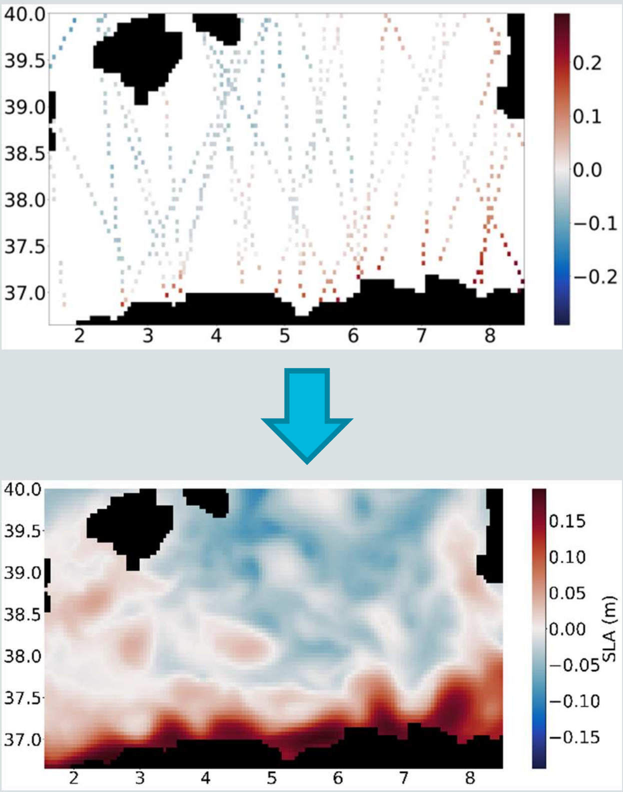
Problems of interest

Characterization and decomposition operators

$$\mathbf{y}_n = \sum_{k=1}^{K} \alpha_{nk} f_{\theta_k}(\mathbf{x}_n) + \boldsymbol{\omega}_n$$



Interpolation of altimetry fields from satellite data



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PRESENTATION OUTLINE

1. NON-NEGATIVE DECOMPOSITION OF OPERATORS

- Models and Algorithms
- Applications
  - Forecasting of Dynamical Systems
  - Segmentation of Sea Surface Dynamics

2. INTERPOLATION OF SEA LEVEL ANOMALIES FROM SATELLITE DATA

- Problem formulation
- Observation System Simulation Experiment
- Results

3. VALORIZATION

4. CONCLUSION AND PERSPECTIVES

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PART 1: NON-NEGATIVE DECOMPOSITION OF OPERATORS

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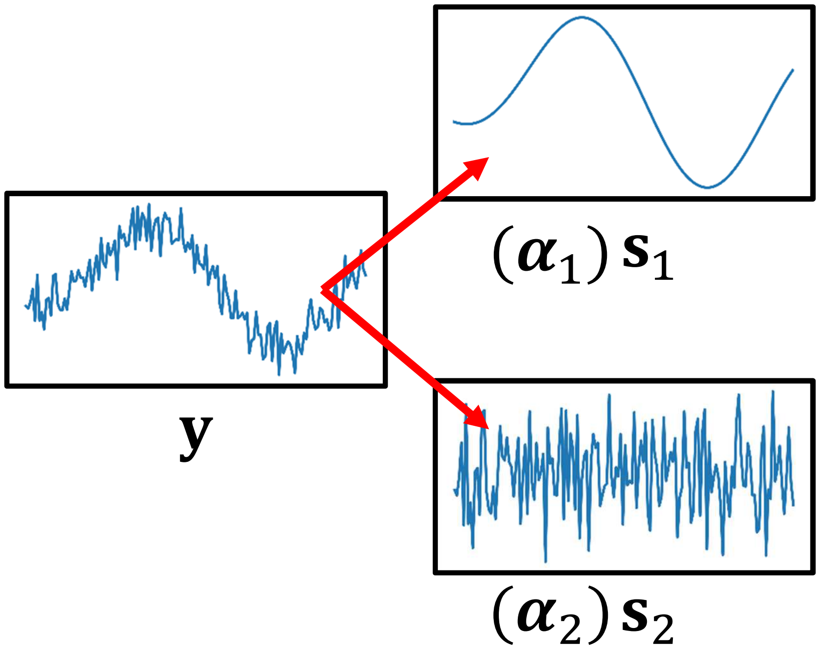
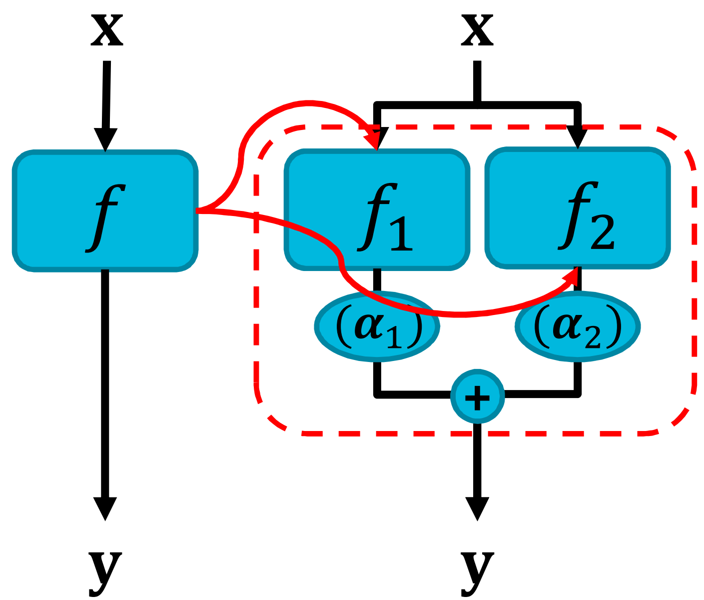
Operator decomposition

Source separation:



⇔

Operator decomposition:



$$\mathbf{y}_n = \sum_{k=1}^{K} \alpha_{nk}\mathbf{s}_k + \boldsymbol{\omega}_n$$

$$\text{s. t. } \mathcal{C}\left(\alpha_{n1}, \dots, \alpha_{nK}, \mathbf{s}_1, \dots \mathbf{s}_K\right)$$

$$\mathbf{y}_n = \sum_{k=1}^{K} \alpha_{nk} f_{\theta_k}\left(\mathbf{x}_n\right) + \boldsymbol{\omega}_n$$

$$\text{s. t. } \mathcal{C}\left(\alpha_{n1}, \dots, \alpha_{nK}, f_{\theta_1}, \dots, f_{\theta_K}\right)$$

Joint EOFs:
[Hotelling,1933; Hannachi et al., 2007]

$$\mathbf{C} = \frac{1}{N}\mathbf{Y}_1^T\mathbf{Y}_2 = \mathbf{V}\mathbf{\Lambda}\mathbf{U}^T = \sum_{r=1}^{R} \lambda_r \mathbf{v}_r \mathbf{u}_r^T$$

- Widely used in oceanography and atmospheric sciences
- *Orthogonal* decomposition of cross-correlation
- Find orthogonal modes that maximize explained variance

Dynamic Mode Decomposition:
[Schmid, 2010]

- Linearization+Eigendecomposition
- *Choice of observation functions* $\mathbf{g}(\mathbf{x}_n)$
- *Time invariance of operator* **K**

$$\mathbf{x}_{n+1} = \mathbf{f}(\mathbf{x}_n) \qquad \mathbf{g}(\mathbf{x}_n) = \mathbf{K}\mathbf{g}(\mathbf{x}_{n-1})$$

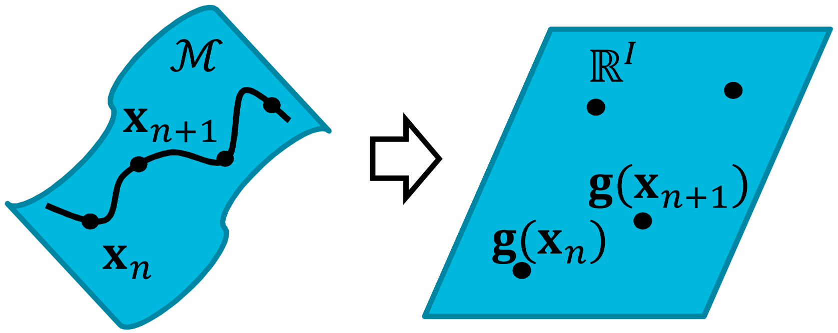


FIGURE 2: DMD

Classically:

- Orthogonal decompositions (EOF, PCA)
- ℓ_2-norm penalization
- Strong hypotheses

But, no guarantees in terms of:

- Relevance
- Interpretability

Explore new decompositions

Blind source separation:

- New formulations
  - Non-negativity
  - Sparsity

$$\mathbf{y}_n = \sum_{k=1}^{K} \alpha_{nk} \mathbf{s}_k + \boldsymbol{\omega}_n$$
$$\text{s. t. } \mathcal{C}\left(\alpha_{n1}, \ldots, \alpha_{nK}, \mathbf{s}_1, \ldots \mathbf{s}_K\right)$$

$\Downarrow$

$$\mathbf{y}_n = \sum_{k=1}^{K} \alpha_{nk} f_{\theta_k}(\mathbf{x}_n) + \boldsymbol{\omega}_n$$
$$\text{s. t. } \mathcal{C}\left(\alpha_{n1}, \ldots, \alpha_{nK}, f_{\theta_1}, \ldots, f_{\theta_K}\right)$$

Linear functions: $\boldsymbol{\beta}_k$

MODELS AND ALGORITHMS

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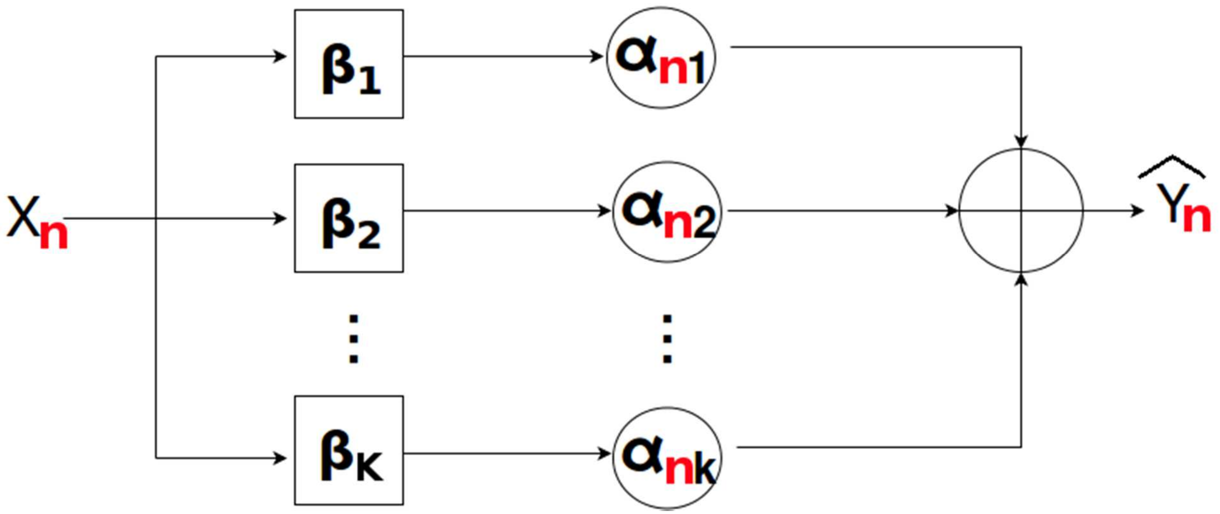
Model formulation

Relationship between observable variables $\mathbf{x}_n$ and $\mathbf{y}_n$

- Non-negative superposition of linear modes



$$\mathbf{x}_n \in \mathbb{R}^J$$
$$\mathbf{y}_n \in \mathbb{R}^I$$
$$\boldsymbol{\beta}_k \in \mathbb{R}^{I\times J}$$
$$\alpha_{nk} \in \mathbb{R}^+$$

FIGURE 3: General model block diagram

$$\mathbf{y}_n = \sum_{k=1}^{K} \alpha_{nk}\boldsymbol{\beta}_k \mathbf{x}_n + \boldsymbol{\omega}_n$$

$$\text{Subject to } \begin{cases} \alpha_{nk} \geq 0, & \forall\, k \in [1,K], \forall n \in [1,N] \\ ||\boldsymbol{\beta}_k||_F = 1, & \forall\, k \in [1,K] \end{cases}$$

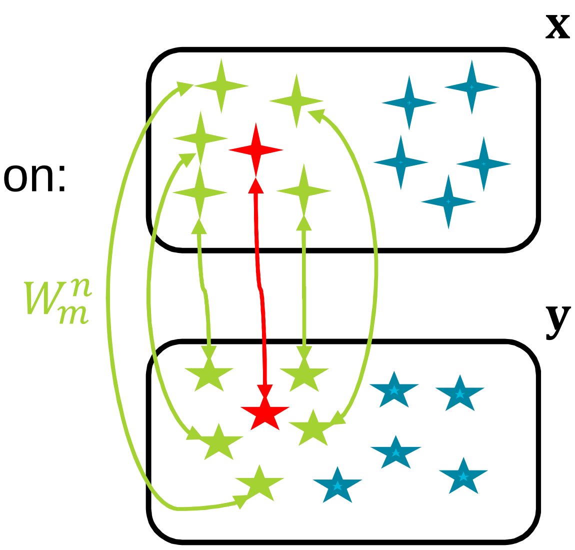
Model calibration

$$\forall n, \quad \begin{cases} \left[\hat{\alpha}_{nk}, \hat{\boldsymbol{\beta}}_k\right] = \underset{\alpha_{nk}, \boldsymbol{\beta}_k}{\operatorname{argmin}} & \sum_{m=1}^{N} W_m^n \left(\left\| \mathbf{y}_m - \sum_{k=1}^{K} \alpha_{nk} \boldsymbol{\beta}_k \mathbf{x}_m \right\|_F^2 \right) \\ \alpha_{nk} \geq 0, & \forall k \in [1, K] \\ ||\boldsymbol{\beta}_k||_F = 1, & \forall k \in [1, K] \end{cases}$$

Use multiple observation pairs for parameter estimation:

- Weights W_m^n for considered observation pairs
  - Similarity to the current observation

- **Non-linear**
- **Non-convex**



Partial minimization over one set of parameters: **linear** and **convex**

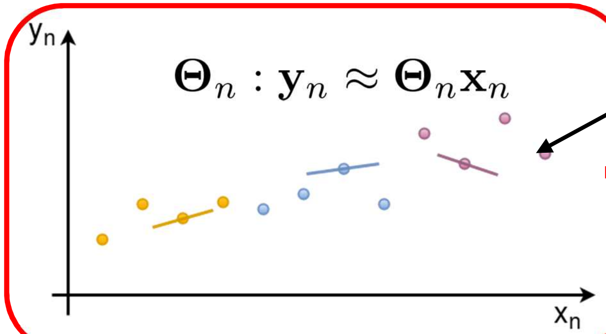
Alternating Least Squares (ALS) algorithm: Alternate partial minimizations until convergence

$\boldsymbol{\beta}$ update
- Estimate β_k with fixed α_{nk}
- Normalization constraint

α update
- Estimate α_{nk} with fixed β_k
- Non-negativity constraint

$$\boldsymbol{\Theta}_n = \left(\sum_{m=1}^{N} W_n^m \mathbf{y}_m \mathbf{x}_m^T \right) \left(\sum_{m=1}^{N} W_n^m \mathbf{x}_m \mathbf{x}_m^T \right)^{-1}$$

Local linear operator decomposition:



$$\begin{cases} \boldsymbol{\Theta}_n = \sum_{k=1}^{K} \alpha_{nk} \boldsymbol{\beta}_k + \boldsymbol{\omega}_n \\ \alpha_{nk} \geq 0, \forall k \in [1, K], \forall \in [1, N] \\ ||\boldsymbol{\beta}_k||_F = 1, \forall k \in [1, K] \end{cases}$$

Dictionary learning:
- Wide variety of algorithms exist [Lee & Seung, 1999; Aharon et al, 2007; Hoyer, 2004]
- Constraints can be changed easily

Algorithm synthesis and comparison

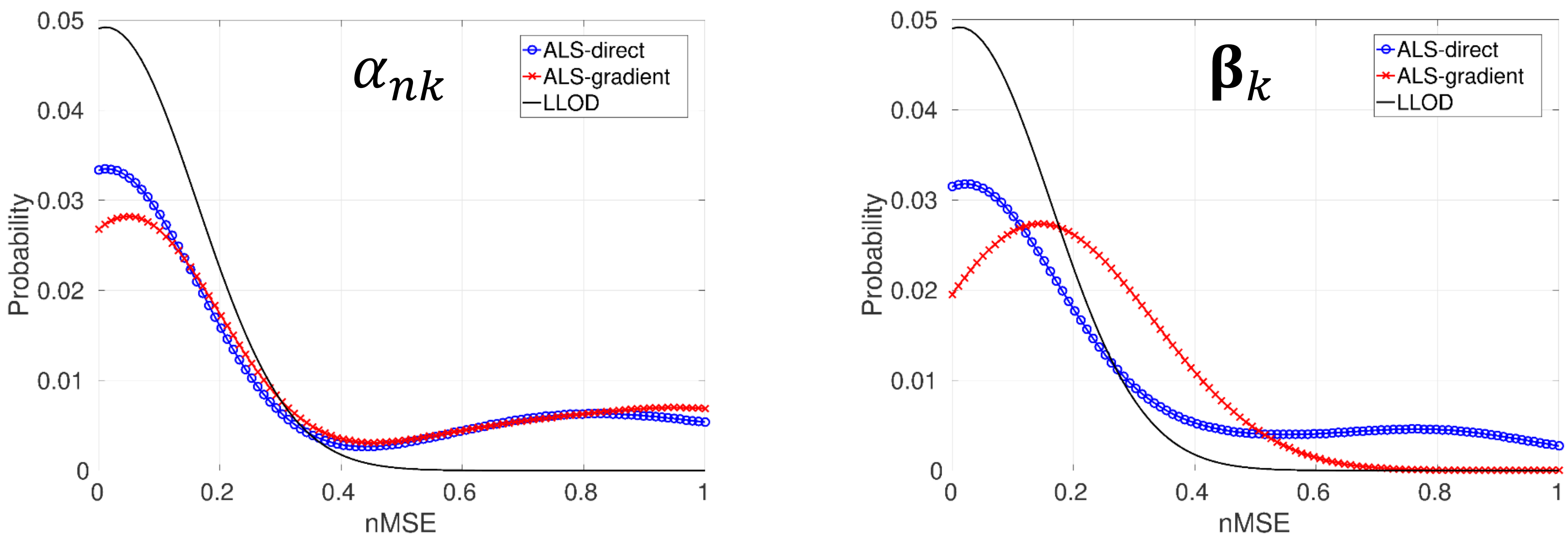


FIGURE 4: Distribution of nMSE for the estimation of model parameters

Dictionary-based decomposition of local linear operators

- Best performance under favorable settings

ALS-direct/ALS-gradient:

- Less stable
- May prove useful under non-ideal settings

APPLICATIONS

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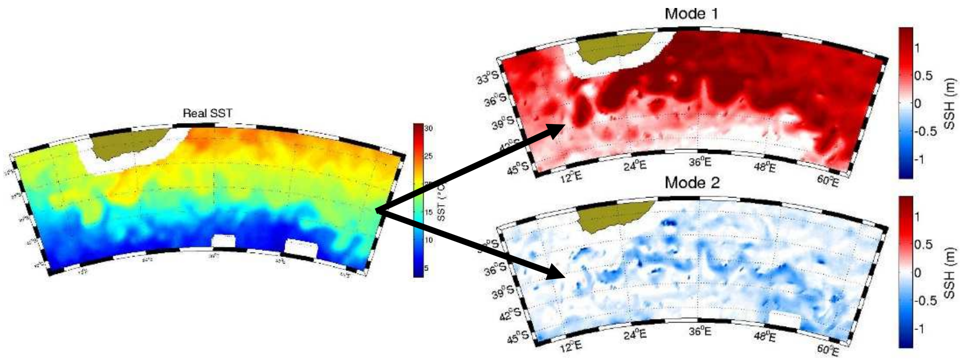
Decomposition of upper ocean dynamics

$$\mathbf{x}_n = \mathcal{F}_T(\mathrm{SST}) \qquad \mathbf{y}_n = \mathcal{F}_H(\mathrm{SSH})$$

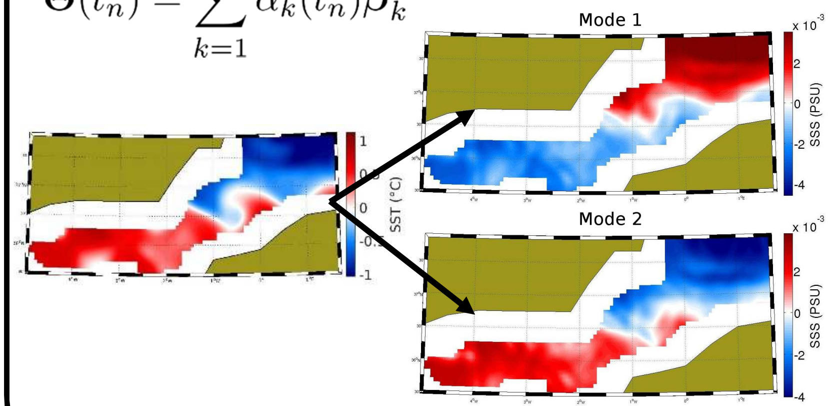
$$\mathbf{y}(s_i,t_i) = \sum_k \alpha_k\,(s_i,t_i)\boldsymbol{\beta}_k\,\mathbf{x}(s_i,t_i)$$



SST SSH

$$SSS(t_n,p) = \boldsymbol{\Theta}(t_n)vec\left(\mathcal{P}_{SST}(t_n,p)\right),\ \forall p$$

$$\boldsymbol{\Theta}(t_n) = \sum_{k=1}^{K} \alpha_k(t_n)\boldsymbol{\beta}_k$$



SST SSS

Decomposition of forecasting operators

$$\mathbf{s}(t+\partial t) = \mathbf{A}\left(\mathbf{s}(t)\right)\mathbf{s}(t) \longrightarrow \mathbf{A}\left(\mathbf{s}(t)\right) = \sum_{k=1}^{K} \alpha_k\left(\mathbf{s}(t)\right)\boldsymbol{\beta}_k$$

Analog forecasting of Lorenz ‘96 dynamics

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Analog forecasting of Lorenz '96 dynamics

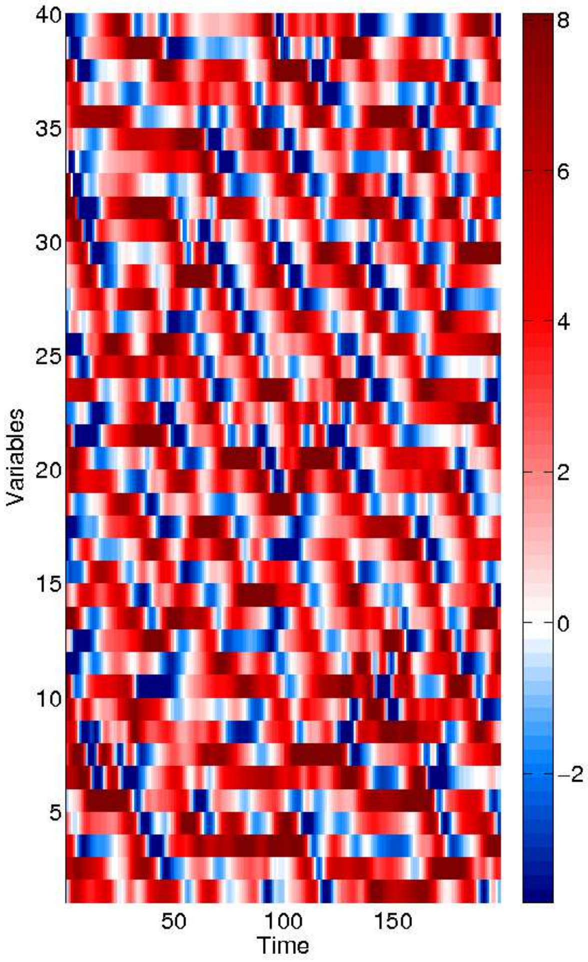


FIGURE 5: Lorenz '96 model

Case study: Lorenz '96 dynamical system

$$\frac{\partial \mathbf{s}_i}{\partial t} = \left(\mathbf{s}_{i+1} - \mathbf{s}_{i-2}\right)\mathbf{s}_{i-1} - \mathbf{s}_i + F \quad \forall i \in 1, L$$

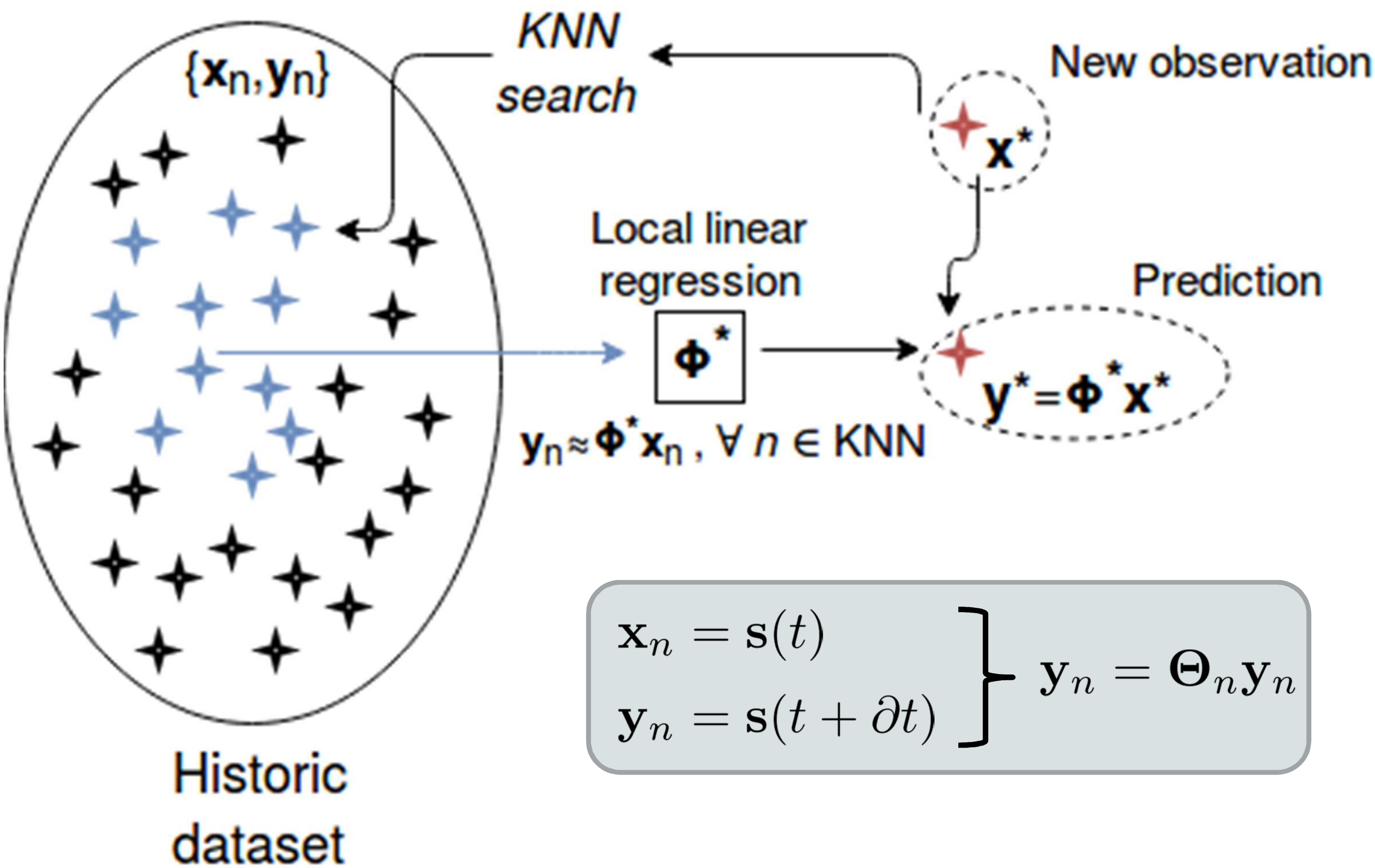
- Developed to study predictability issues in weather forecasting
- Representative of chaotic geophysical dynamical systems (e.g. the atmosphere)

Forecasting:

- For a 40-variable Lorenz '96 time series $\mathbf{s}(t)$

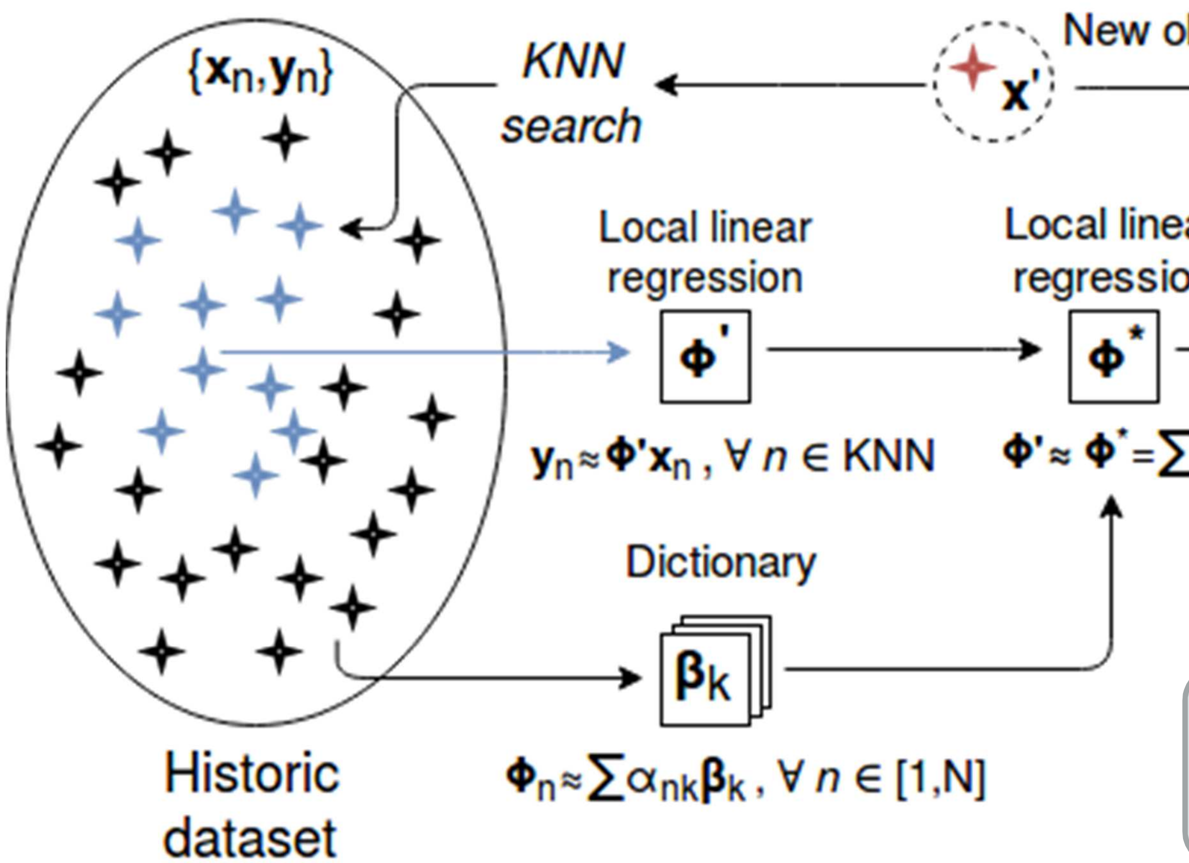
$$\mathbf{s}(t + \partial t) = \mathbf{A}\left(\mathbf{s}(t)\right)\mathbf{s}(t)$$

Analog forecasting of Lorenz ’96 dynamics



$$\left.\begin{aligned}\mathbf{x}_n &= \mathbf{s}(t)\\ \mathbf{y}_n &= \mathbf{s}(t+\partial t)\end{aligned}\right\} \mathbf{y}_n = \mathbf{\Theta}_n \mathbf{y}_n$$

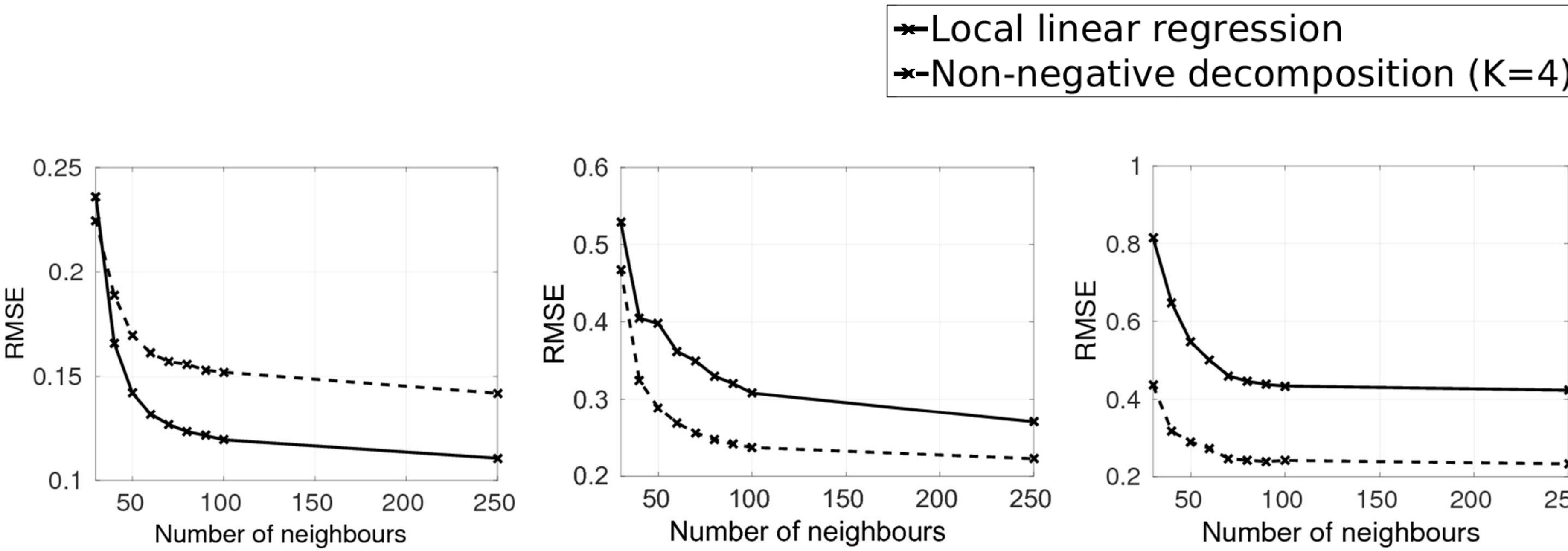
FIGURE 6: Analog forecasting



$$\mathbf{A}\left(\mathbf{s}(t)\right) = \sum_{k=1}^{K} \alpha_k \left(\mathbf{s}(t)\right) \boldsymbol{\beta}_k$$

FIGURE 7: Non-negative decomposition of analog forecasting operators

Analog forecasting of Lorenz ’96 dynamics



(a) $N = 2 \times 10^5$
No noise

(b) $N = 2 \times 10^5$
$\sigma^2_{noise} = 0.1$

(a) $N = 2 \times 10^3$
No noise

FIGURE 8: RMSE vs number of analogs for classic analog forecasting and non-negative decomposition of the classic analog forecasting operator using **K=4** modes

Segmentation of SST/SSS Sea Surface Dynamics

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Segmentation of SST/SSS Sea Surface Dynamics

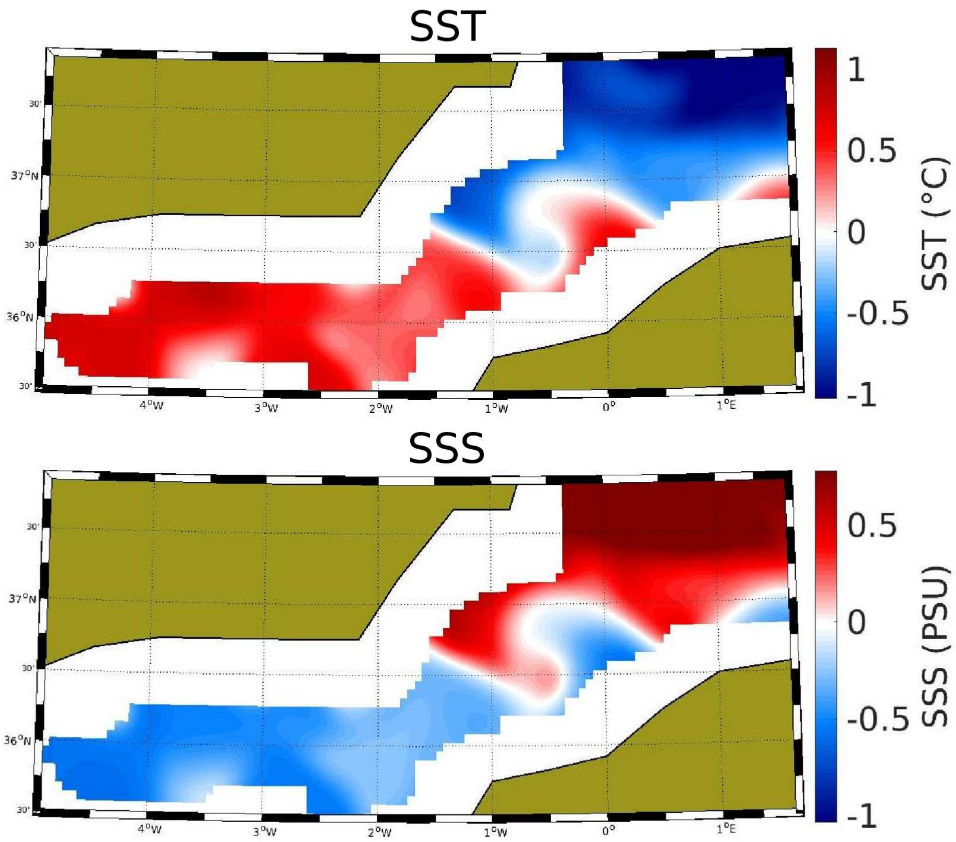


FIGURE 9: SST/SSS fields on March 22nd, 2011

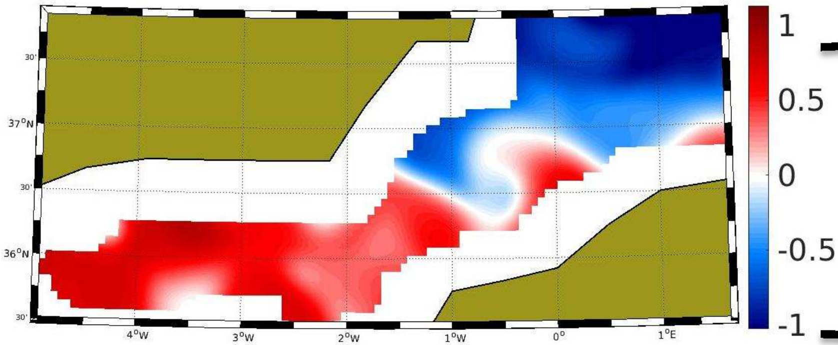
Case study in the Alboran Sea:

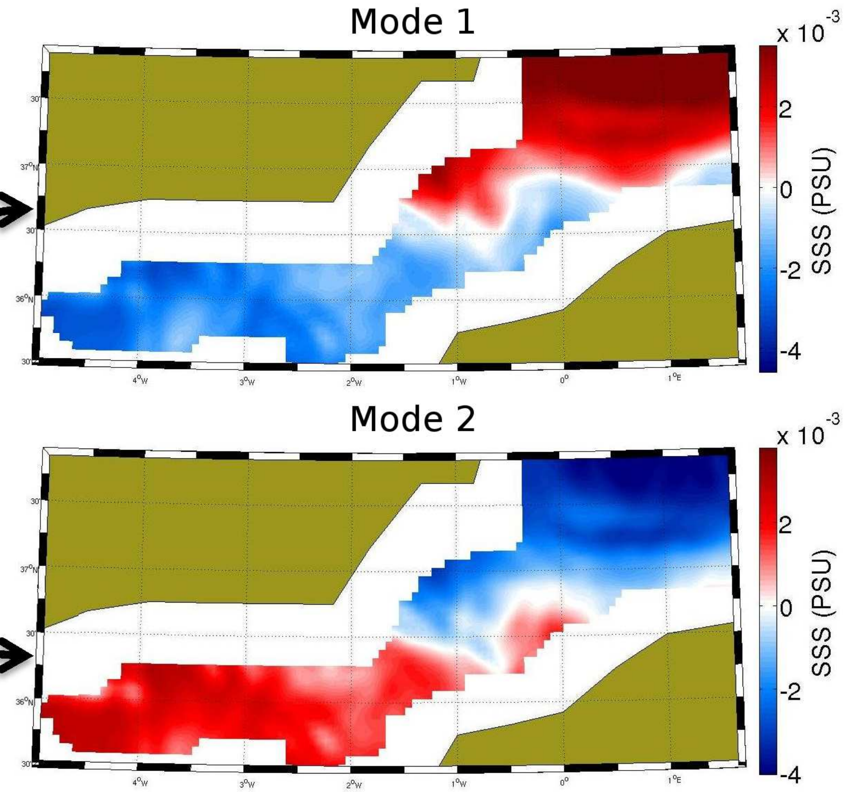
- Daily WMOP synthetic anomaly images (2009-2012)
  - *Sea surface temperature (SST)*
  - *Sea surface salinity (SSS)*
- Cold water intake from the Atlantic thought the Gibraltar Strait
- Strong seasonal patterns
- Inversion of SST/SSS correlation

$$SSS(t_n, p) = \mathbf{\Theta}(t_n) vec\left(\mathcal{P}_{SST}(t_n, p)\right), \forall p$$

$$\mathbf{\Theta}(t_n) = \sum_{k=1}^{K} \alpha_k(t_n) \boldsymbol{\beta}_k$$

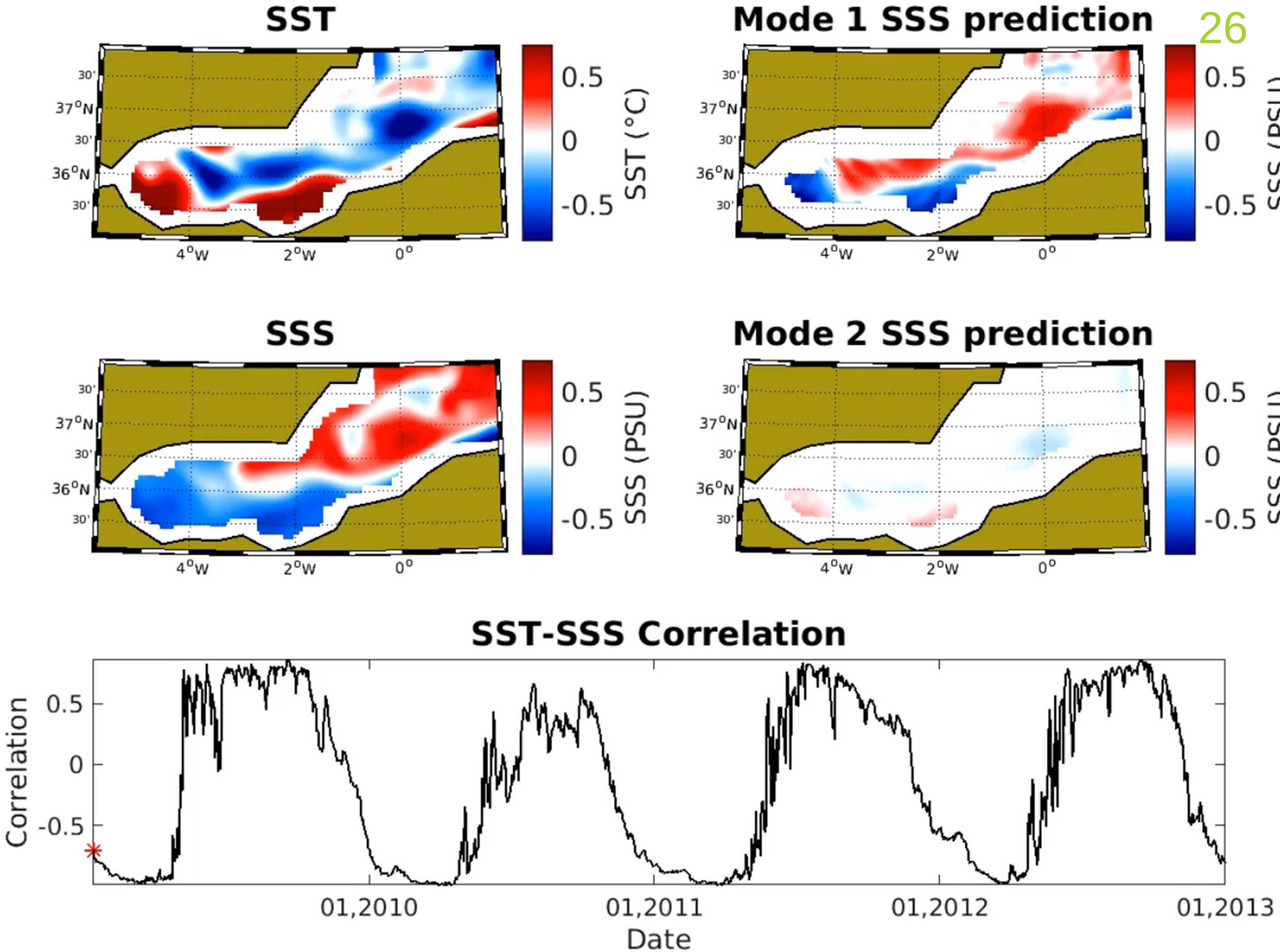
Mode 1 : **inversion** of correlation between SST/SSS fields





Mode 2: **coherent** SST/SSS relationship

FIGURE 10: Modal SSS field predictions from the SST field on March 22nd, 2011


SST
Mode 1 SSS prediction
SSS
Mode 2 SSS prediction
SST (°C)
SSS (PSU)
0.5
0
-0.5
37°N
36°N
30'
4°W
2°W
0°
SST-SSS Correlation
Correlation
Date
01,2010
01,2011
01,2012
01,2013

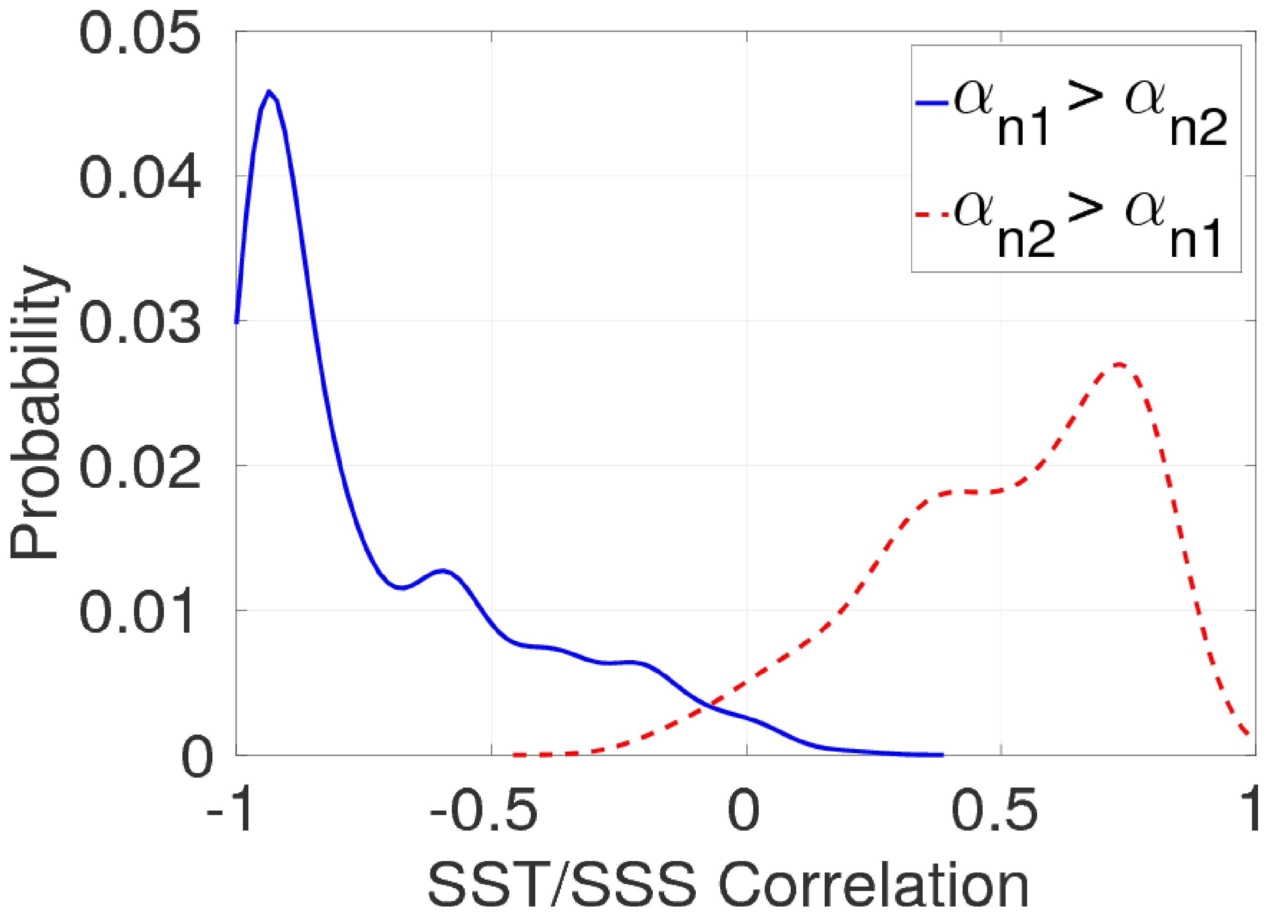


FIGURE 11: Distribution of SST/SSS correlation coefficients

PART 2: INTERPOLATION OF SEA LEVEL ANOMALY FIELDS FROM SATELLITE-DERIVED REMOTE SENSING DATA

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Interpolation of altimetry fields

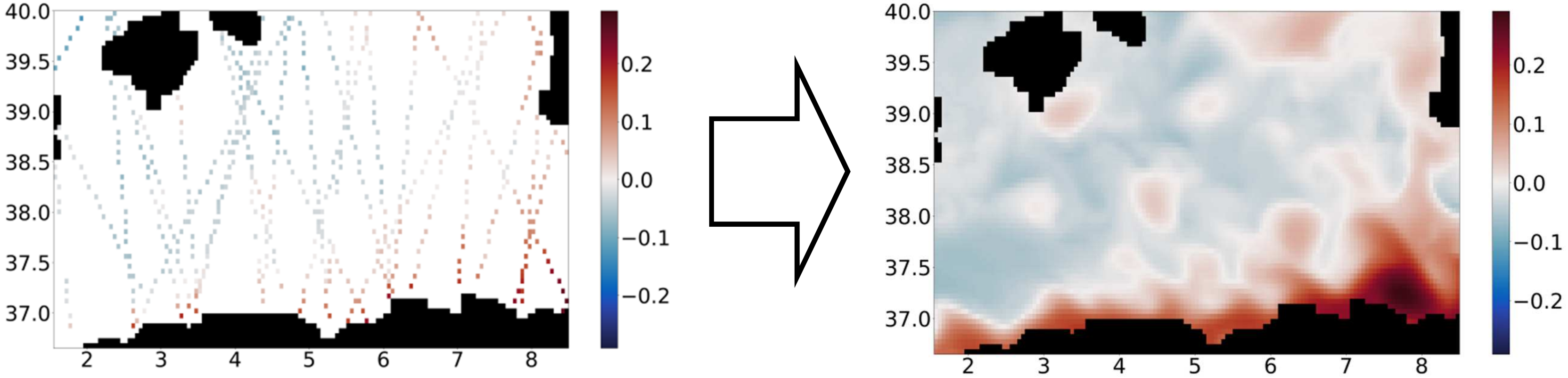


FIGURE 12: Interpolation of satellite data

Key issue in oceanography

Main difficulty: Irregular and partial sampling of the ocean surface

- Multiple data sources
  - Different spatio-temporal sampling strategies
- Missing data: up to **90%**

Current limitation: Scales <100 km not accurately reconstructed

Beyond the 100 km limit

<u>Model-based approaches:</u>

<u>State-of-the-art:</u> Optimal Interpolation [Bretherton et al., 1976]

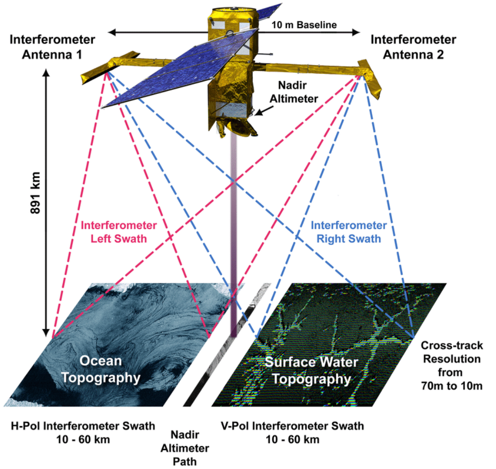
- Gaussianity
- Mean spatio-temporal covariance structures

<u>New approaches:</u> Additional physically-motivated constraints

- OI+Bathymetry [Escudier et al., 2013]
- Dynamic interpolation [Ubelmann et al., 2014]

<u>New developments in instrumentation:</u>

<u>SWOT</u>
[Fu & Ferrari, 2008]



<u>SKIM</u>
[Ardhuin et al., 2018]

We focus on exploring <u>data-driven alternatives</u>

Problem Formulation

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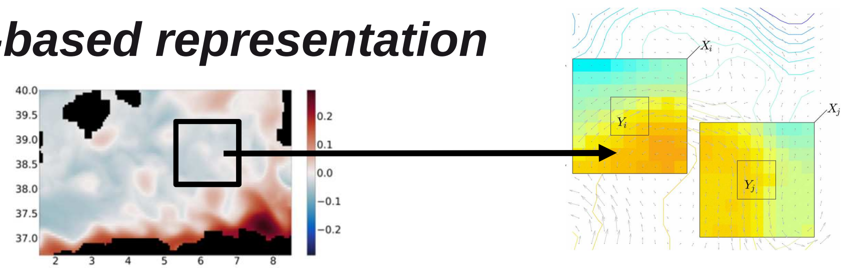
State-space formulation

$$\begin{cases} \mathbf{x}(t) & = & \mathcal{M}\left(\mathbf{x}(t-\delta t)\right) + \boldsymbol{\epsilon}(t) \\ \mathbf{y}(t) & = & \mathcal{H}\left(\mathbf{x}(t), \Omega(t)\right) + \boldsymbol{\eta}(t) \end{cases}$$

Dynamical model
Observation model

Patch-based representation

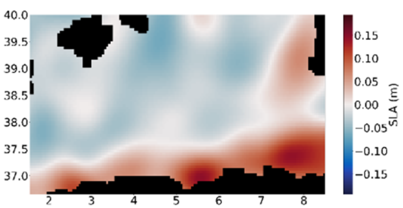


Interpolate each patch independently

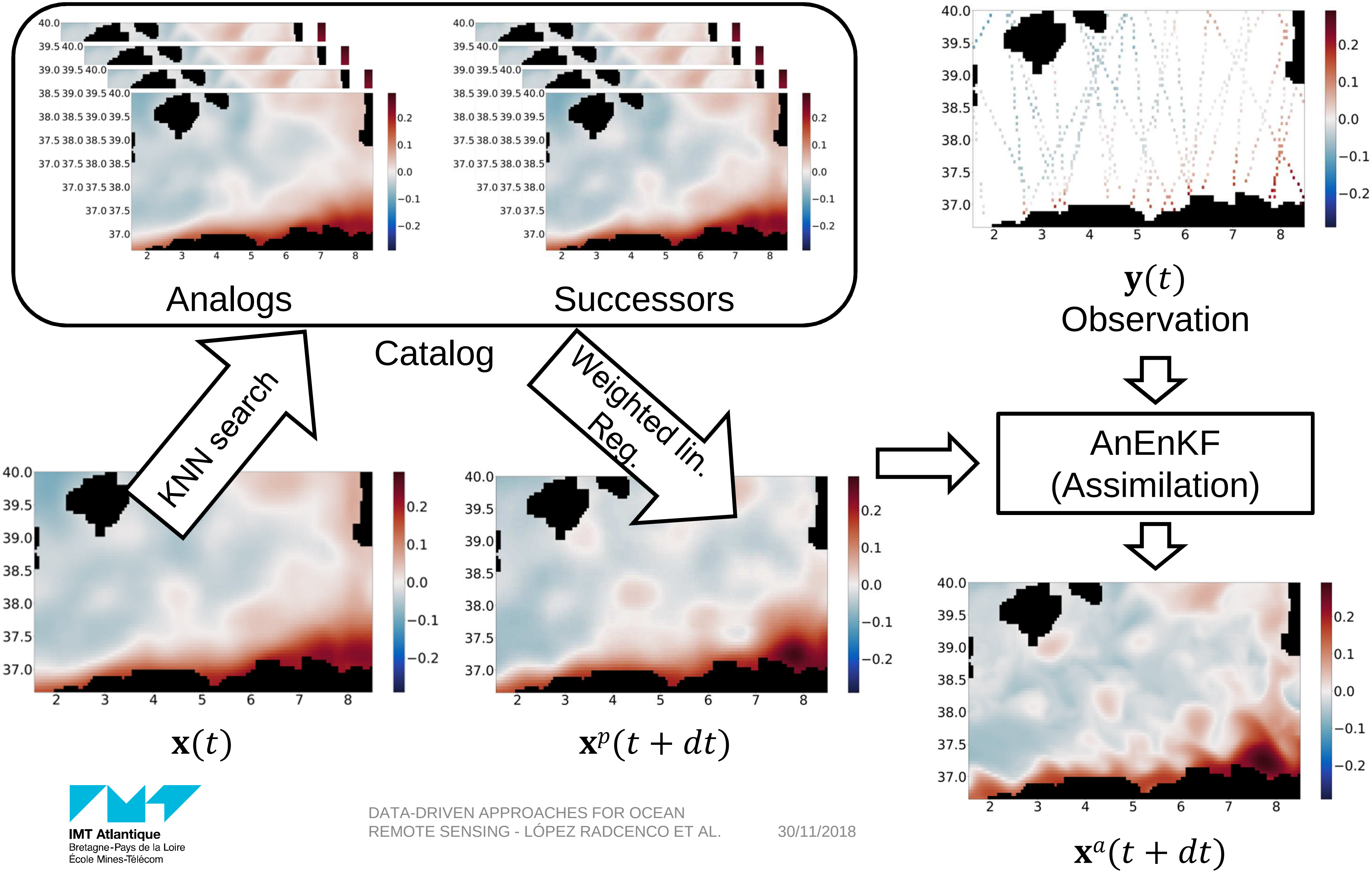
Multi-scale approach

$$\mathbf{x} = \bar{\mathbf{x}} + \boxed{d\mathbf{x}} + \zeta$$

Scales >100 km
Resolved by OI



Analog data assimilation



Observing system simulation experiment

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Satellite altimetry observations

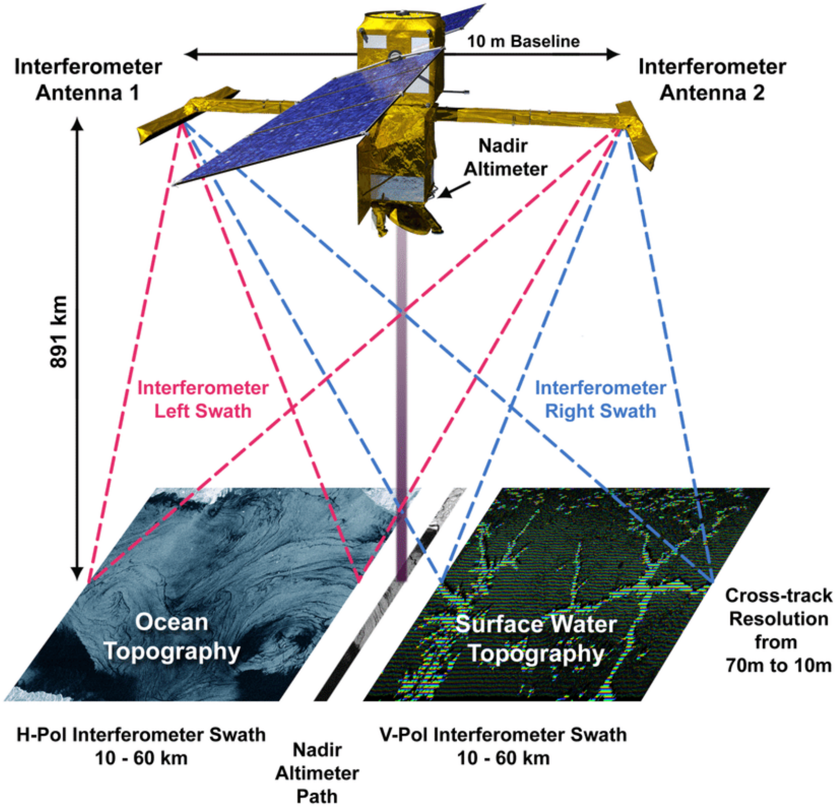

FIGURE 13: SWOT satellite

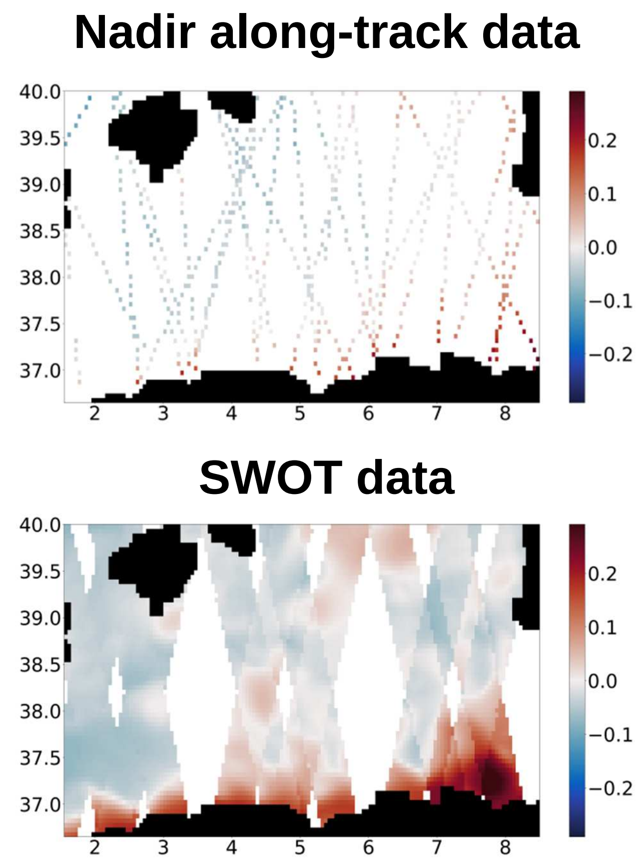

FIGURE 14: Difference between AT and SWOT altimetry observations

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Observing System Simulation Experiment

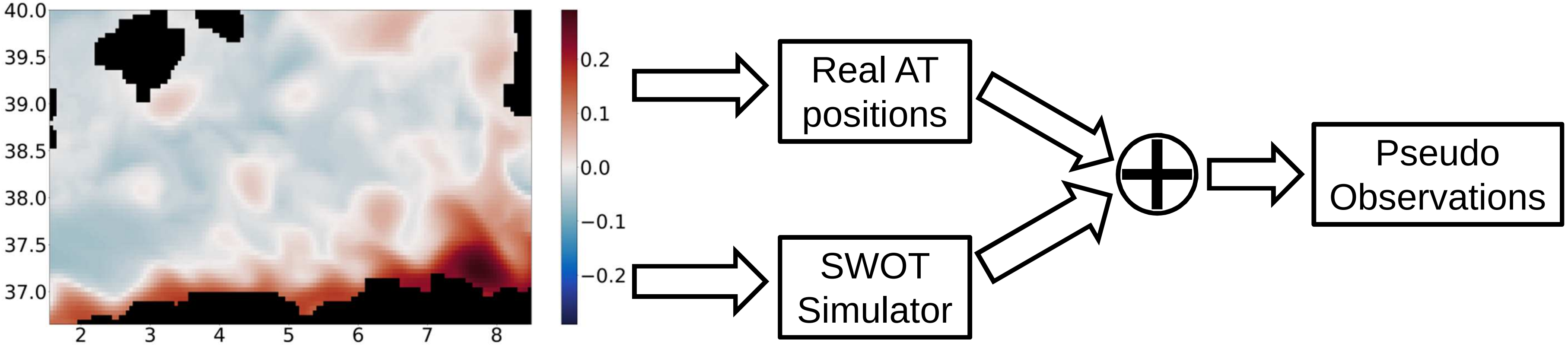

FIGURE 15: Observing System Simulation Experiment

Case study in the Western Mediterranean Sea, from 2010 to 2014

- Synthetic SLA (Sea Level Anomaly) fields simulated with the WMOP model
- Along-track observations : real satellite tracks (4 altimeters in 2014)
- Pseudo-SWOT observations: SWOT simulator (JPL-NASA)

Tested methods: Optimal Interpolation, DINEOF, Non-negative decomposition of linear interpolation operators, **Analog data assimilation**

Pseudo-observations

Pseudo-observations: Observations accumulated on a $t_0 \pm D$ time window

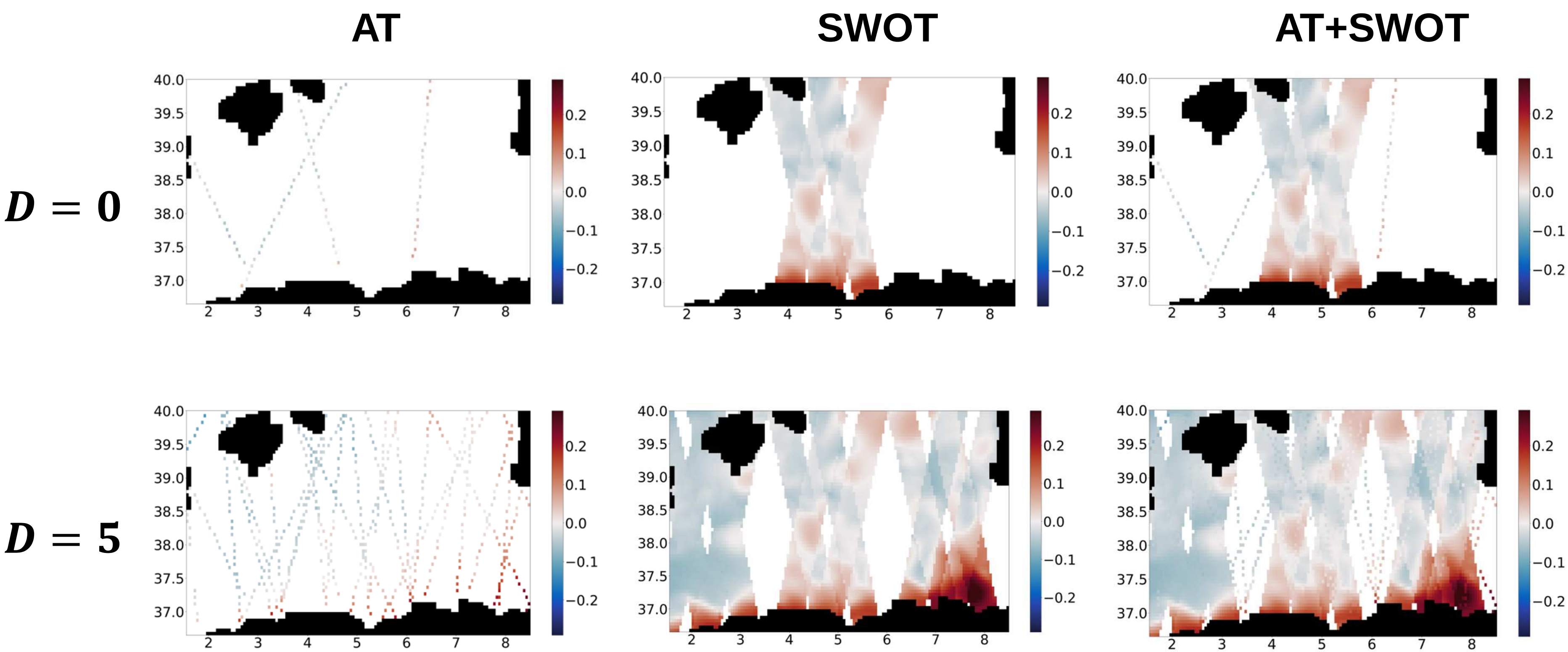

FIGURE 16: Pseudo-observations obtained from along-track (AT) and SWOT data

Results

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Results

TABLE 1: Root mean squared error (Correlation) for AnDA SLA and SLA gradient (rSLA) reconstruction from nadir along-track observations (AT_D) and wide-swath SWOT observations ($SWOT_D$). For each type of observations, both daily observations (*D*=0) and observations accumulated on a time window $t_0 \pm D$ with *D*=5 days are considered. Best result in **bold**.

Setting	SLA	∇SLA
AT_0	0.02395 (0.9186)	0.005507 (0.6989)
AT_5	0.01978 (0.9457)	0.004699 (0.7660)
$\mathbf{SWOT_0}$	**0.01810** (**0.9543**)	**0.004436** (**0.7857**)
$SWOT_5$	0.01920 (0.9502)	0.004345 (0.7913)
OI	0.02927 (0.8451)	0.006655 (0.6052)

Results

TABLE 2: Root mean squared error (Correlation) for AnDA SLA and SLA gradient (rSLA) reconstruction from the fusion of nadir along-track observations (AT_D) and wide-swath SWOT observations ($SWOT_D$). For each type of observations, both daily observations (*D*=0) and observations accumulated on a time window $t_0 \pm D$ with *D*=5 days are considered. Best result in **bold**.

Setting	SLA	∇SLA
$AT_0 + SWOT_0$	0.01742 (0.9576)	0.004375 (0.7934)
$AT_5 + SWOT_5$	0.01876 (0.9523)	0.004318 (0.7952)
$\mathbf{AT_5 + SWOT_0}$	**0.01687 (0.9607)**	**0.004286 (0.8051)**
OI	0.02927 (0.8451)	0.006655 (0.6052)

With respect to OI:

- **42% (14%) improvement** in terms of **RMSE (correlation)** for $\boldsymbol{SLA}$
- **35% (33%) improvement** in terms of **RMSE (correlation)** for $\boldsymbol{\nabla SLA}$

Results

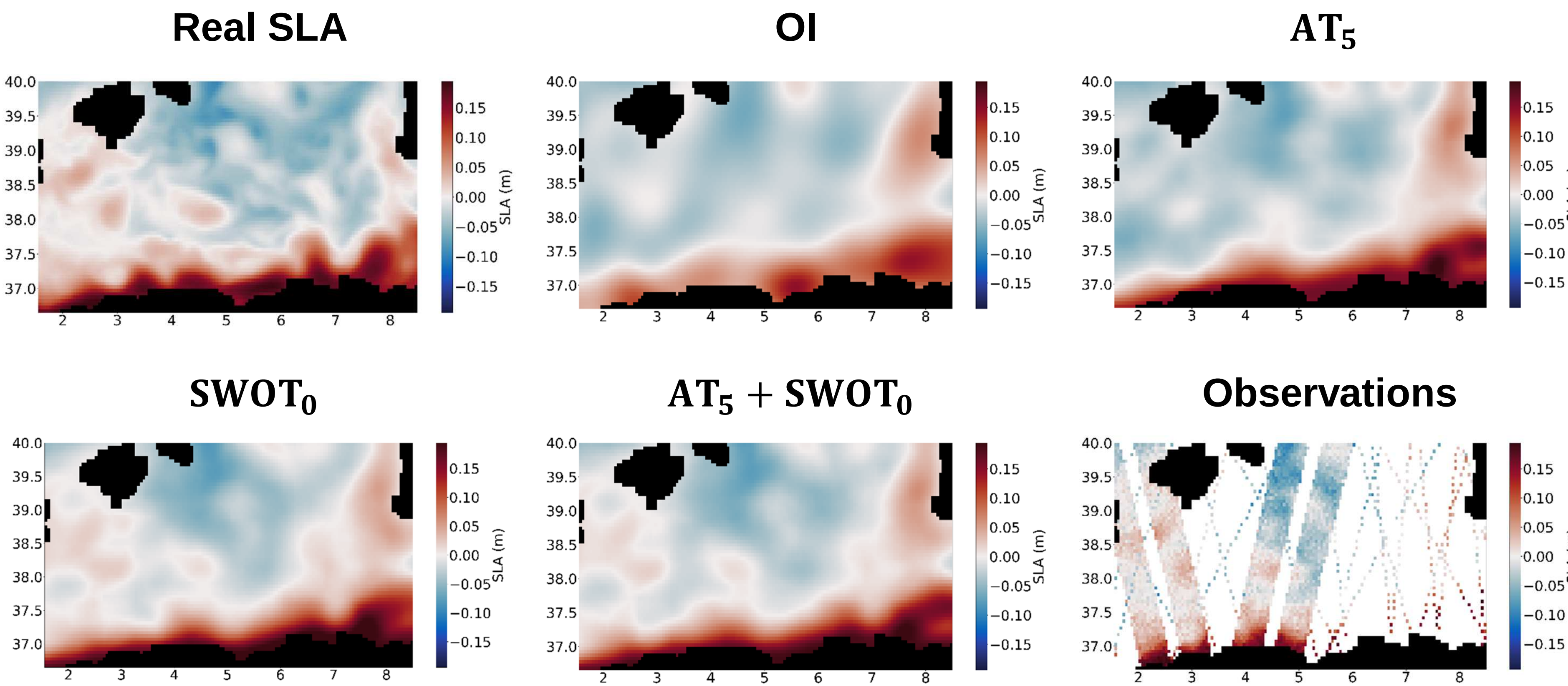

FIGURE 17: SLA fields interpolation results for Optimal Interpolation and for the AnDA assimilation of AT_5, SWOT_0 and $\mathrm{SWOT}_0 + AT_5$ data. Ground-truth fields and observations included as reference.

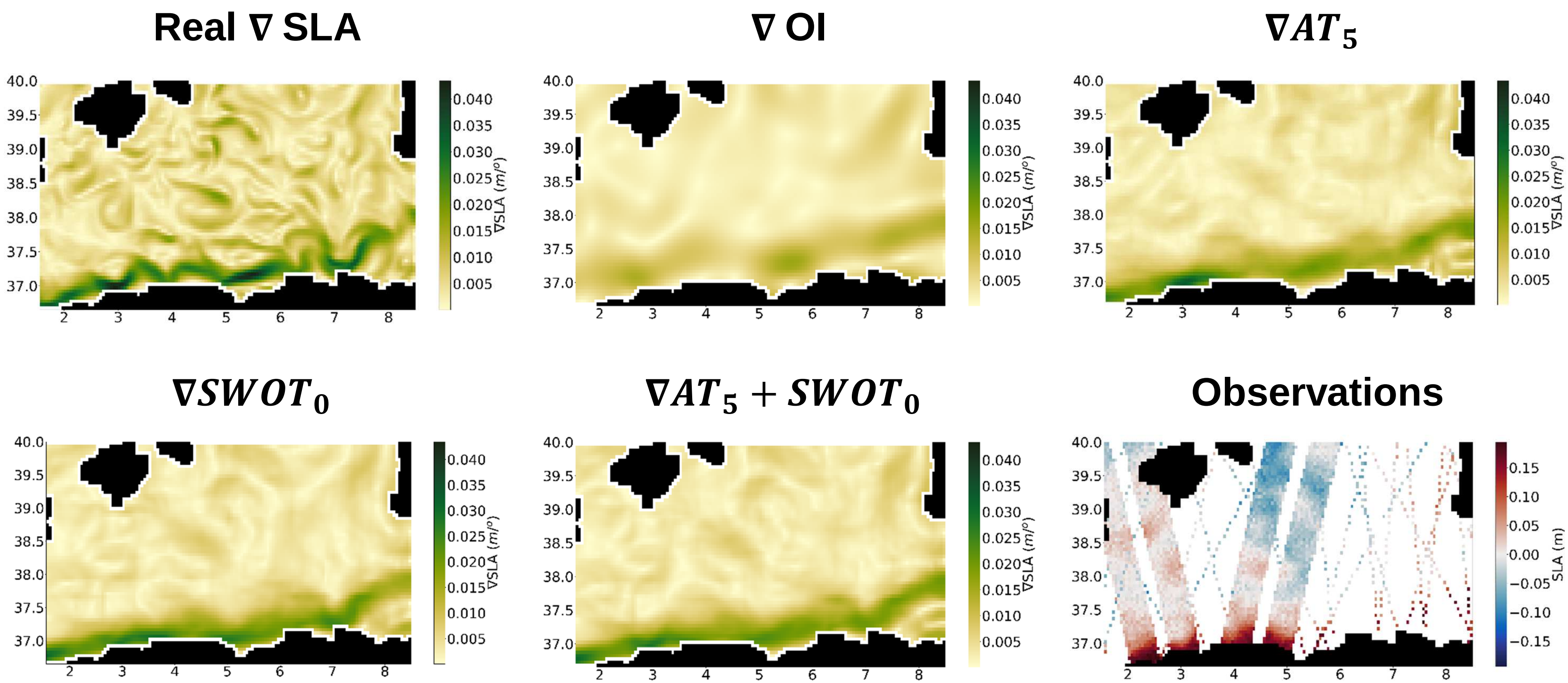

FIGURE 18: ∇SLA fields interpolation results for Optimal Interpolation and for the AnDA assimilation of AT_5, SWOT_0 and $\mathrm{SWOT}_0 + AT_5$ data. Ground-truth fields and observations included as reference.

VALORIZATION

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5 International Conference papers

- M. Lopez-Radcenco, A. Aissa-El-Bey, P. Ailliot, R. Fablet, and P. Tandeo. Non-negative decomposition of linear relationships: application to multi-source ocean remote sensing data. In *ICASSP 2016 : 41st IEEE International Conference on Acoustics, Speech and Signal Processing*, pages 4179–4183, 2016
- M. Lopez-Radcenco, A. Aissa-El-Bey, P. Ailliot, and R. Fablet. Non-negative decomposition of geophysical dynamics. In *ESANN 2017 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning*, Bruges, Belgium, April 2017
- R. Fablet, M. Lopez-Radcenco, J. Verron, B. Mourre, B. Chapron, and A. Pascual. Learning multi-tracer convolutional models for the reconstruction of high-resolution SSH fields. In *IGARSS 2017: 2017 IEEE International Geoscience and Remote Sensing Symposium*, Fort Worth, Texas, USA, July 2017
- M. Lopez-Radcenco, R. Fablet, A. Aissa-El-Bey, and P. Ailliot. Locally-adapted convolution-based super-resolution of irregularly-sampled ocean remote sensing data. In *ICIP 2017 IEEE International Conference on Image Processing*, Beijing, China, September 2017
- M. Lopez-Radcenco, A. Pascual, L. Gomez-Navarro, A. Aissa-El-Bey, and R. Fablet. Analog data assimilation for along-track nadir and SWOT altimetry data in the Western Mediterranean Sea. In *IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, Valencia, Spain, July 2018

2 National Conference papers

- M. Lopez-Radcenco, A. Aissa-El-Bey, P Tandeo, and R. Fablet. Décomposition Nonnégative de Dynamiques Géophysiques. In *GRESTSI 2017: XXVIème colloque du GRETSI*, Juan-Les-Pins, France, September 2017
- M. Lopez-Radcenco, A. Pascual, L. Gomez-Navarro, A. Aissa-El-Bey, and R. Fablet. Assimilation par Analogues de Données Altimétriques Nadir et SWOT dans la Mer Méditerranée Occidentale. In *Conférence Française de Photogrammétrie et de Télédétection (CFPT)*, Marne-la-Vallée, France, June 2018

2 Journal papers

- M. Lopez-Radcenco, R. Fablet, and A. Aissa-El-Bey. Non-negative observation-based decomposition of operators. *IEEE Transactions on Signal Processing*, Submittted
- M. Lopez-Radcenco, A Pascual, L. Gomez-Navarro, A. Aissa-El-Bey, and R. Fablet. Can SWOT Data Improve the Reconstruction of Sea Level Anomaly Fields? Insights for Datadriven Approaches in the Western Mediterranean Sea. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, Submittted

CONCLUSION AND PERSPECTIVES

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Conclusions

Explore data-driven approaches for ocean remote sensing

Non-negative decomposition of operators:

- Relevant models
- Efficient and mathematically-sound algorithms
- Relevant applications in various scientific contexts
  - Segmentation of upper ocean dynamics from satellite data
  - Analog forecasting of dynamical systems

Interpolation of SLA fields from satellite data:

- Different sampling patterns: SWOT mission
- Data-driven fusion of AT and SWOT observations:
  - Clear performance gain from the fusion of AT and SWOT observations

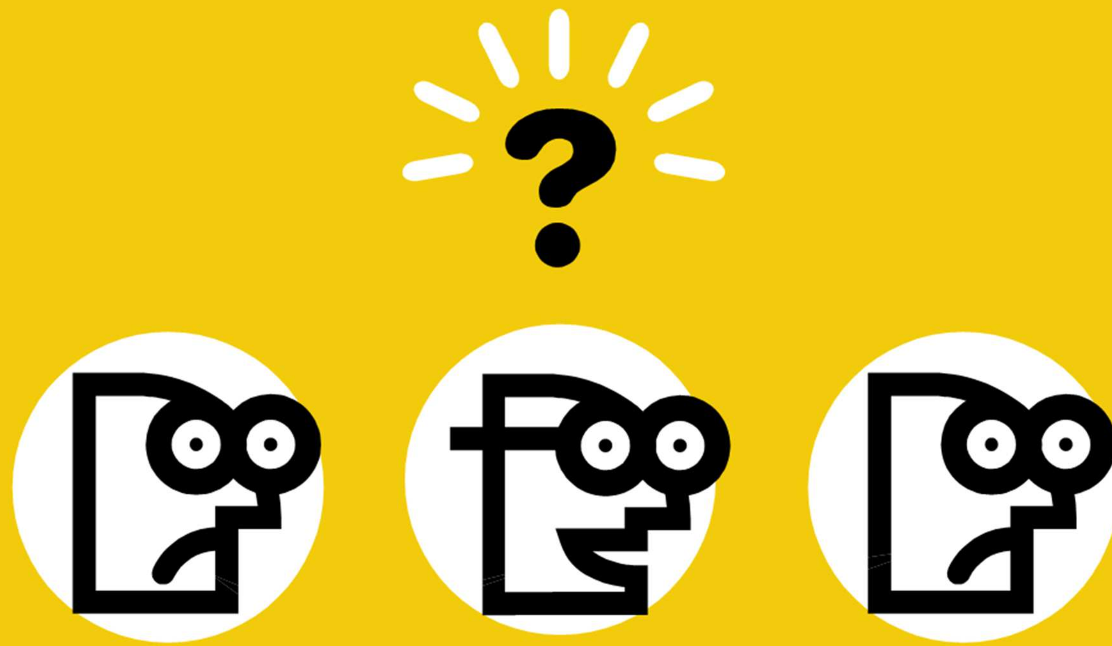
<u>Non-negative decomposition of operators:</u>

- Further improve robustness of models
- Explore alternative constraints (sparsity)
- Explore non-linear model extensions
- Further study geophysical interpretation of model parameters
- Explore new applications (or extend previous ones)

<u>Interpolation of SLA fields from satellite data:</u>

- Filtering SWOT noise: key issue
  - Combine AnDA with current efforts to pre-process SWOT noise
- Complementary sources of altimetry data or alternative dynamical tracers (SST, SSS, etc.)
- Efficient exploitation of 2D information in SWOT:
  - Observation gradients
  - Finite size Lyapunov exponents

Thank you for your attention



It's QUESTION TIME !!