Deep Sea Surface Height Multivariate Interpolation

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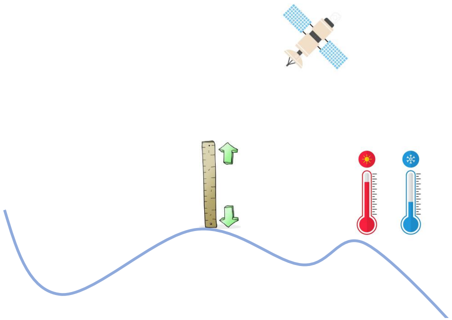
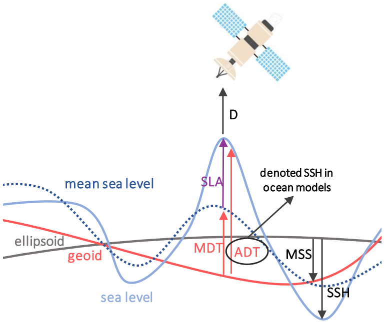
Multi-Variate satellite surface observations of the ocean

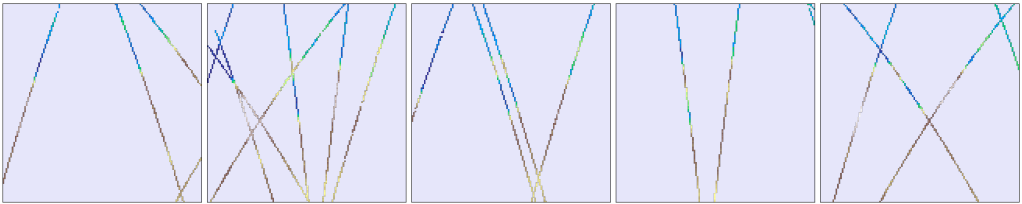


Sea Surface Height

- Used to derive surface currents to geostrophic approximation
- Measurement principle : return time of a radar pulse
- Nadir-pointing altimeters : only measure data along their ground tracks [a]



a. We use the L3 reprocessed DUACS data.

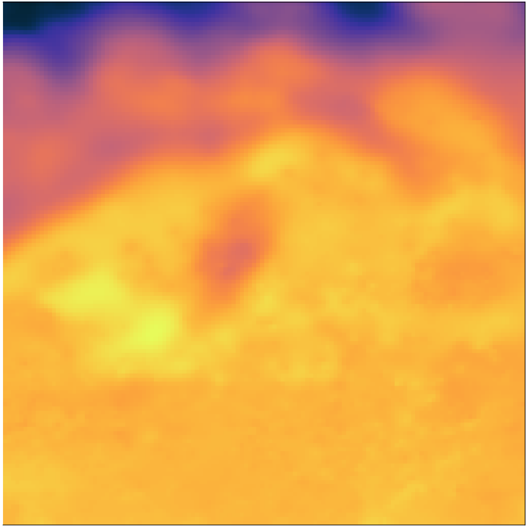


Sea Surface Temperature

- Measurement principle : Direct infra-red image with high resolution (1/25°)
- Clouds introduce gaps in data
- L4 SST fields [a] : obtained through linear Optimal Interpolation combining several satellites and in-situ data.
- Noise : high-frequency instrumental errors and blurring.
- Advected by the currents.

a. We use the Multiscale Ultra-high Resolution dataset

SST MUR



Data

Observing System Simulation Experiment

We use an OSSE : we emulate satellite observations on a simulation (GLORYS12, CMEMS).

We assume that $\mathbf{Y} = \mathcal{H}(\mathbf{X}) + \varepsilon$

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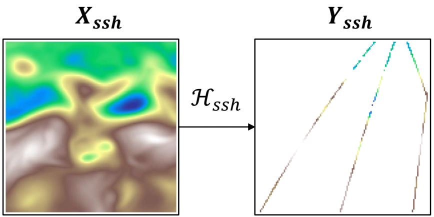

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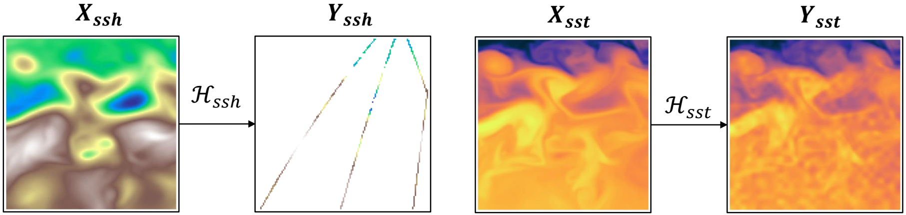

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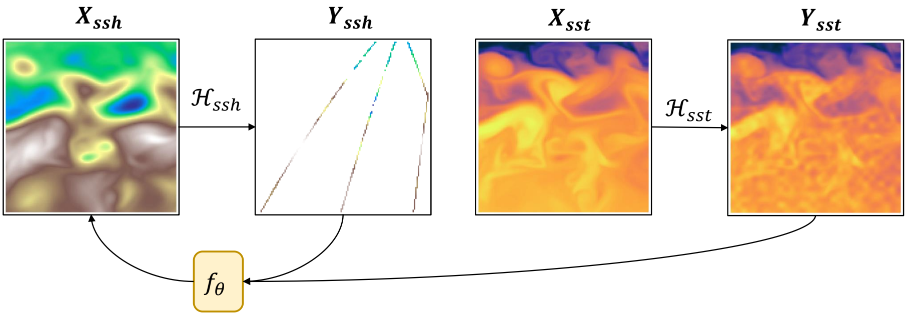
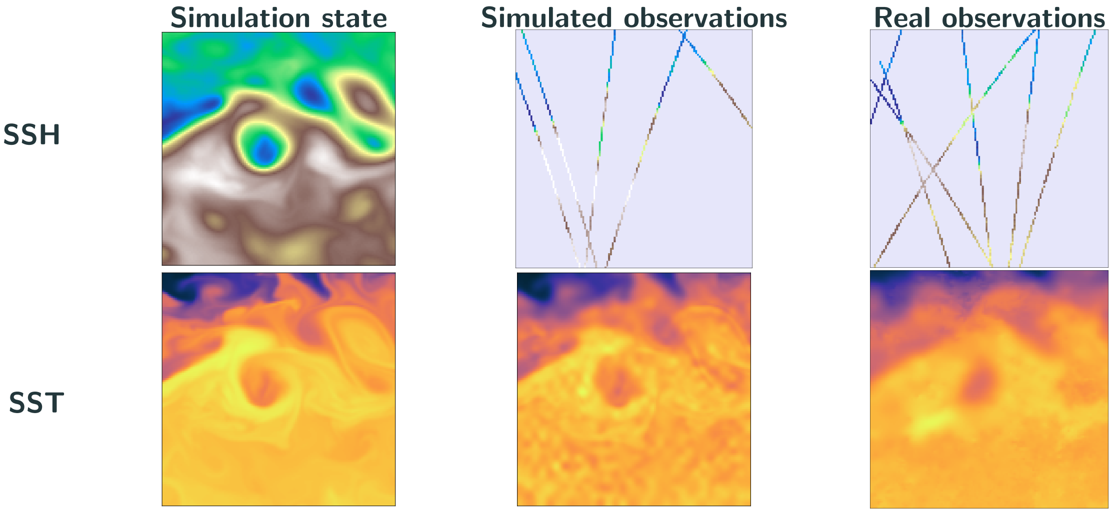
- f_θ : NN inversion $\mathcal{H}_{ssh}$ using SSH and SST observations

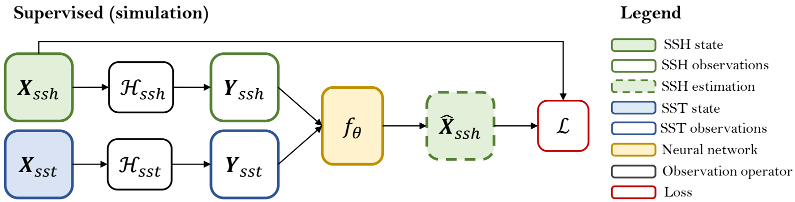


Domain gap ?


Simulation state
Simulated observations
Real observations
SSH
SST

Proposed Method : simulation pre-training and observations fine-tuning

Learning method



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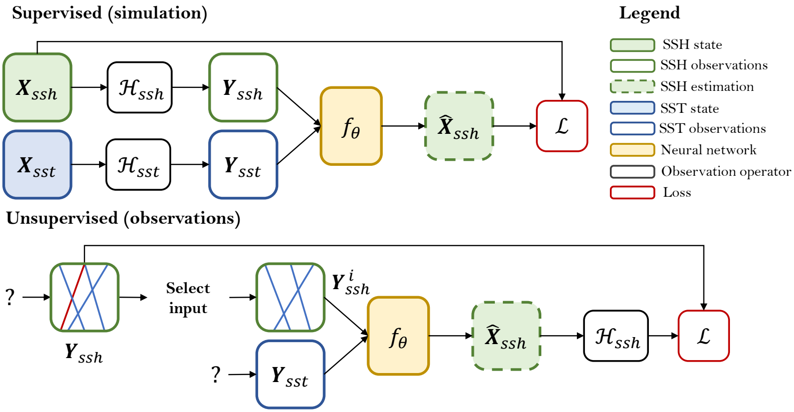

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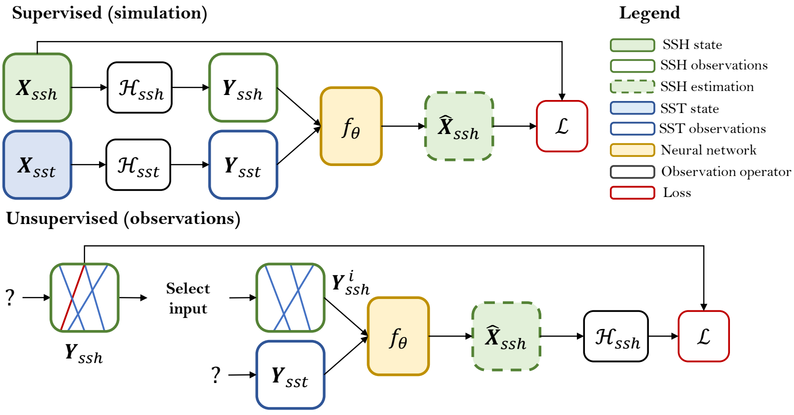

- Subset input data $\mathbf{Y}^i_{ssh}$, and estimates $\hat{\mathbf{X}}_{ssh}$ from $(\mathbf{Y}^i_{ssh}, \mathbf{Y}_{sst})$.

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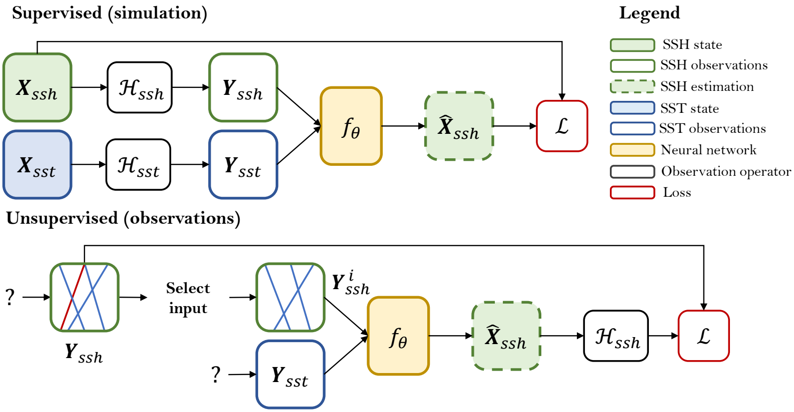

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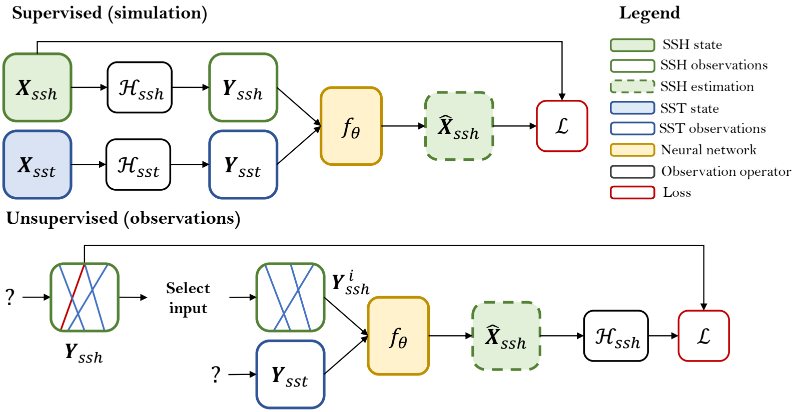

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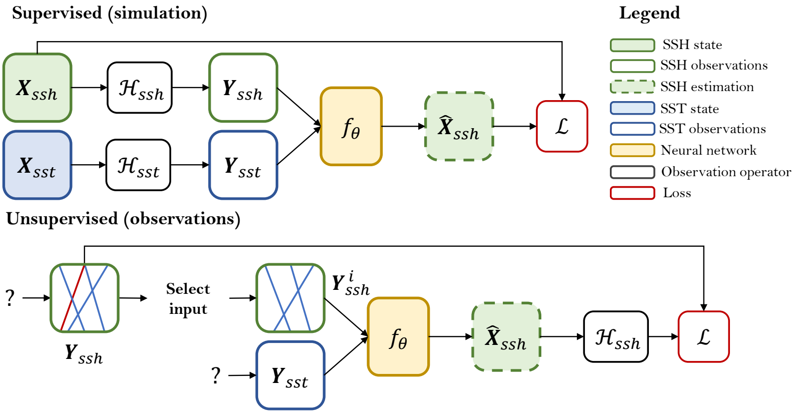

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- Apply $\mathcal{H}_{ssh}$ to $\hat{\mathbf{X}}_{ssh}$ before computing the loss.
- Removing some input observations helps to estimate the entire map accurately.
- f_θ : Attention-Based Encoder Decoder taking 21 days of observations.

Results

Ocean Data Challenge 2021

Evaluation on a real observation dataset : the *Ocean Data Challenge 2021*.

- 1 year of data on the Gulf Stream area
- Provides state-of-the-art reconstruction methods
- Evaluation on independent data
- Metrics : μ the RMSE score (in cm), σ_t its temporal std (in cm), λ_x the half-resolved spatial wavelength (in km)

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We want to test :

- SST impact : training using SSH, $SSH + nSST$, $SSH + SST$
- The learning strategy

Comparing training strategies

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Learning method	μ	σ_t	λ_x	μ	σ_t	λ_x	μ	σ_t	λ_x
Observation	6.52	1.95	111	6.13	1.84	104	—	—	—

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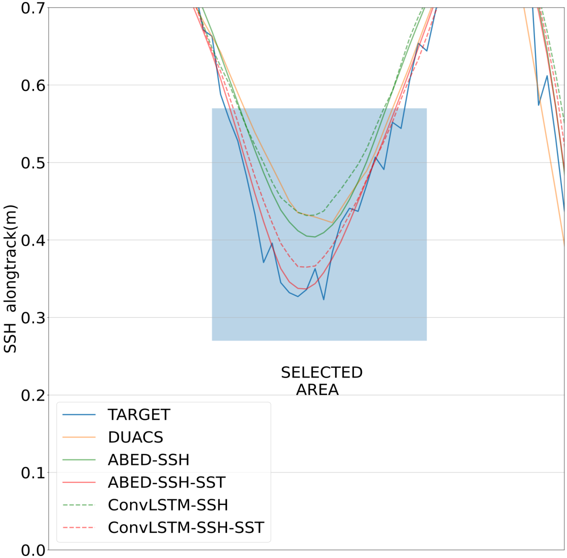
Comparing training strategies

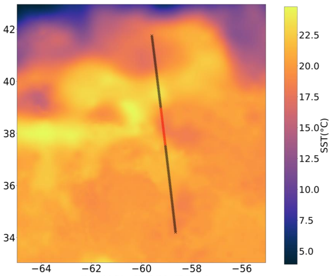
Given the supervised and the unsupervised learning, we derive 3 strategies ;

- **Observations only** : unsupervised training on real-world observations.
- **Simulation only** : supervised training on simulation and direct inference on real-world data.
- **Both** : Supervised pre-training on simulation and unsupervised fine-tuning on real-world observations.

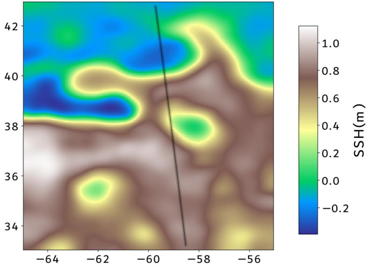
Input data	SSH			SSH+nSST			SSH+SST		
Learning method	μ	σ_t	λ_x	μ	σ_t	λ_x	μ	σ_t	λ_x
Observation	6.52	1.95	111	6.13	1.84	104	—	—	—
Simulation	6.35	1.9	112	6.2	1.87	108	6.85	2.22	111
Both	6.27	1.85	110	**5.77**	1.64	**102**	**5.77**	**1.6**	103

Improvements brought by SST





ABED-SSH-SST



Conclusion

- Pre-training and fine-tuning improve the reconstruction.
- Especially with SST.

Thank you for your attention

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SCAN ME

State-of-the-art comparison

Method	SST	NN	Learning	$\mu(cm)$	$\sigma_t(cm)$	$\lambda_x(km)$
DUACS	✗	✗	✗	7.66	2.66	138
DYMOST	✗	✗	✗	6.75	2.00	121
MIOST	✗	✗	✗	6.75	2.00	121
BFN	✗	✗	✗	7.46	2.59	114
4DVarNet	✗	✓	simulation	6.56	1.84	104
MUSTI	✓	✓	observation	6.26	1.96	107
ConvLstm	✗	✓	observation	6.82	1.86	108
ConvLstm	✓	✓	observation	6.29	**1.60**	**102**
ABED-SSH	✗	✓	both	6.27	1.85	110
ABED-SSH-SST	✓	✓	both	**5.74**	1.61	**102**

Architecture

Attention-Based Encoder-Decoder (ABED).

- Two encoding blocks reducing spatial dimensions
- Spatio-Temporal Attention modules *(inspired by CBAM)*
  - Temporal attention : performs channel and temporal attention together
  - Spatial attention
- Decoding blocks to increase spatial dimensions