Explore Machine Learning Surrogate Model of Ocean Surface and its Application in Data Assimilation

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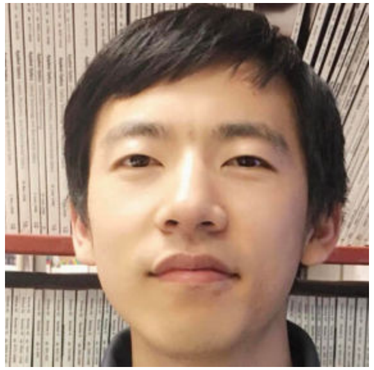
Texas A&M participants



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Nayana Venukanthan

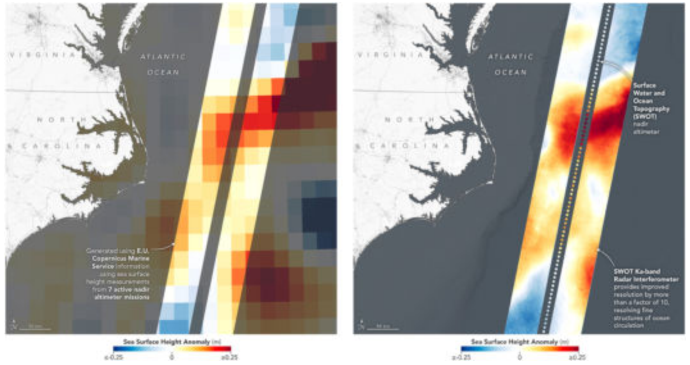
Roy An

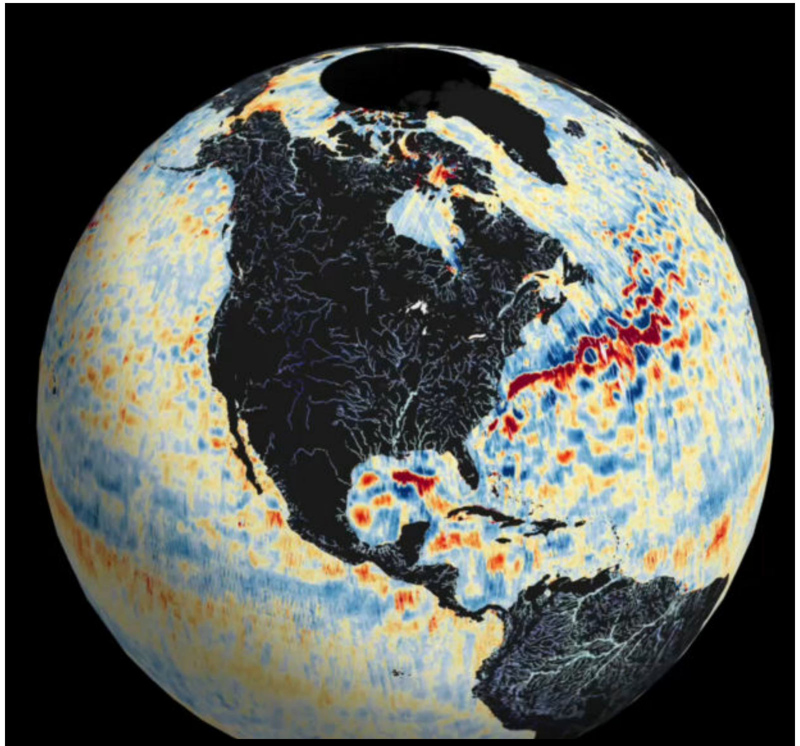
Suyue Li

Sandra Manult

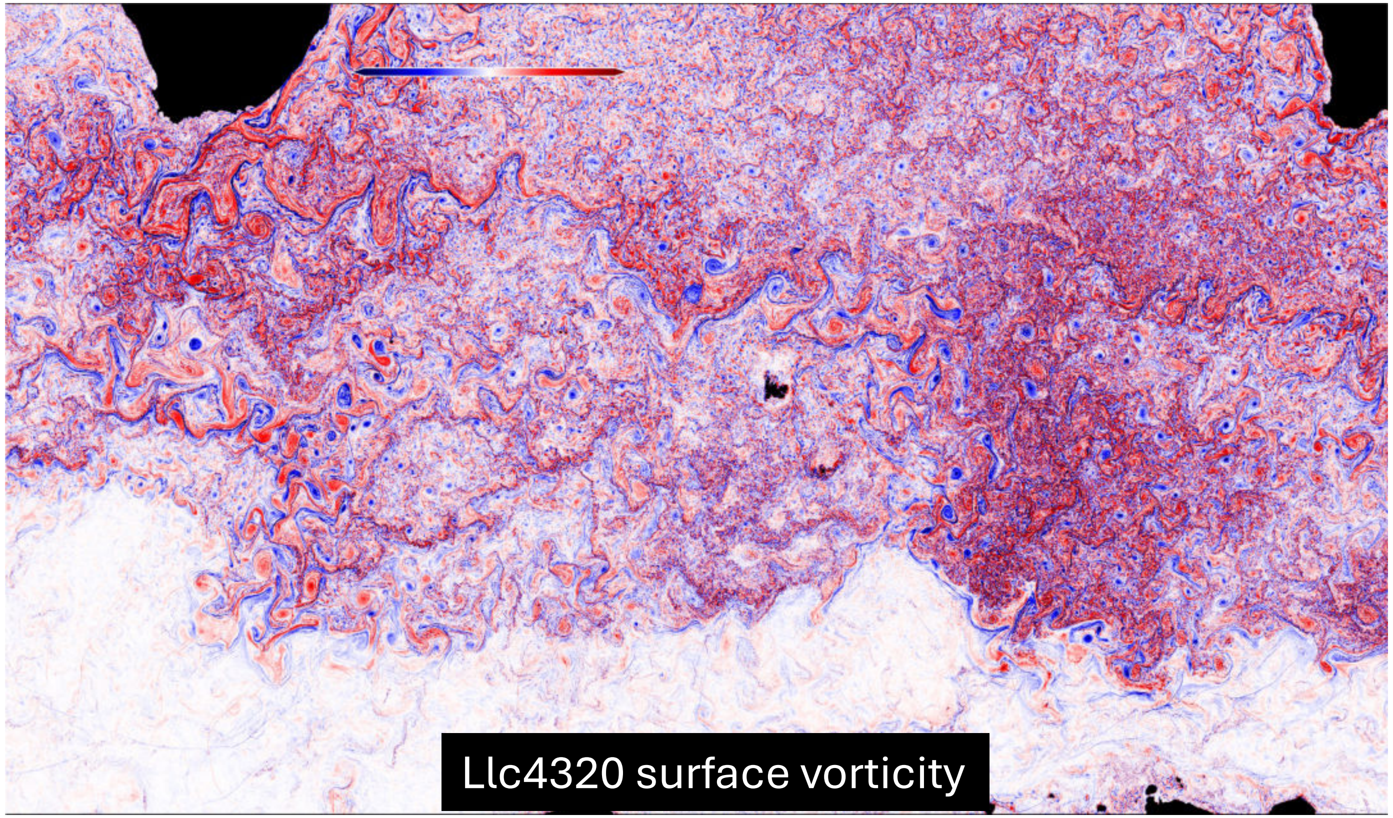
Motivation

The first project (NASA AIST) started in 2021





21-day SWOT SSH



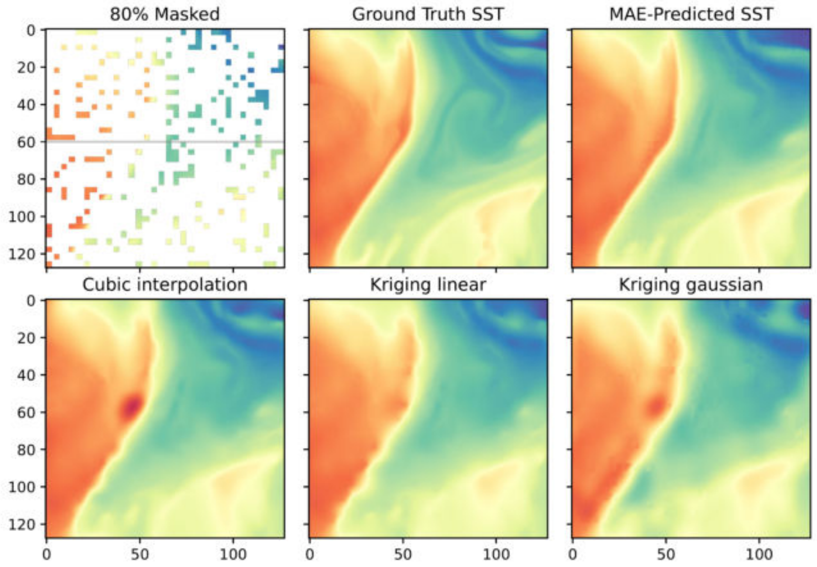
Llc4320 surface vorticity

Projects we tried

- Reconstruct infrared SST under cloud (Goh et al. 2025)
- Reconstruct infrared SST with multiple step of infrared and microwave SST (Zhao et al., 2026, revision)
- Gridding altimeter ssh (Nadir, Nadir+SWOT)
- Foundation models using spherical Fourier neural operator (SFNO)
- Can the foundation model be ‘aware’ of physics?

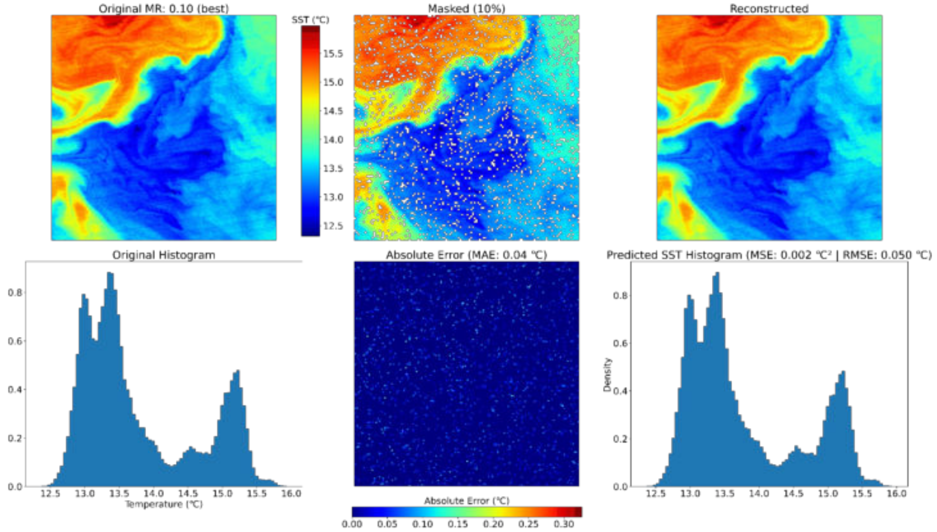
MAESSTRO Generalizes to Unseen SST Datasets
Reconstruct high-resolution SST under cloud

LLC2160



Based on facebook MAE repo (He et al. 2021).
Trained on llc4320, and validated on llc2160

VIIRS SST



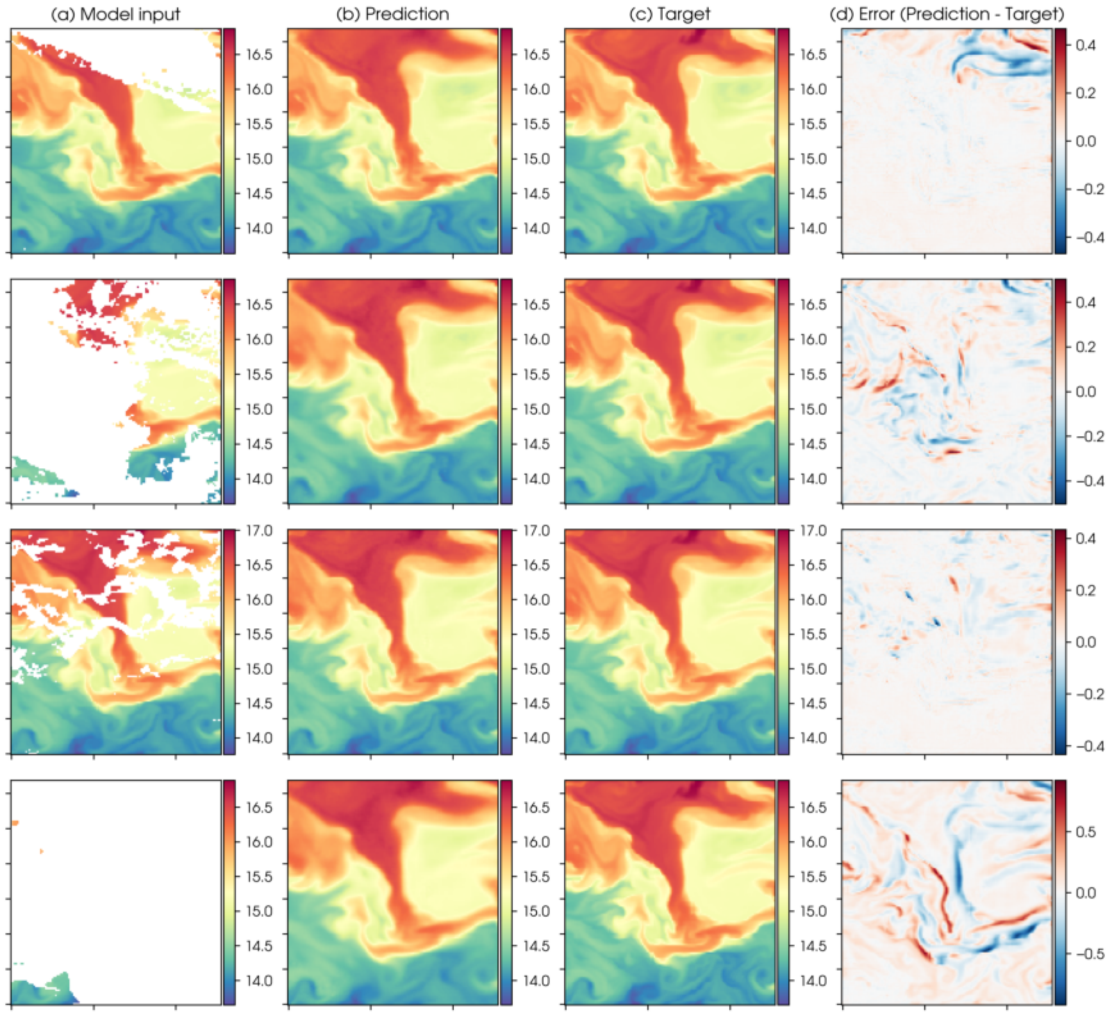
Applied to VIIRS satellite data as validation

Goh et al. 2024 Ocean Sciences

Multi-time SST retrieval

(Unet Convolutional Autoencoder)

- Take advantage of multiple time high-resolution SST observations, one can fill the large cloud gaps
- Results on the right is based on llc4320 simulations (for feasibility exploration)

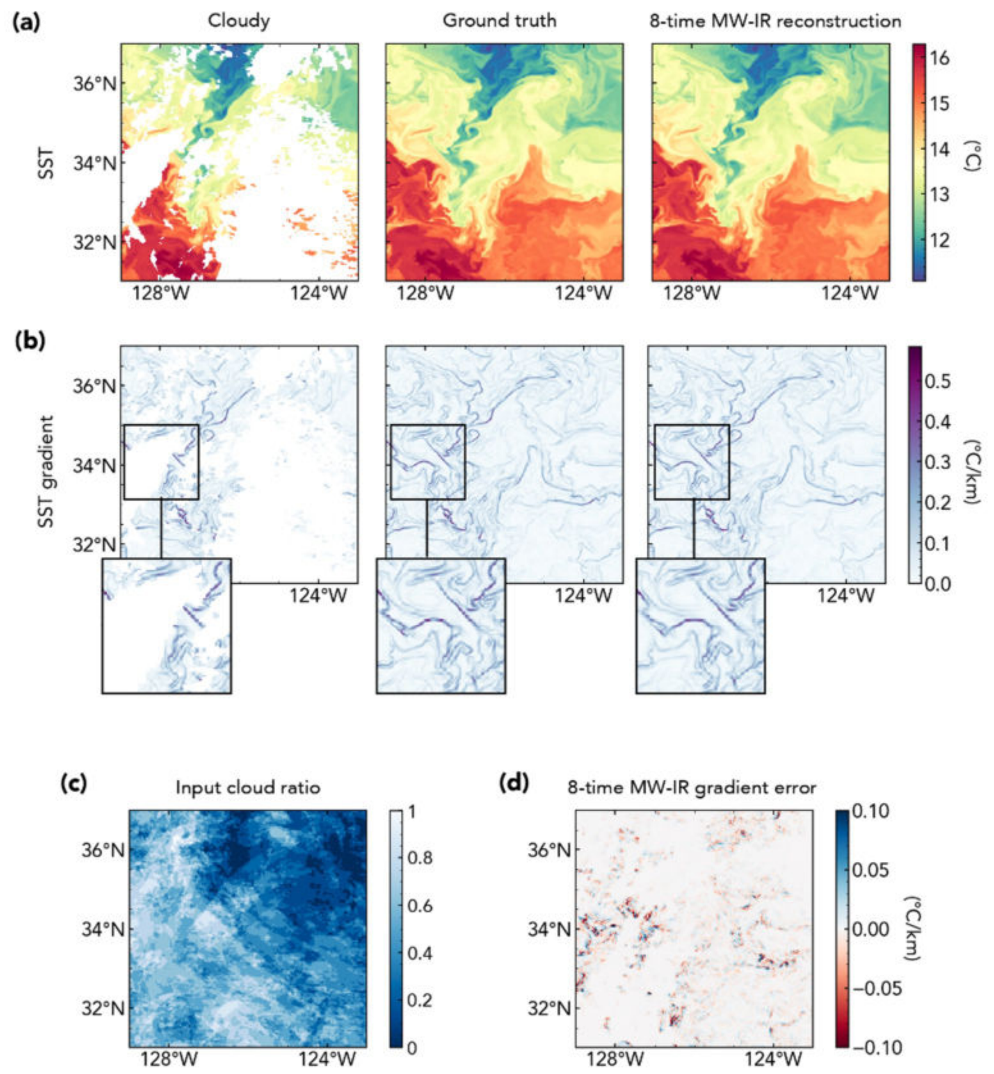


Zhao et al. 2026 under second revision

Reconstruction of High-Resolution SST under Clouds with a Multi-Satellite Multi-Temporal Model

Technical details

1. Training pairs using real cloud masks (GHRSST NOAA/STAR L3S) and cloud-free SST (MITgcm LLC4320 SST)
2. 6-hourly SST snapshots
3. Unet with 18 layers and 23.6M total parameters



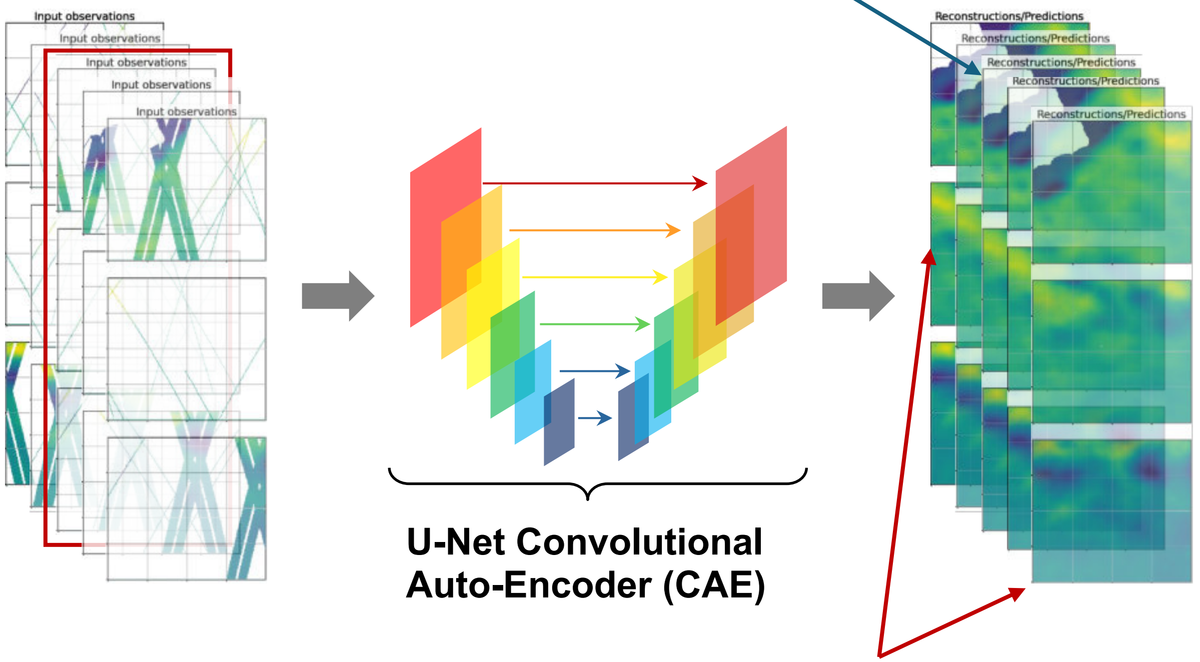
Gridding Sea surface height from altimeters

- Reconstructing the full time series might reduce performance at the outer (i.e., the first and last) days

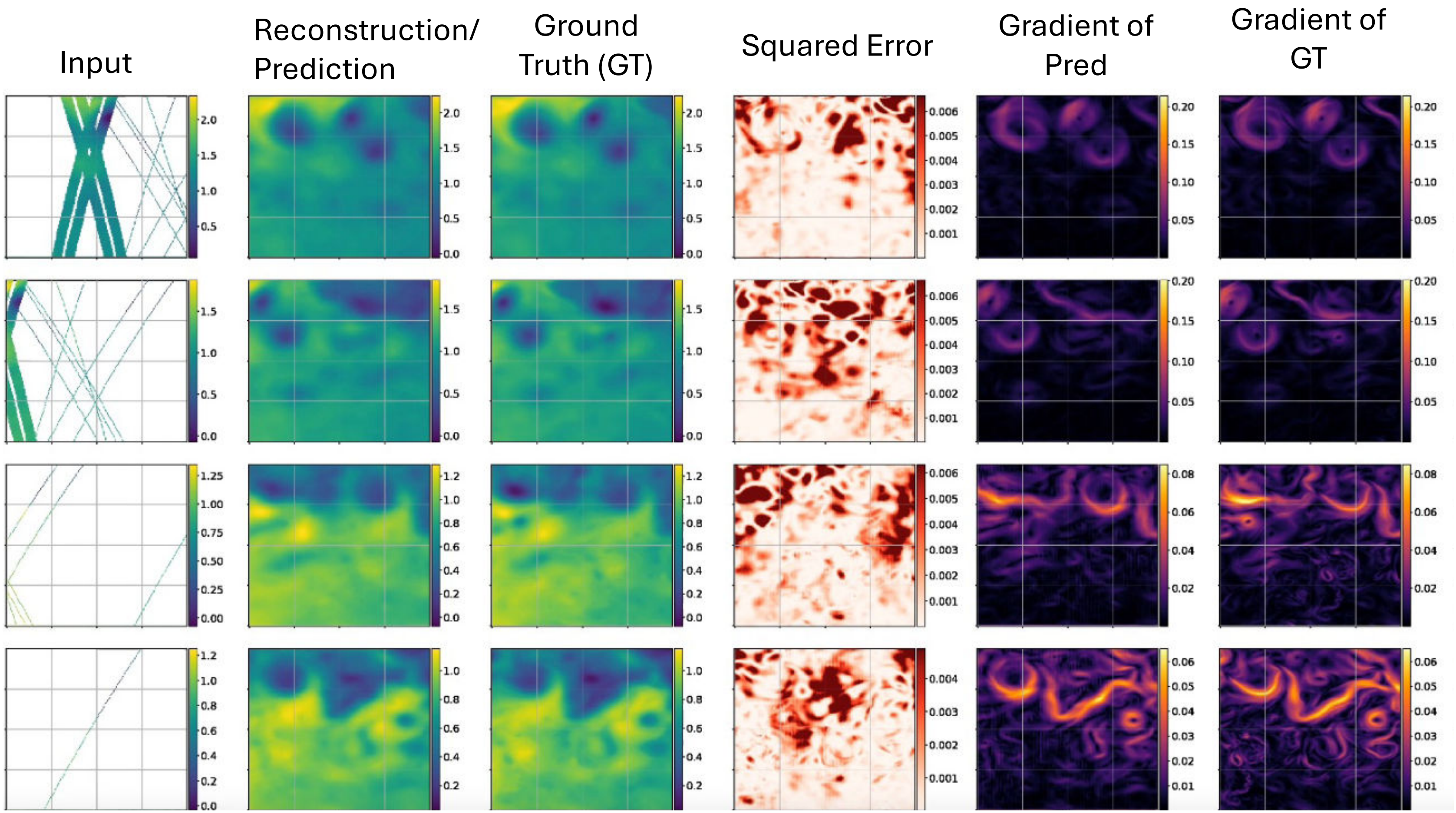
- Modify model and loss function to only reconstruct the middle day

- Weighted loss function which integrates a gradient difference loss to specifically addresses sharp transitions in dynamic regions of the ocean

Try reconstructing only the middle day, which has the most "anchor" information



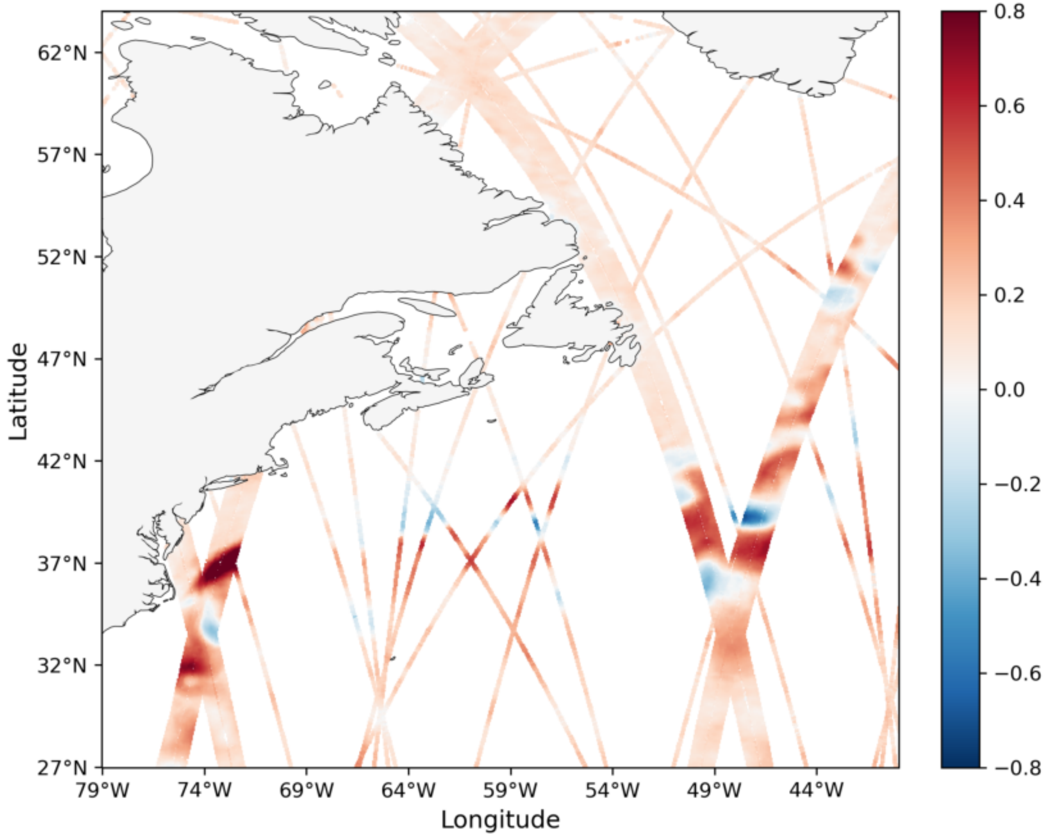
Outer snapshots lack neighboring information for a good reconstruction



Simulated SWOT + 4 nadir using NEMO NATL60 simulation (1/60th degree)

Input Data: Sea Surface Height from Five Nadir Altimeters plus SWOT Level-3

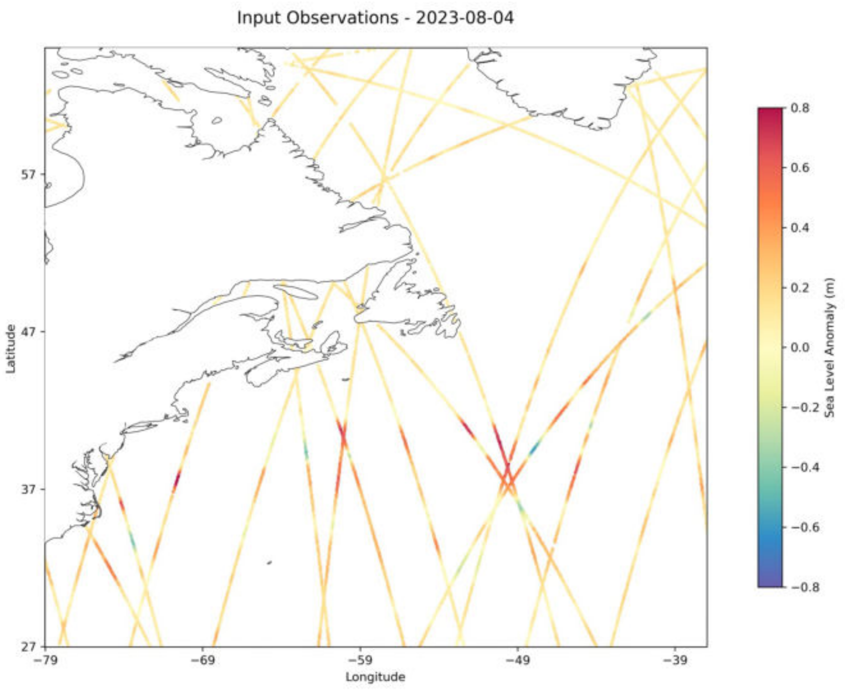
5-Satellite+SWOT SSH (m): 8/12/2023



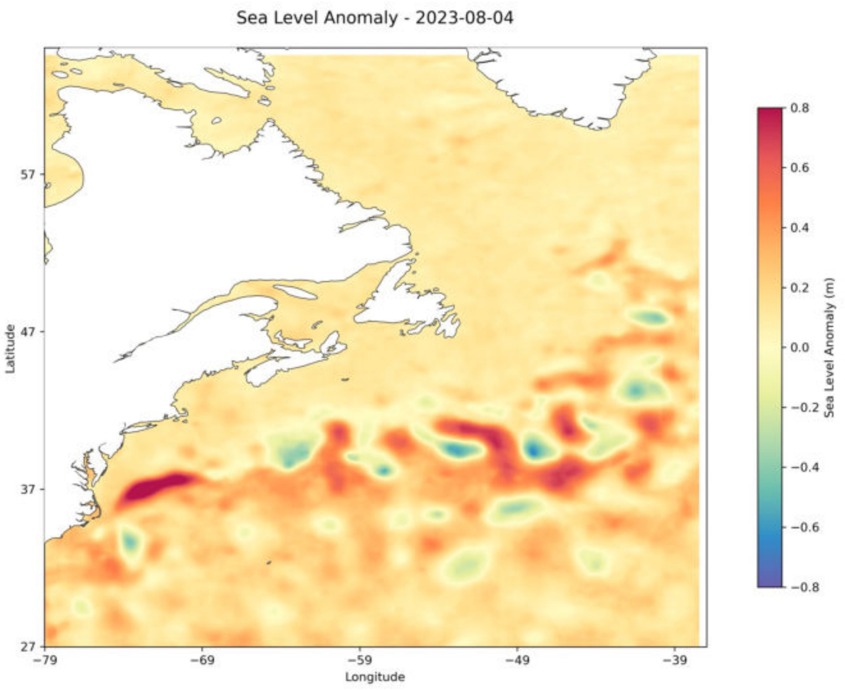
- Nadir Altimetry: Jason-3, Sentinel-3A, Sentinel-3B, CryoSat-2, SARAL/AltiKa
- SWOT: Level-3
- Region: North Atlantic (27°N-65°N, 79°W-40°W)
- Time Period: August 1- December 31, 2023
- Temporal Resolution: Daily Composite
- Spatial Resolution: Mapped to 0.05° x 0.05°

5 month rollout on five satellite (CryoSat-2, Jason-3, SARAL/AltiKa, Sentinel-3A, Sentinel-3B) and SWOT combined daily data

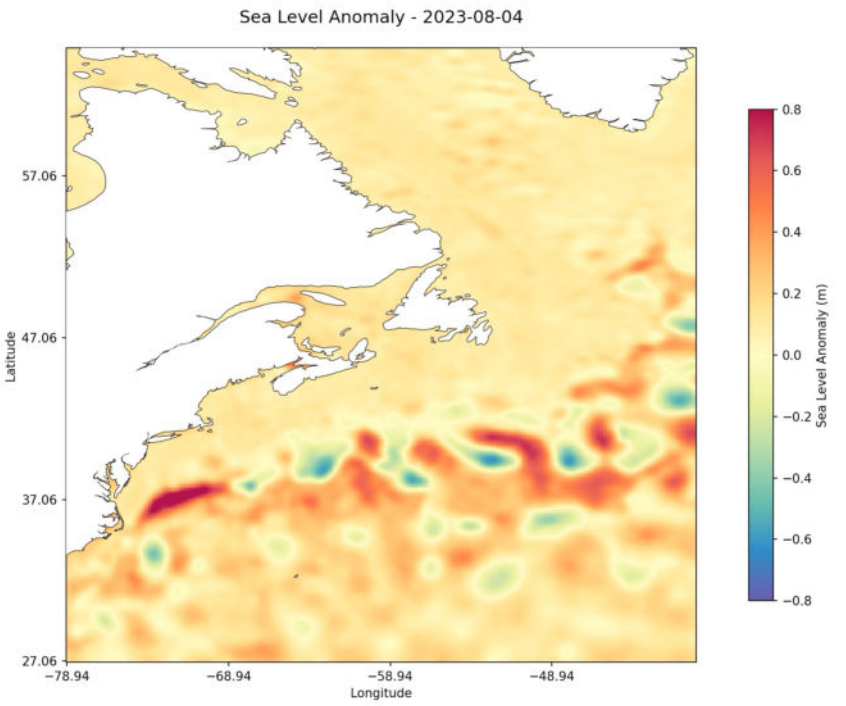
Real Observations



Our Model

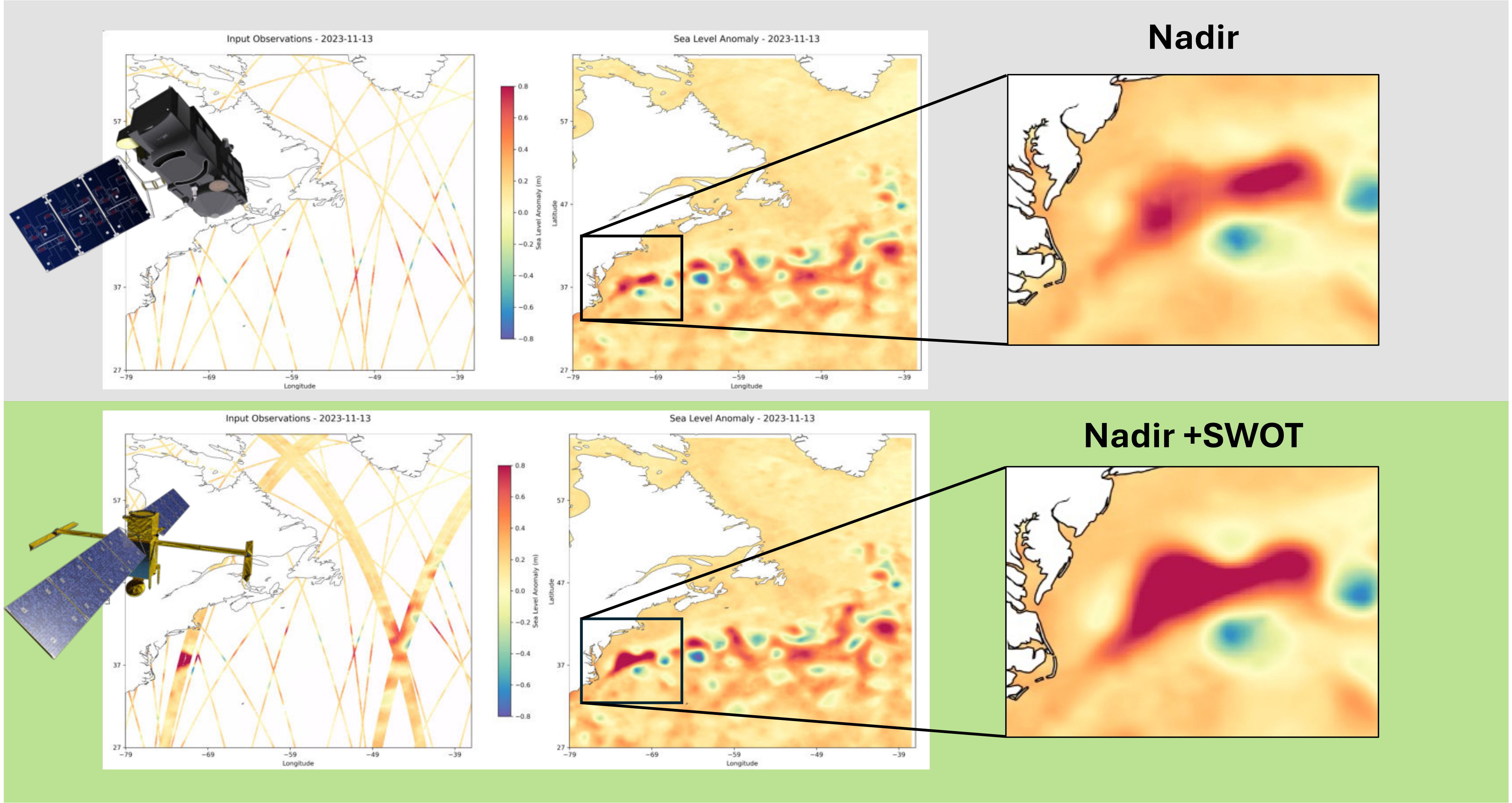


AVISO*

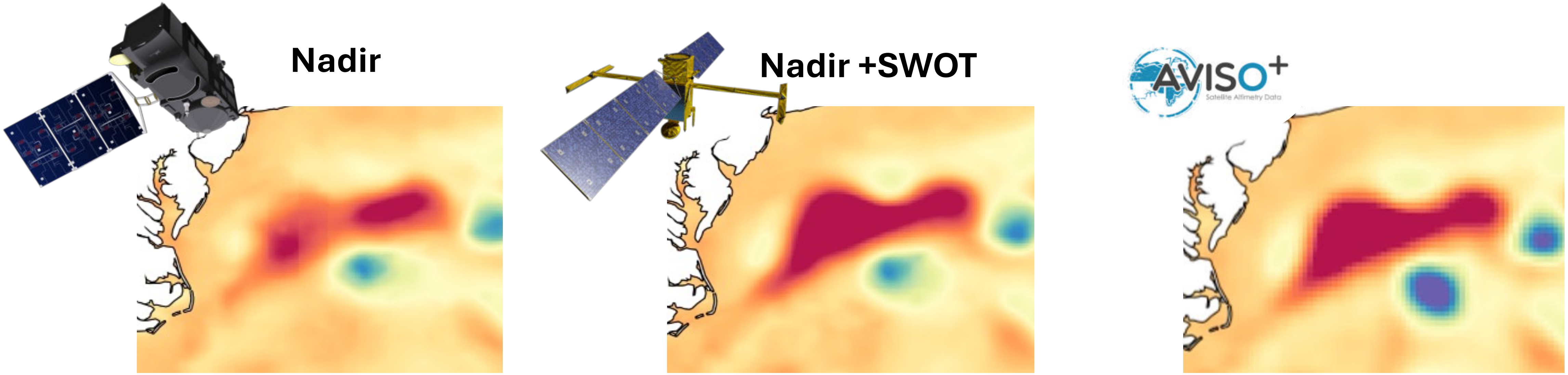


*Aviso is a widely used reference product which utilizes statistical interpolation techniques that is a consistent benchmark for evaluating reconstruction accuracy.

Value of SWOT Observations for Reconstruction



Value of SWOT Observations for Reconstruction



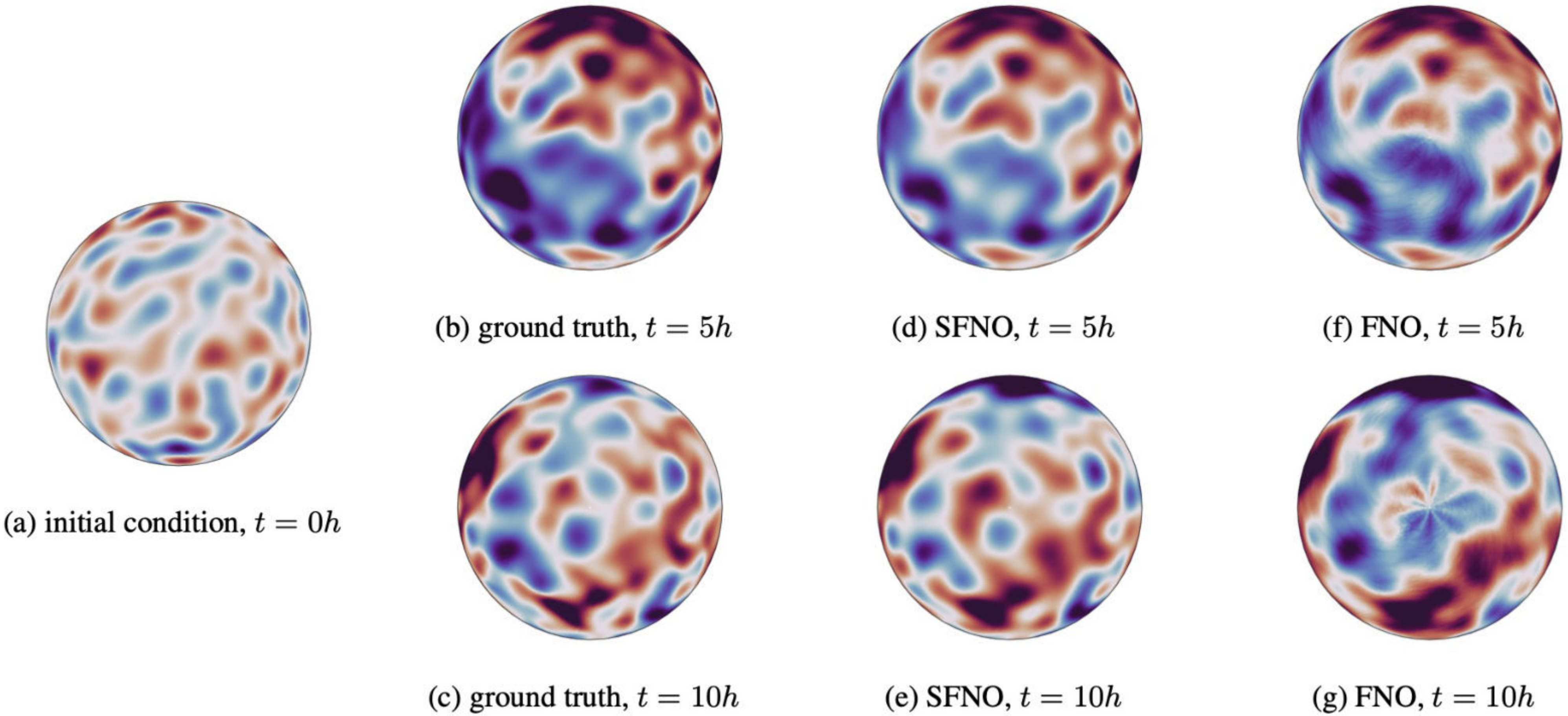
Adding SWOT observations produces reconstructions whose mesoscale shapes and gradients are more consistent with AVISO fields.

Operator learning for a surrogate model

- Goal: learn a map between functions, not just between finite vectors.

$$\mathcal{G} : a(\mathbf{x}) \mapsto u(\mathbf{x})$$

Spherical Fourier Neural Operator



(a) initial condition, $t = 0h$

(b) ground truth, $t = 5h$

(d) SFNO, $t = 5h$

(f) FNO, $t = 5h$

(c) ground truth, $t = 10h$

(e) SFNO, $t = 10h$

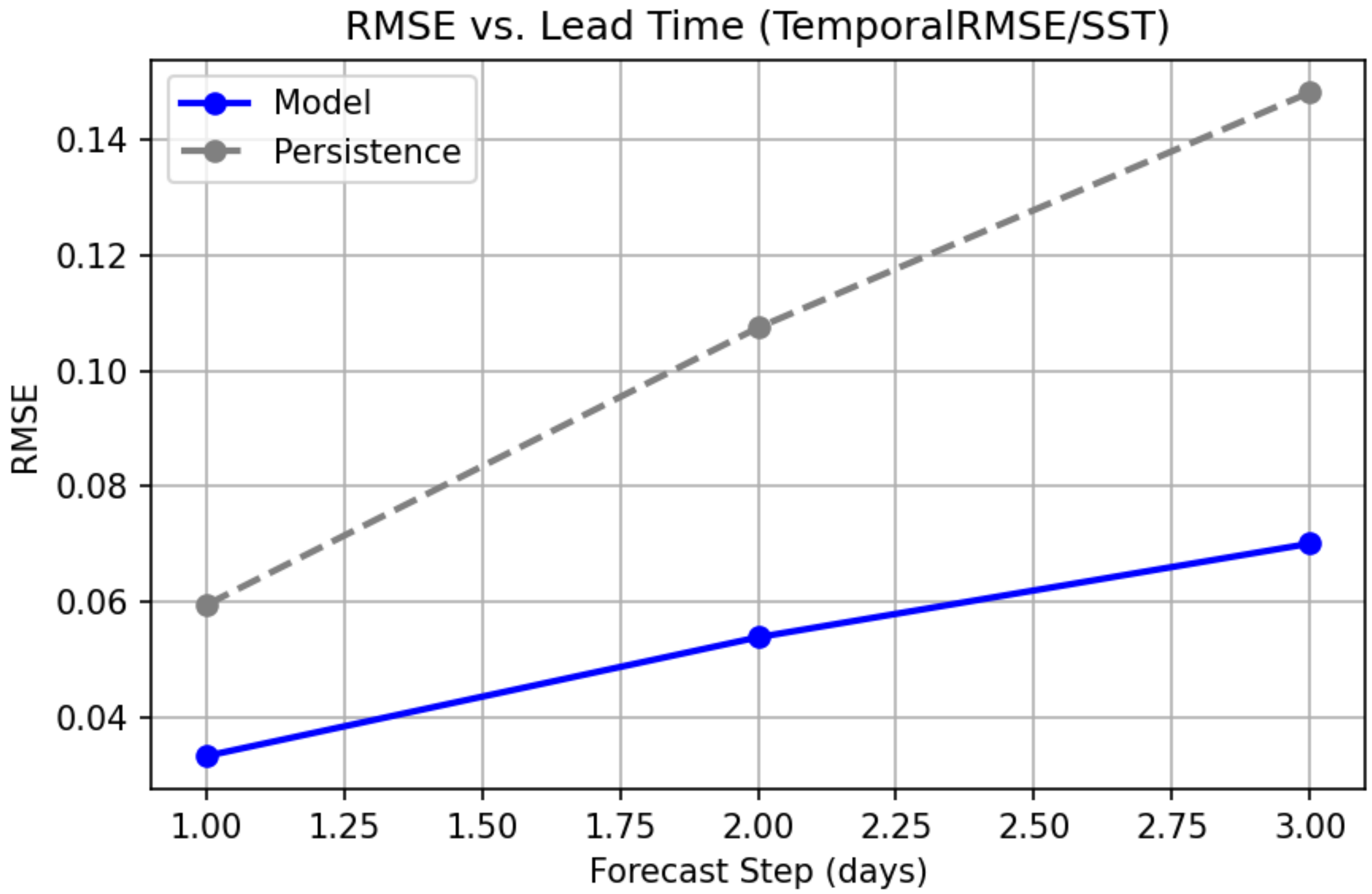
(g) FNO, $t = 10h$

Bonev et al. 2023

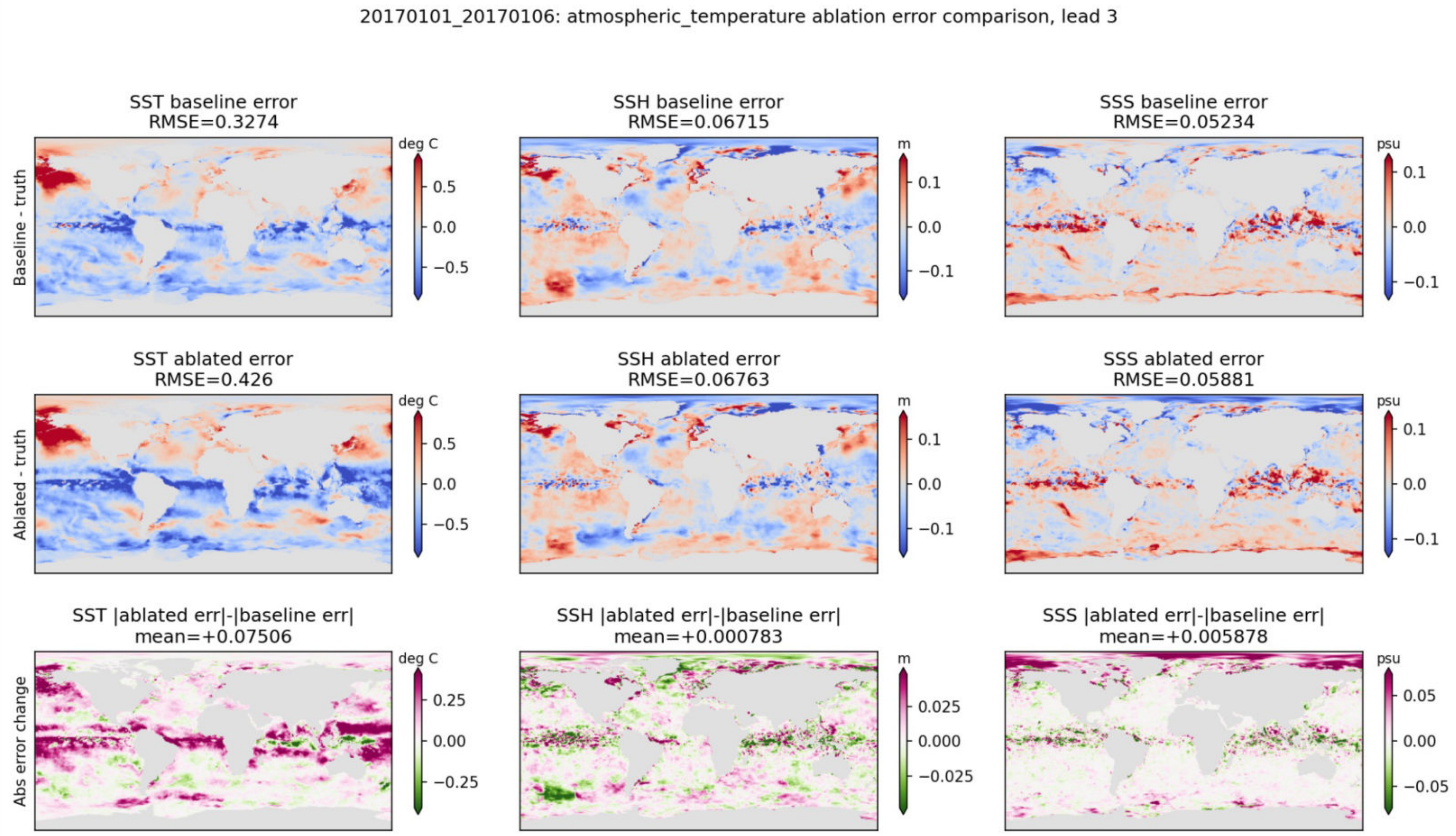
Dataset

ECCO v4r4 daily gridded 0.5-deg grid (1992-2017)

- Training: 1992 - 2012
- Validation: 2013-2017
- Surface Physical Variables
  - **Ocean**: SST, SSH, SSS, U, V
  - **Atmosphere**: temperature, humidity, pressure, winds
- Time
  - Daily
  - 3 days as input, predict 1-, 3-, 7-day output)
  - Phased using: sin(2pi*t/365), cos(2pi*t/365)


RMSE vs. Lead Time (TemporalRMSE/SST)
Model
Persistence
RMSE
0.04
0.06
0.08
0.10
0.12
0.14
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
Forecast Step (days)

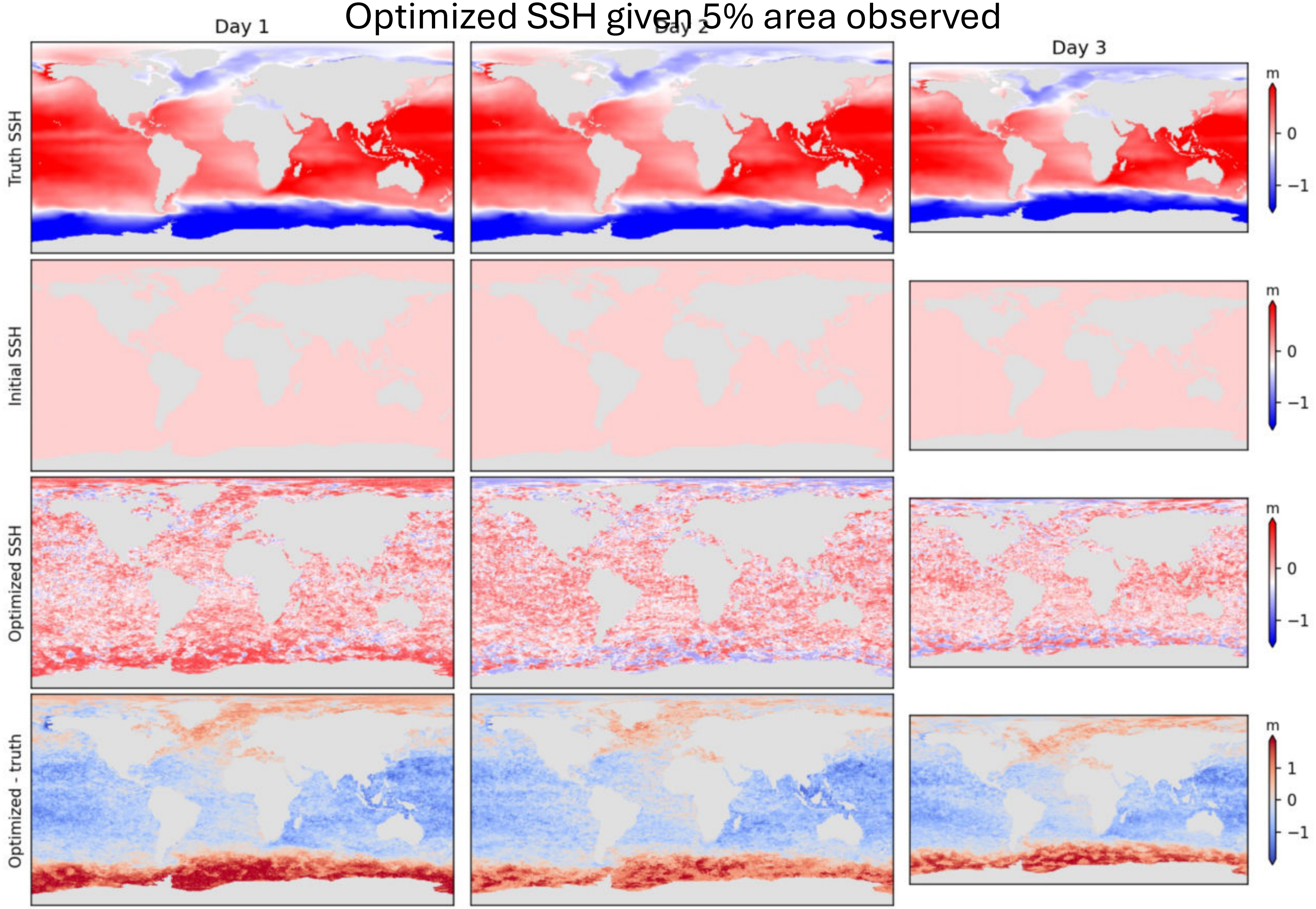
Ablation (missing atmospheric temperature forcing)



Does the surrogate 'understand' the physics?
The answer is no.

Optimize the day 1-3 input fields to minimize the misfits between forecast and observations during day 4-6.

Optimized SSH given 5% area observed



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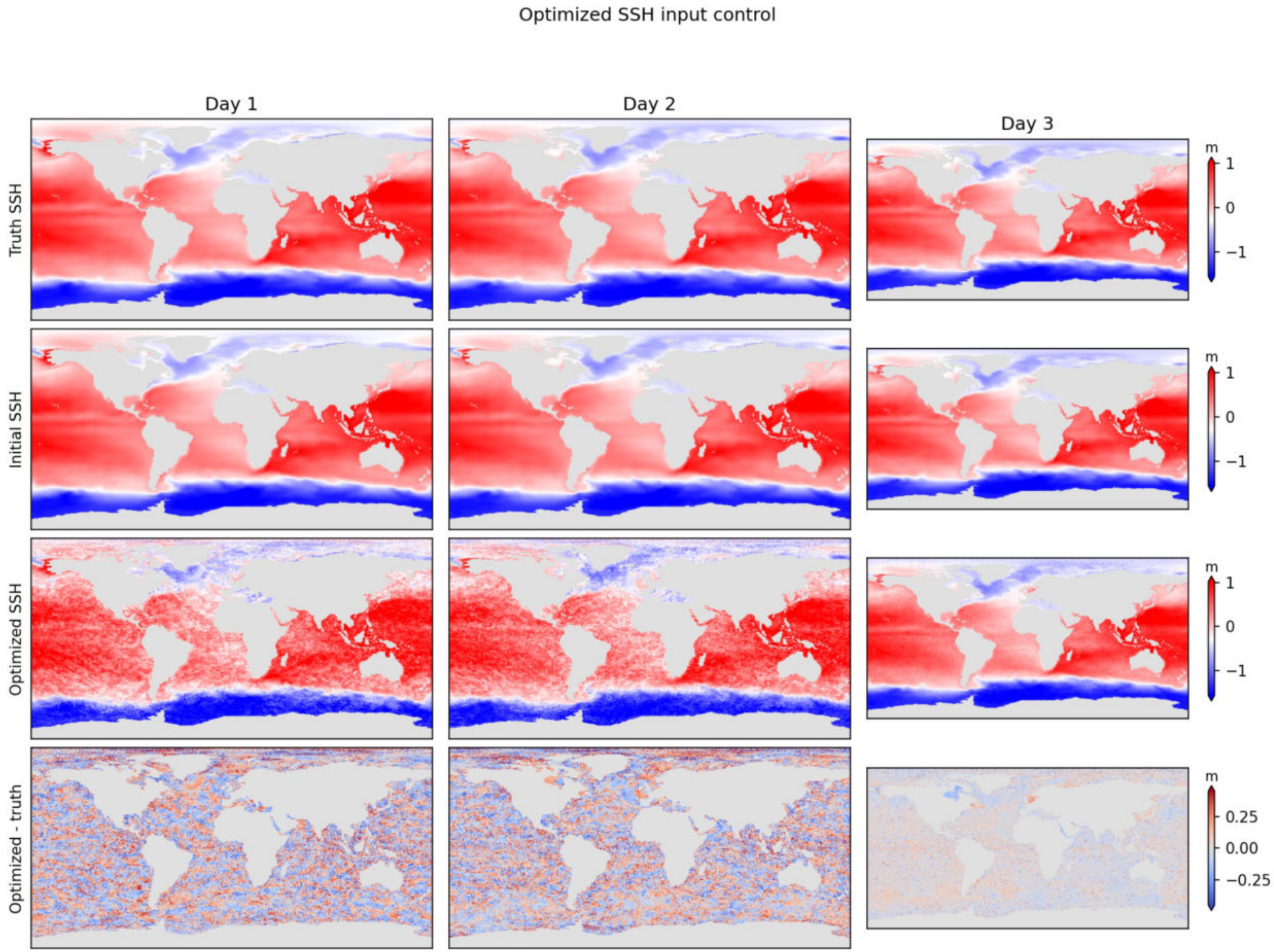

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We will commence reviewing applications on May 20th and continue on a rolling basis until we reach our maximum capacity of 50 participants. Final decisions will be communicated no later than June 15, 2026.

Undergraduate applicants to the Data Science in Oceanography program should apply via the following link: Undergraduates apply here.

All other applicants should use the general application form.

Conclusions

- Deep Neural Nets are useful for data processing -- filling the gaps, inferring subsurface state from surface, emulate KPP, climate signals etc.
- Emulators without hardcoded physics (most of the weather forecast ML methods and ocean emulators) do not follow physics and cannot be applied beyond its training scenarios.
- (Personal option) Adopting hybrid-approach (e.g., NeuralGCM) for ‘physics-constrained’ ocean foundation models

Forecast error