

How can ML applied to ocean monitoring benefit climate adaptation action?

Comparing SVR, CNN and DINEOF under simulated cloud cover

MODIS-Aqua

~60% missing

Winter + Summer



CORE QUESTION

How much temporal information is actually useful for reconstructing missing SST pixels?

A laboratory project focused on continuous coastal monitoring products.

Why reconstruct satellite SST?

Clouds create systematic gaps precisely where continuous observations are needed.

SST is operationally valuable

Sea Surface Temperature supports coastal-process monitoring, ocean–atmosphere studies, environmental analysis and numerical-model validation.

The observation problem

Optical and infrared sensors cannot observe the sea surface beneath clouds. Coastal regions may therefore remain partially unobserved for several consecutive days.

Why reconstruction matters

Gap-filling can increase temporal continuity, but the method must recover gradients and mesoscale structures without excessive smoothing.

The challenge is not simply filling pixels — it is preserving physically meaningful spatial variability.

Does more temporal information improve reconstruction?

We test whether increasing the temporal window consistently benefits different reconstruction approaches.

OBJECTIVES

01

Build a controlled validation framework

Use nearly cloud-free SST scenes as Ground Truth and remove ~60% of valid pixels artificially.

02

Compare three reconstruction approaches

Evaluate a traditional EOF-based method against two Machine Learning models: SVR and CNN.

03

Test temporal sensitivity

Vary the amount of neighboring temporal information used by the ML models.

04

Identify method-specific optimal scales

Determine which temporal configuration minimizes error while preserving observed variability.

Working hypothesis

Nearby observations should be more representative of the target-day ocean state, while increasingly distant days may introduce different thermal structures.

→ Optimal window size may therefore depend on the algorithm.

Three reconstruction strategies

The methods differ in how they use spatial and temporal information.

DINEOF

TRADITIONAL BASELINE

**Data Interpolating Empirical
Orthogonal Functions**

Uses the complete ~3-year series

Captures dominant covariance patterns but may smooth sharp structures.

SVR

MACHINE LEARNING

Support Vector Regression

Tested with neighboring-day windows

Learns nonlinear relationships from temporal predictors at each reconstruction target.

CNN

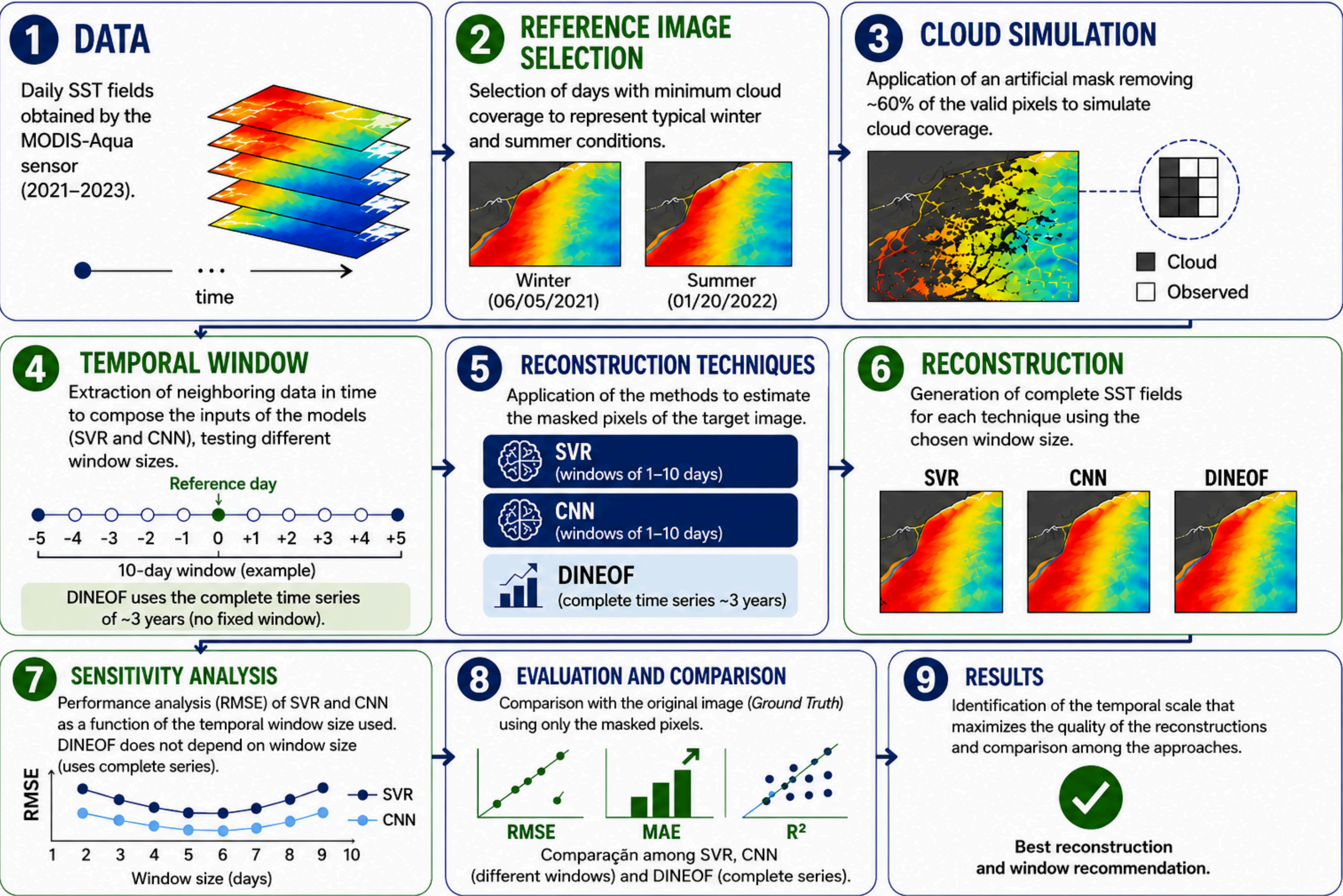
DEEP LEARNING

Convolutional Neural Network

Tested with neighboring-day windows

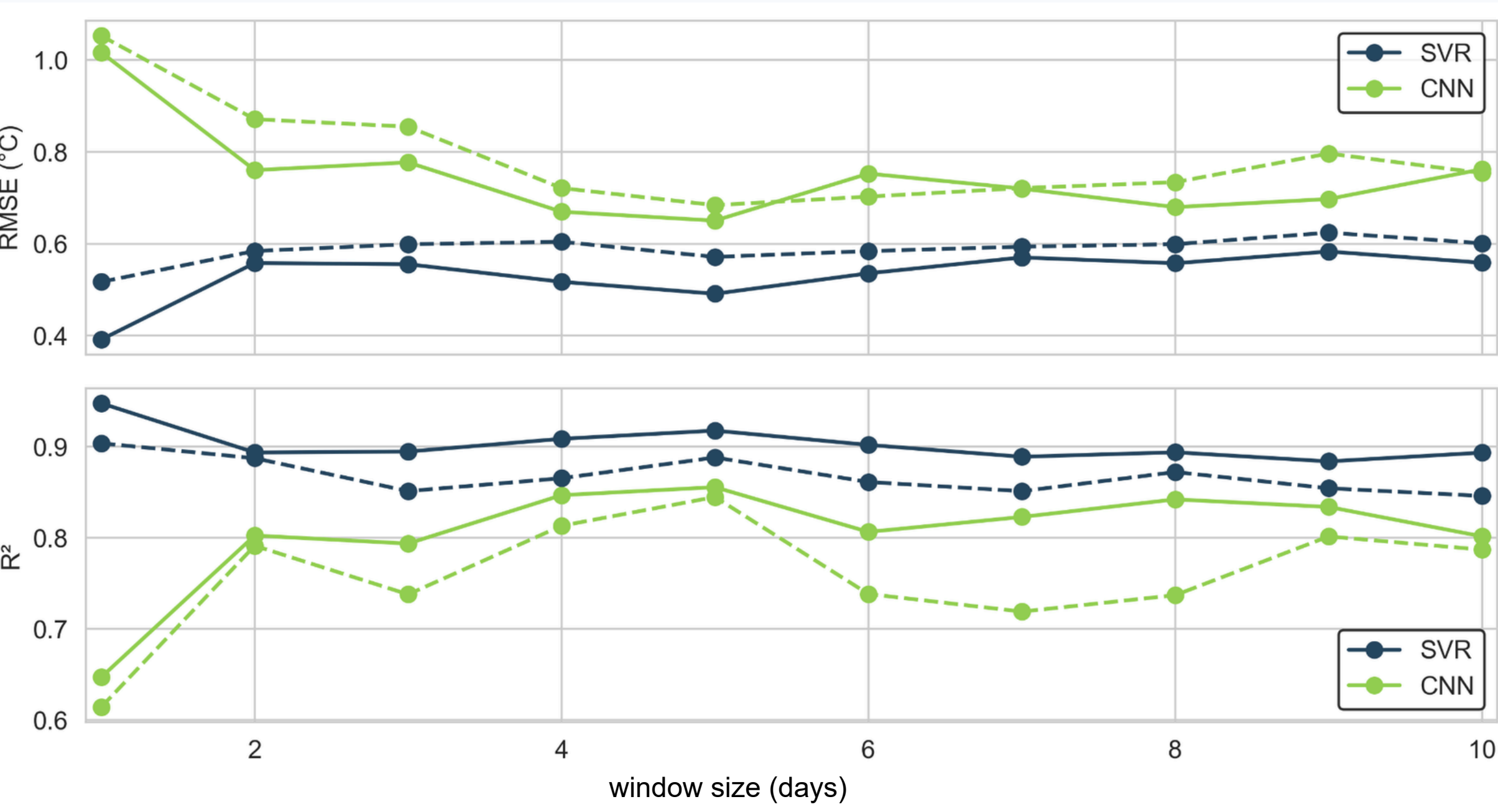
Uses spatial context and temporal information to recover structured fields.

Experimental design



Temporal window matters — but differently for each model

Performance was evaluated across neighboring-day windows; solid and dashed curves represent the two seasonal cases.



KEY PATTERN

SVR favors short temporal context.

Its best configuration is centered close to the target day, suggesting strong short-term SST persistence.

CNN shows a different response, benefiting from a broader temporal context than SVR.

Best-performing configurations

SVR achieved the lowest errors in both seasonal experiments.

WINTER • SVR

0.39 °C

RMSE | $R^2 = 0.947$

SUMMER • SVR

0.52 °C

RMSE | $R^2 = 0.902$

WINTER • DINEOF

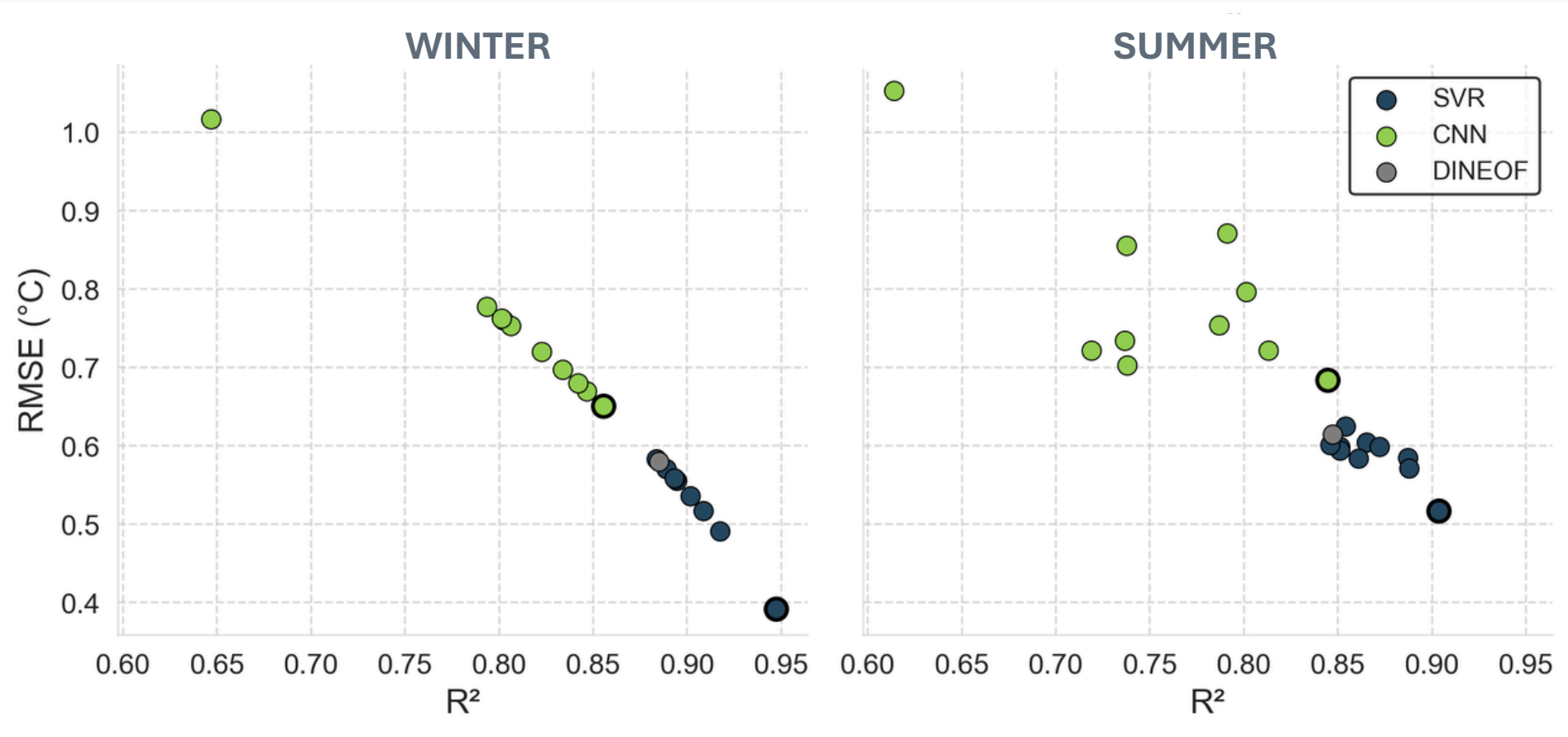
0.58 °C

RMSE | $R^2 = 0.885$

SUMMER • DINEOF

0.61 °C

RMSE | $R^2 = 0.854$



What the numbers show

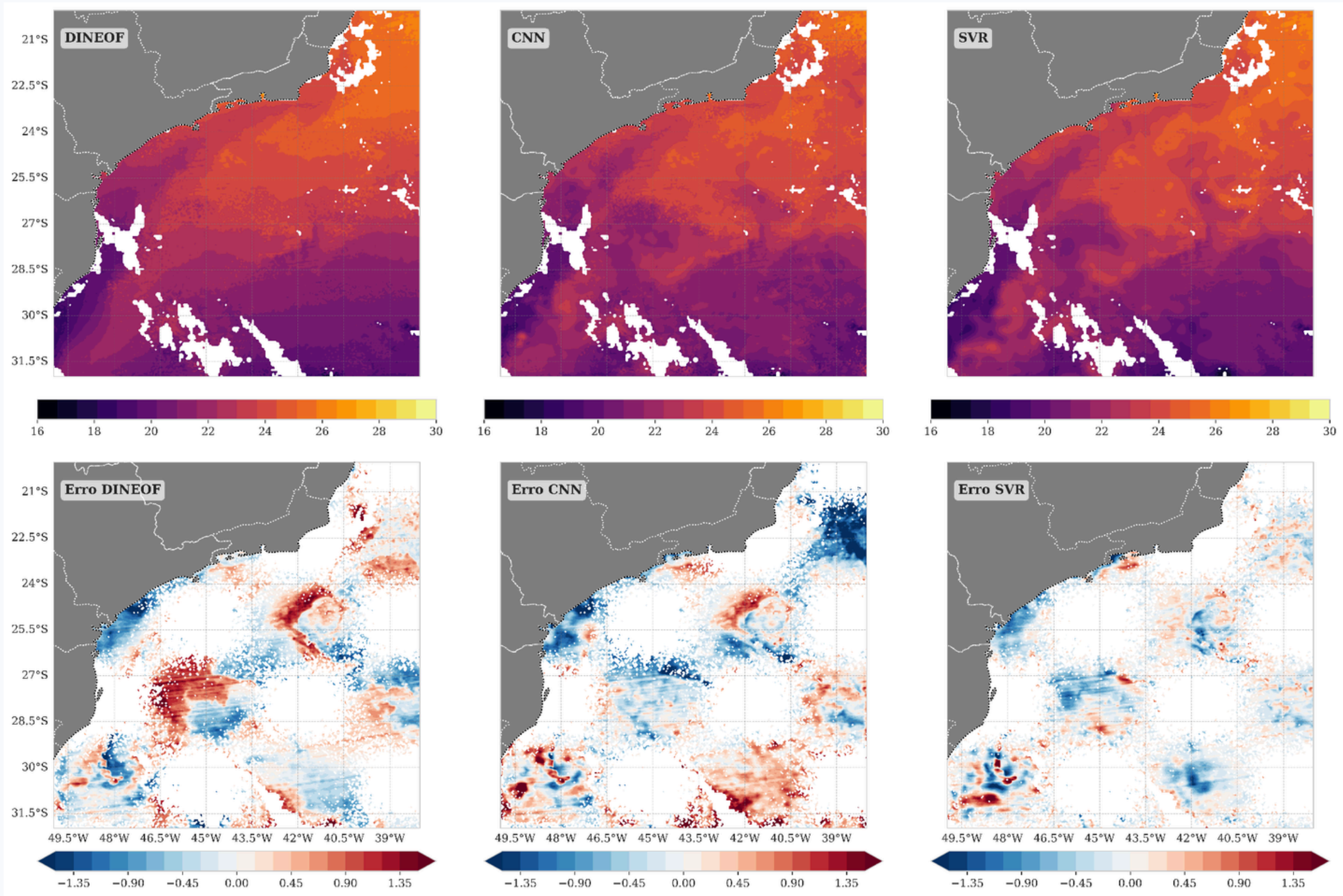
SVR ($t \pm 1$ day) reduced winter RMSE by ~33% relative to DINEOF.

Seasonality remains visible: errors are higher in summer, when SST structures are more variable.

More days $\neq$ more skill.

Winter reconstruction

The spatial error patterns reveal how each method preserves gradients and small-scale SST structures.



WINTER

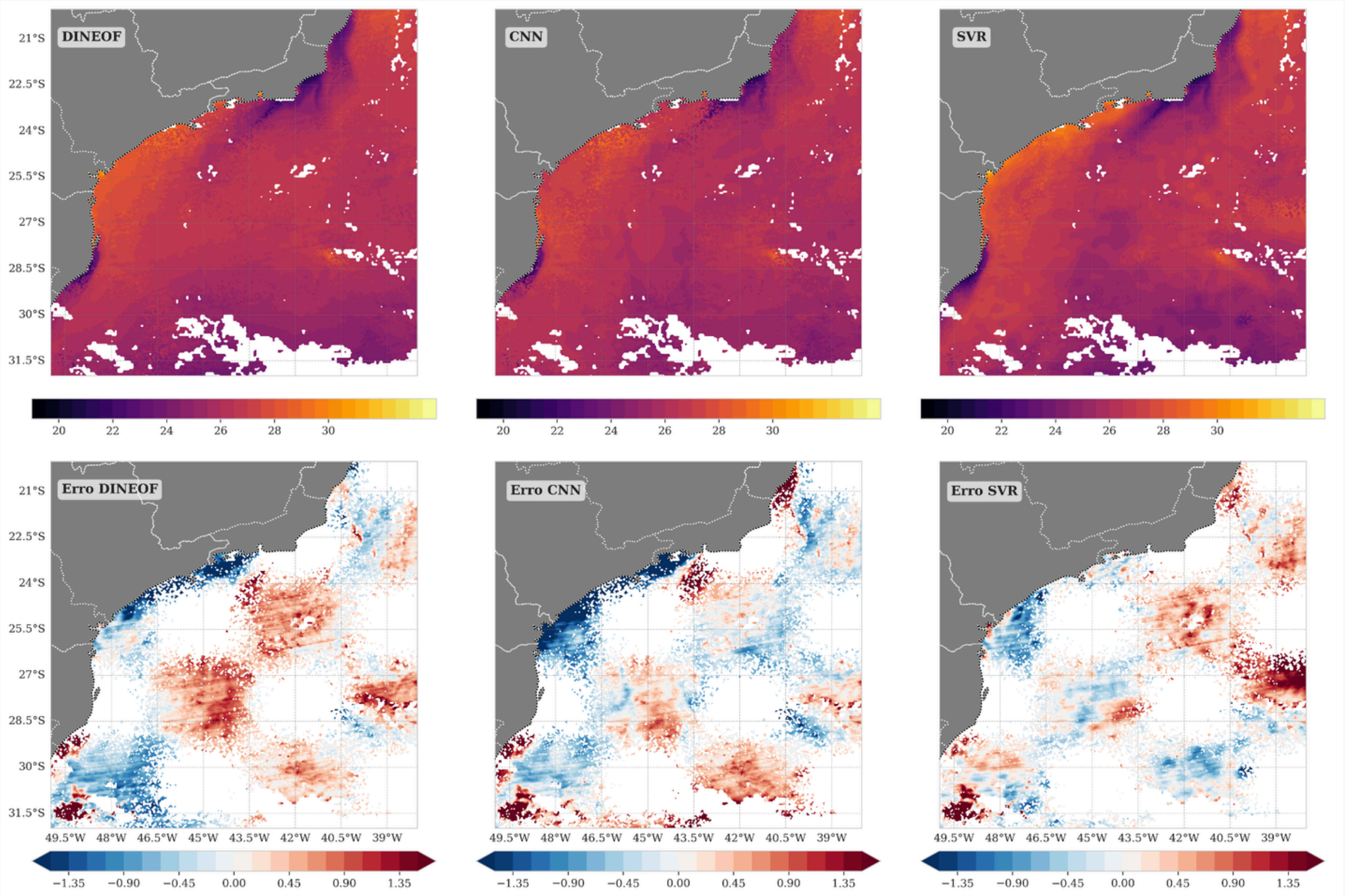
SVR produces the most localized residuals.

The reconstruction better preserves strong thermal gradients, while DINEOF shows more spatial smoothing and CNN retains broader residual structures.

Best: SVR $t \pm 1$ day

Summer reconstruction

Higher spatial-temporal variability makes the reconstruction problem more demanding.



SUMMER

All methods face larger errors in dynamic regions.

Despite the seasonal increase in difficulty, SVR remains the strongest overall performer and retains important spatial structures.

RMSE: 0.52 °C

What did we learn?

Temporal scale is a model parameter, not simply “more information is better.”

1 Short temporal context can be optimal

SVR performed best with $t \pm 1$ day, indicating that observations close to the target date contain the most useful information for this model.

2 Algorithms exploit time differently

CNN benefits from a broader context than SVR, reinforcing that the optimal temporal scale is method-dependent.

3 Seasonality changes reconstruction difficulty

Summer SST variability reduces temporal persistence and increases sensitivity to the selected window.

4 Operational potential is promising

The framework can support more continuous satellite products and can be extended to sea-surface salinity and short-term forecasting.

More temporal information does not necessarily mean a better SST reconstruction.

Next steps

Toward a more realistic and efficient data-imputation framework



1 REALISTIC CLOUD MASKS

Replace idealized synthetic masks with observed cloud patterns presenting ~60% missing-data coverage.

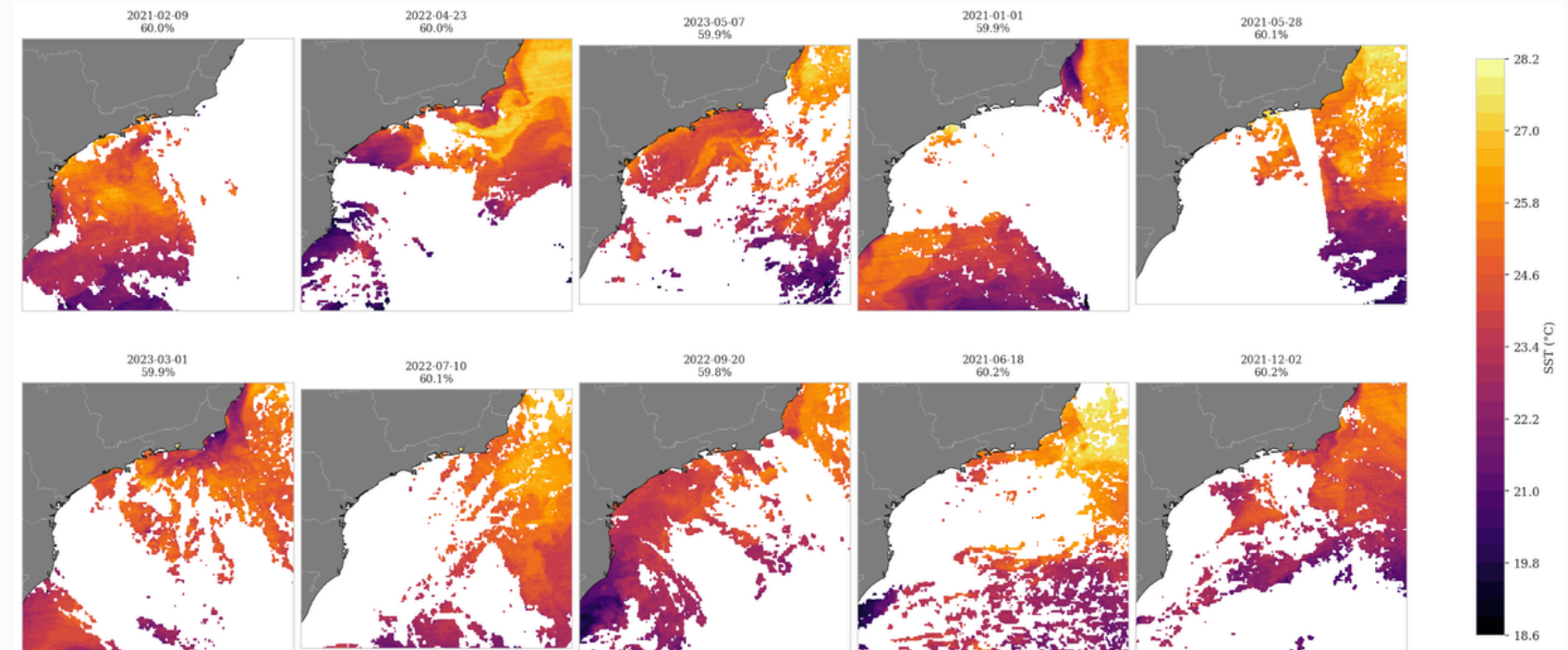
2 SVR OPTIMIZATION

Focus the imputation framework on SVR and tune its hyperparameters to improve reconstruction accuracy and computational efficiency.

3 MULTIVARIABLE APPLICATION

Extend the optimized approach to SST, chlorophyll-a, remote-sensing reflectance and SSS.

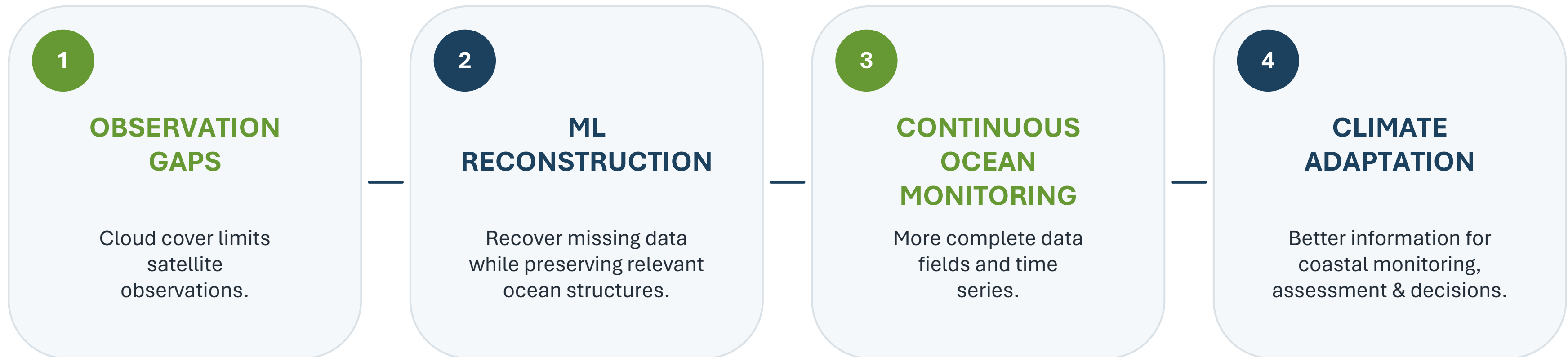
Goal: a robust imputation workflow for multiple satellite ocean variables.



Observed cloud patterns with approximately 60% coverage

From data gaps to climate action

How can ML-based ocean reconstruction support climate adaptation?



ML does not replace ocean observations, it helps transform incomplete observations into more continuous information for climate adaptation.

THANK YOU

Prof. Marcelo Dottori

Oceanographic Institute — University of São Paulo
mdottori@usp.br



**Coastal Hydrodynamics
Laboratory**

