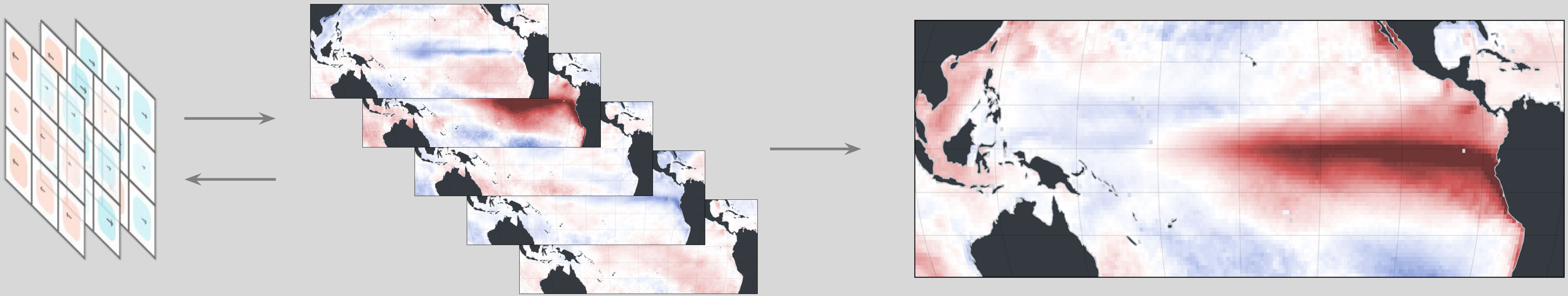
Interpretable ENSO Forecasting using Hybrid Deep Learning Analog Approach



Kinya Toride

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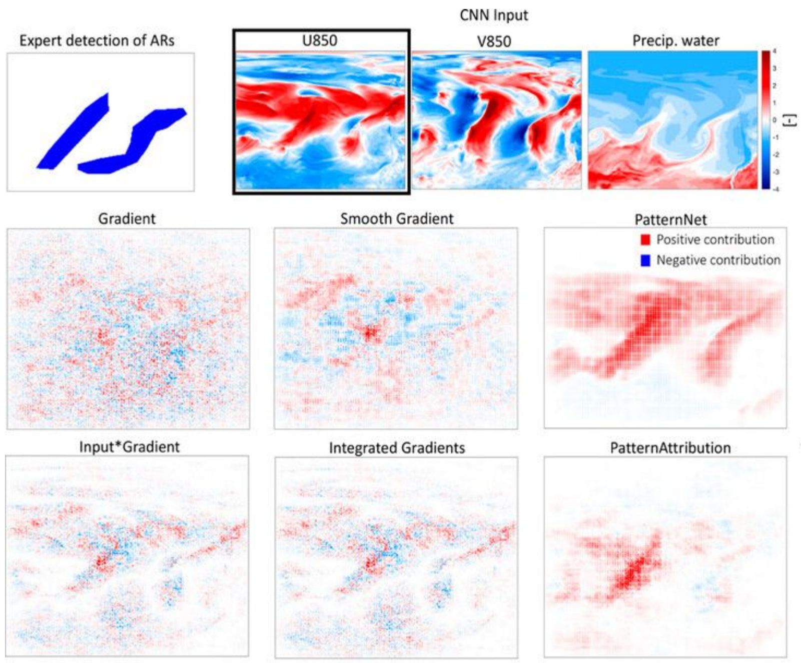
March 5 2024 CESM ESPWG

Machine learning and interpretability

- Machine learning shows promising prediction skill of ENSO.
- However, it is challenging to explain what the "black box" does.
  1. XAI is a *post hoc* explanation of the black box
  2. There is no ground truth for the attribution



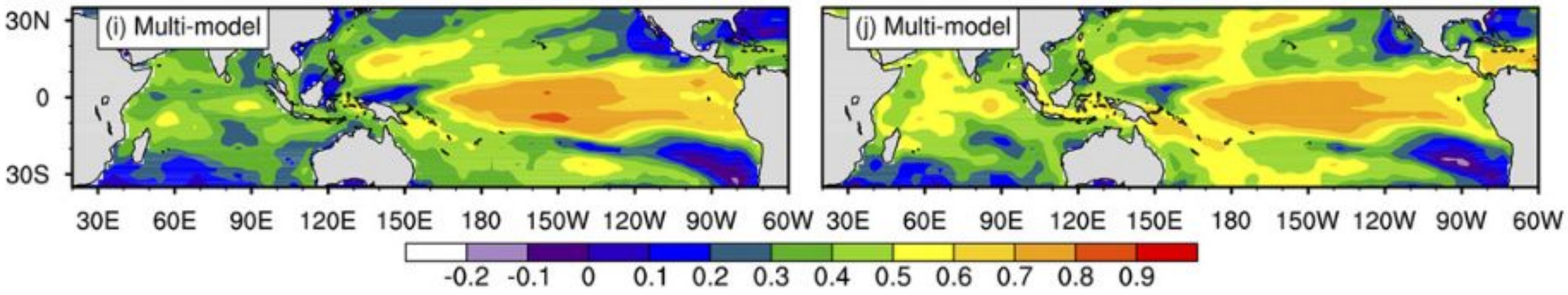
Explanations from different xAI methods for classifying atmospheric rivers (Mamalakis et al. 2022)

“Model-Analog” forecasts

- Forecasts based on resembling states (e.g., Lorenz 1969)
- Model-analog provides a comparable hindcast skill to dynamical models

Model-analog

NMME (dynamical models)

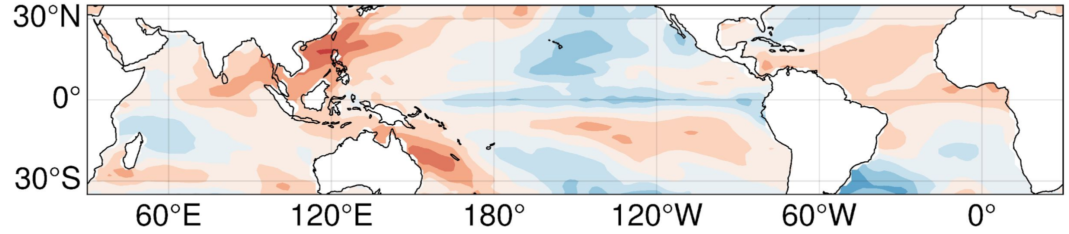


Anomaly correlation of SST forecast at 6 months lead

Ding et al. (2018)

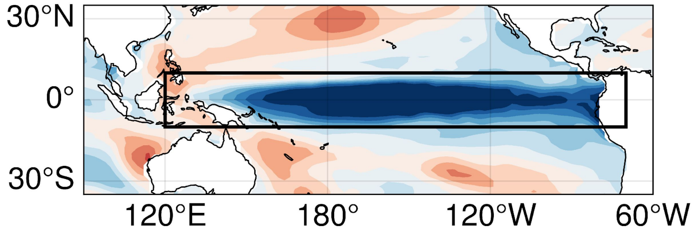
Issue: Initial analogs can evolve to very different states

Initial condition

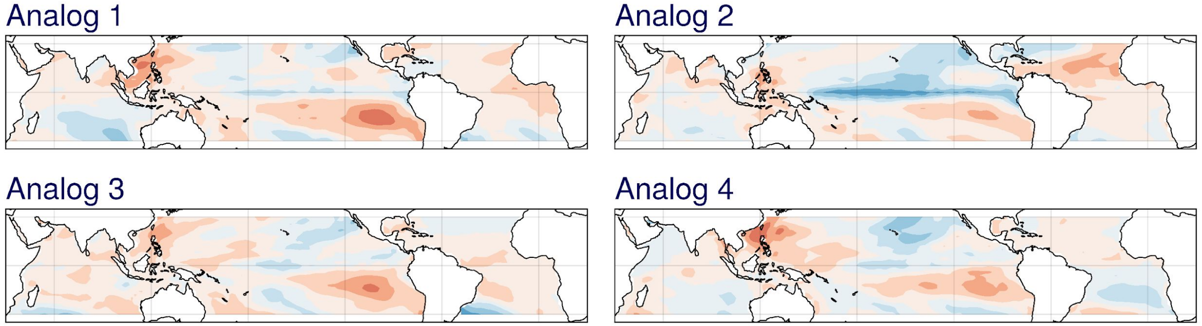


12 months

Target



Analogs (closest conditions)

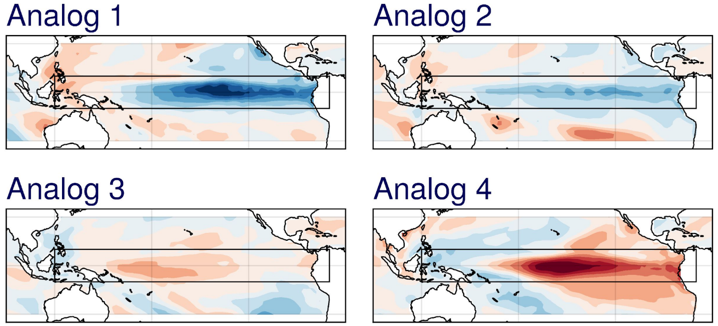


Analogs based on the entire tropical region.

??

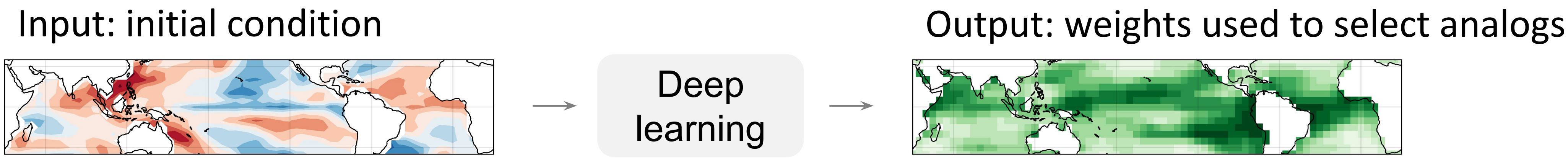
12 months

Analog forecasts



Small errors can grow significantly

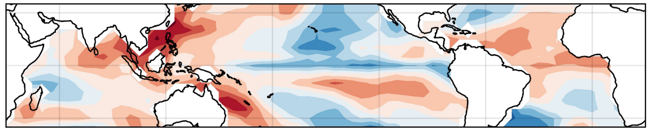
Aim: Use deep learning to constrain error growth



Train DL to find “sensitive region” where initial error growth is significant

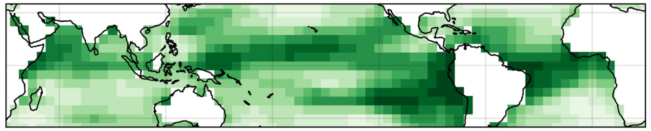
Hybrid deep learning and model-analog (DL + MA)

Input: initial condition



→ Deep learning →

Output: weights used to select analogs



↓

Analog forecasting

Interpretability

- Estimated weights show important (sensitive) regions.
  Objectively evaluated by forecasting skill

- Analog forecasting provides evolution of the entire system.
  Fully based on physical models

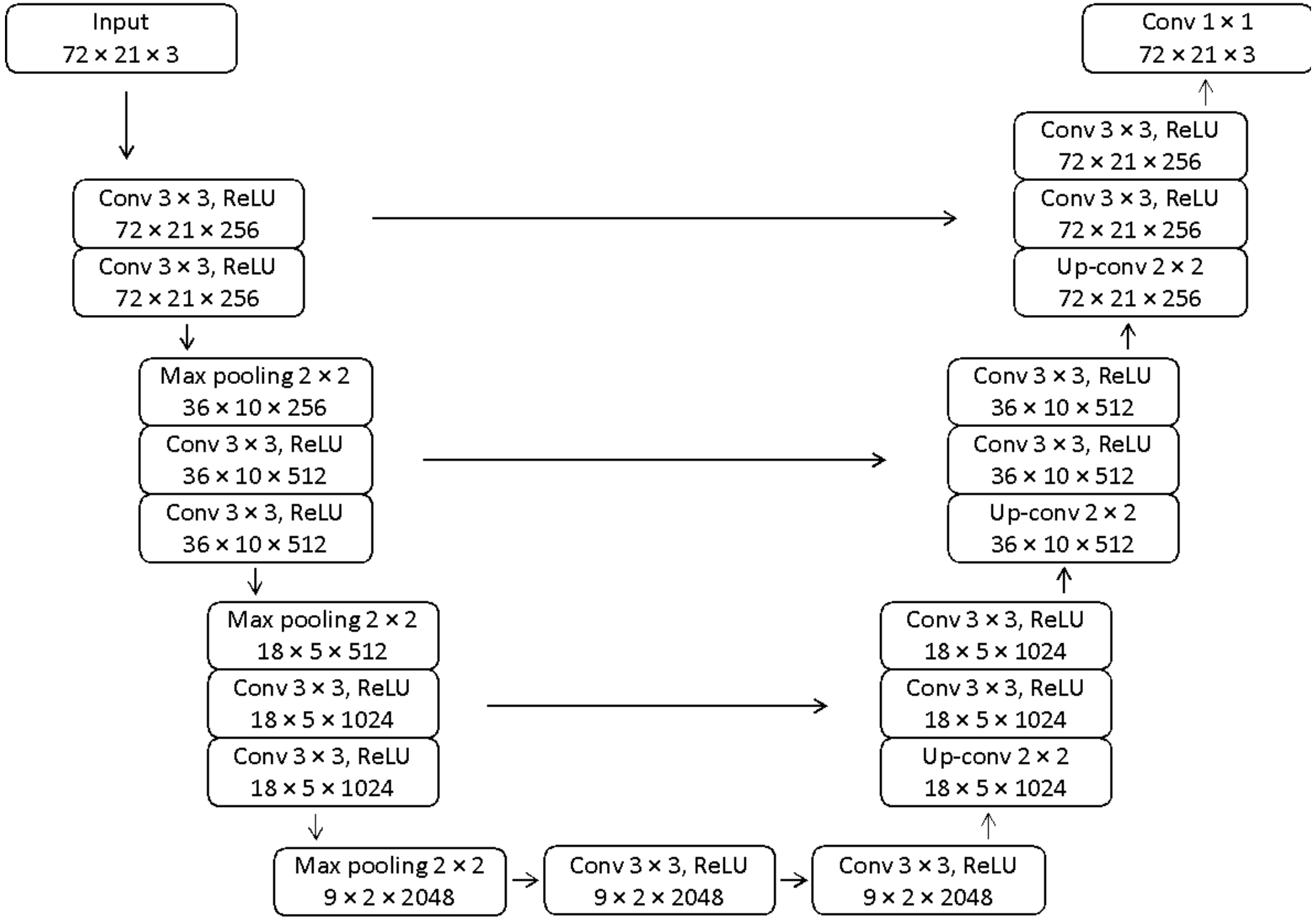
Data: Large-ensemble simulation

CESM2 (climate model)

- 1850–2014, 100 ensembles
- Monthly anomaly
- Sea surface temperature (SST)
- Sea surface height (SSH)
- Zonal wind stress (TAUX)
- 50°S–50°N

	Period	Sample size
Training (library)	1865–1958	94 y × 100 (70%)
Validation	1959–1985	27 y × 100 (20%)
Test	1986–1998	13 y × 100 (10%)

4-layer U-Net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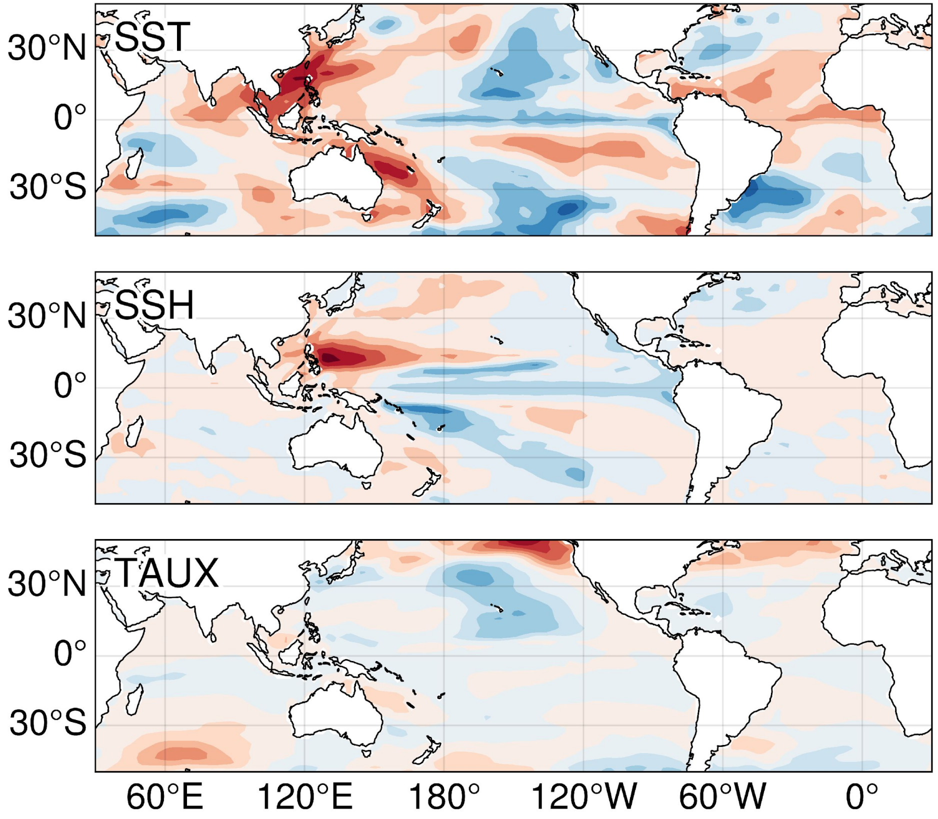
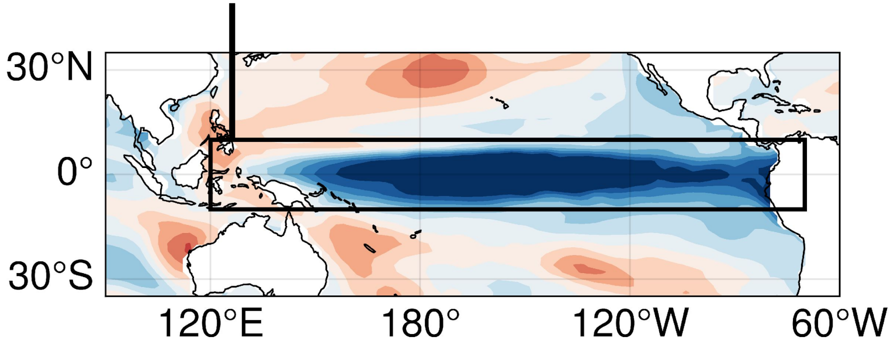
Conv 3 × 3, ReLU
72 × 21 × 256
Conv 1 × 1
72 × 21 × 3

Target: SST pattern over the equatorial Pacific

Initial conditions

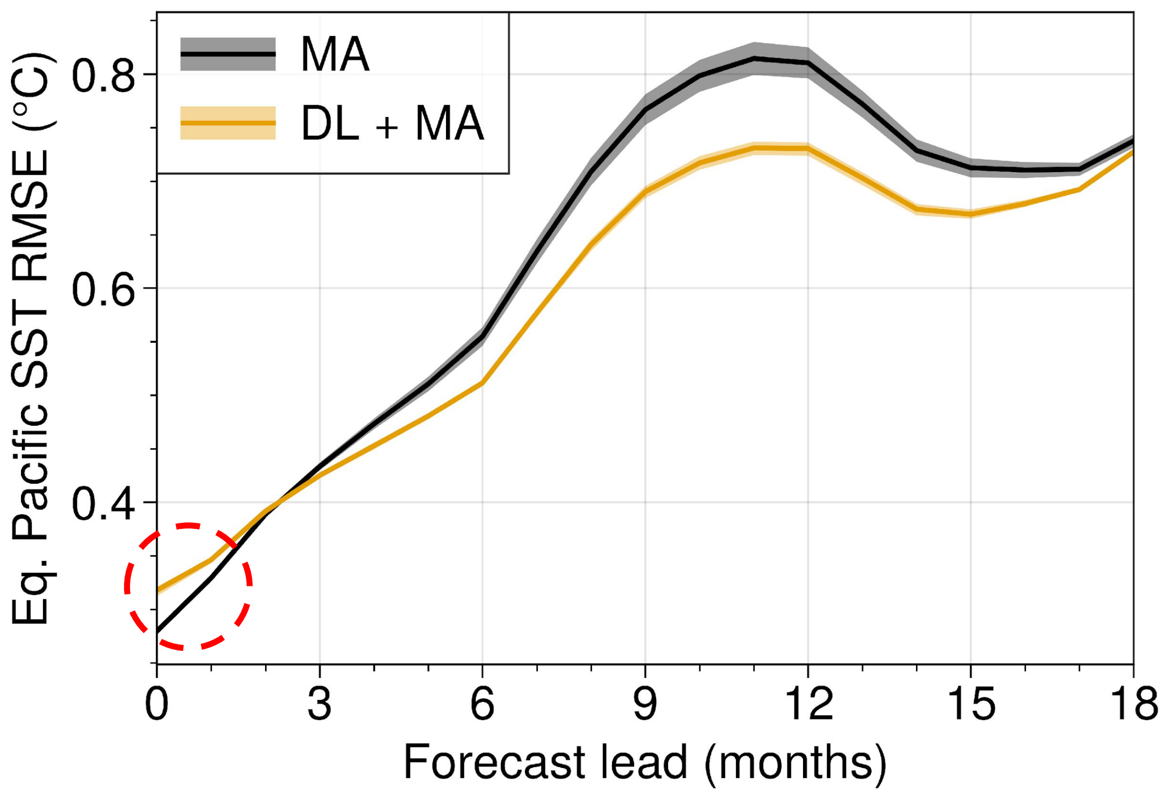


Target: SST pattern



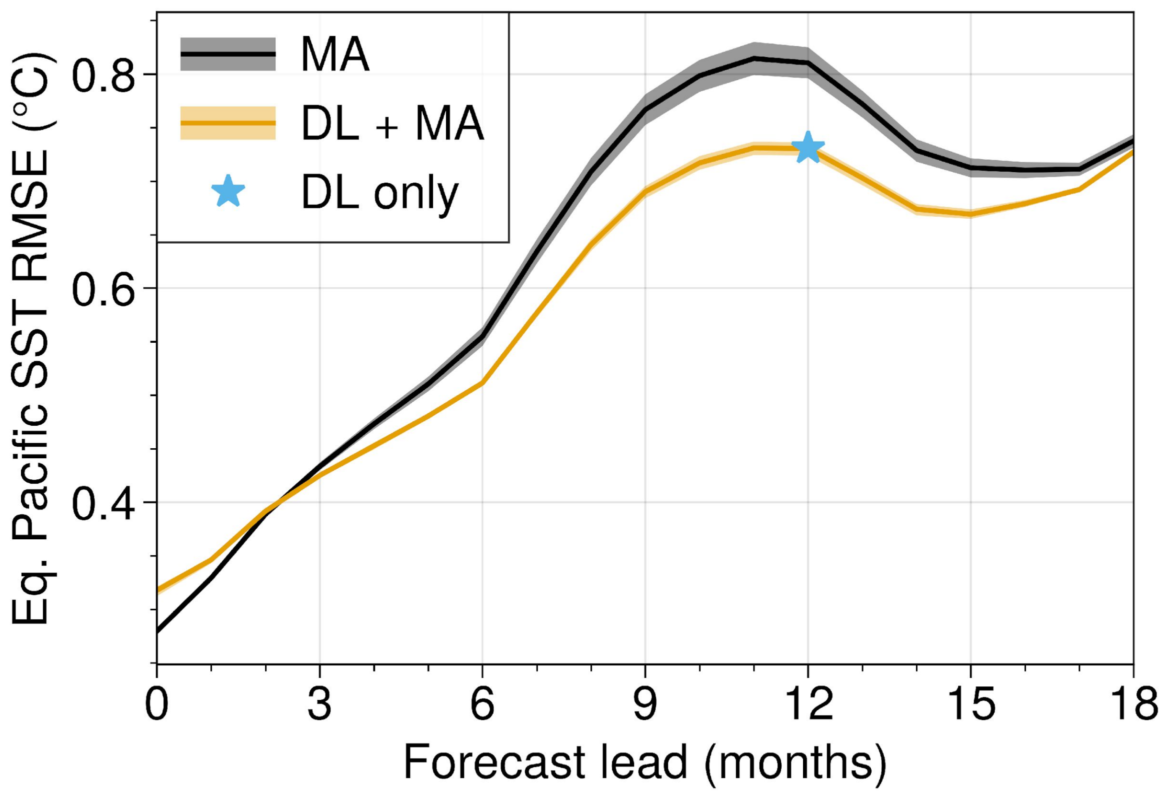
Seasonal-to-annual

10% improvements at 9-12 month lead



More weights are assigned to regions outside the target area

Comparable skill to an equivalent DL-only method

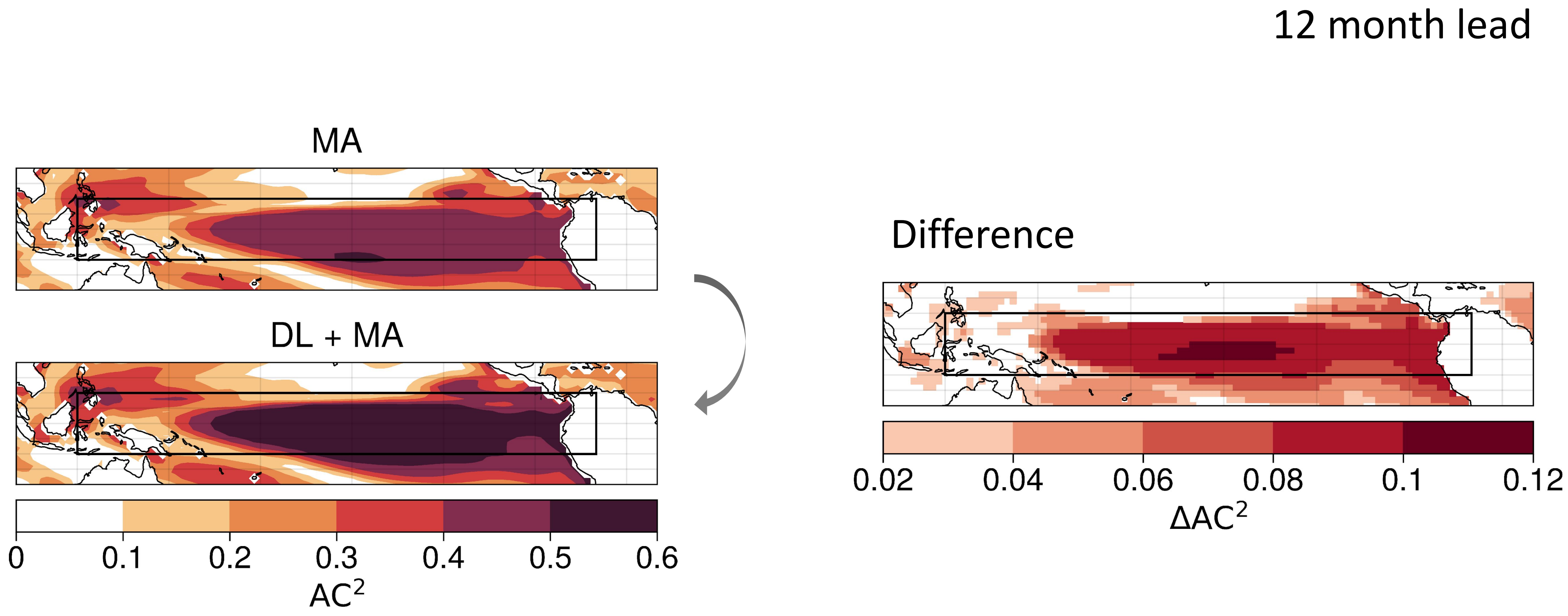


DL-only method

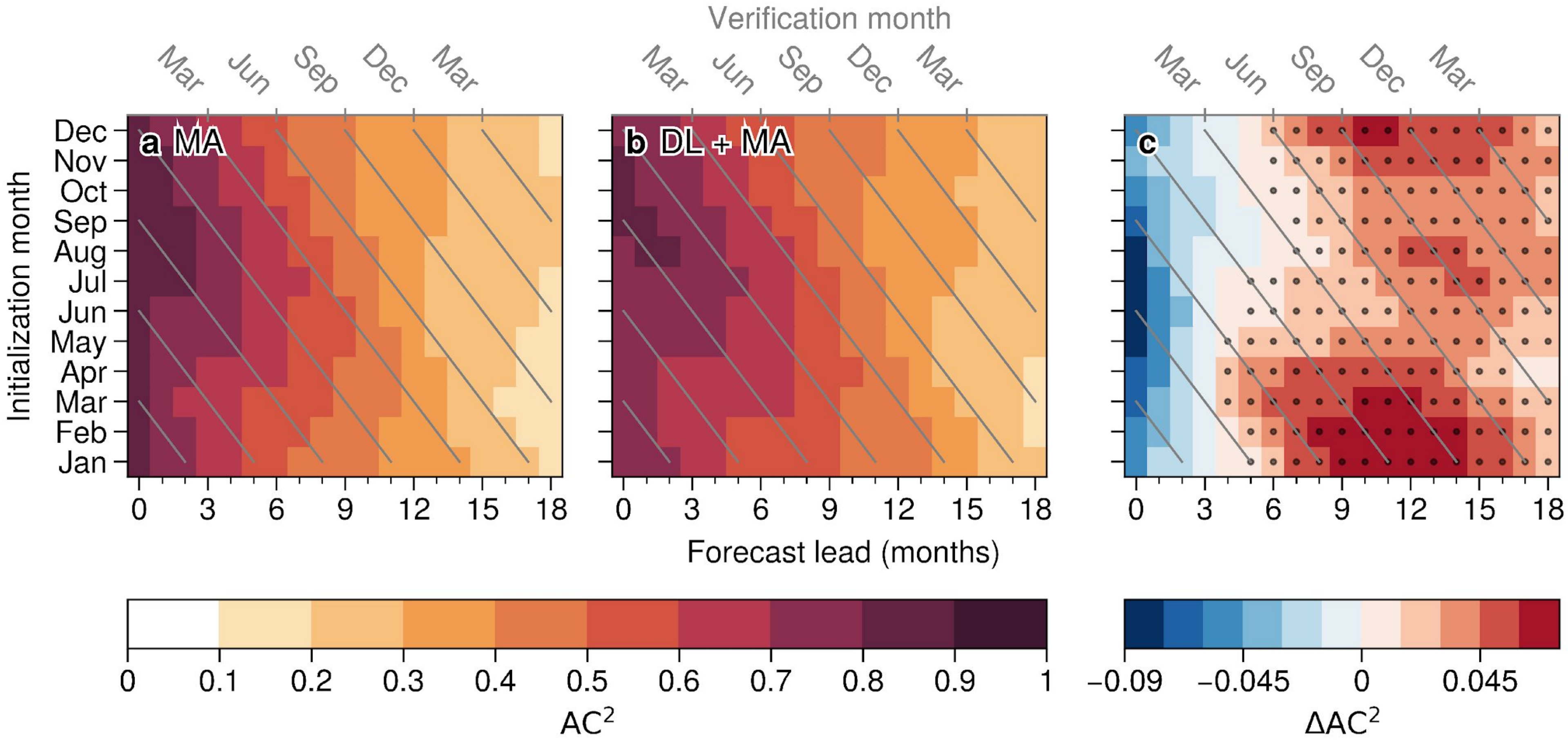
- Same network except for the last layer which predicts equatorial Pacific SST directly.
- Needs to be trained for each lead.

The hybrid method enhances interpretability and captures the time evolution of entire system without compromising DL skill.

The hybrid approach accelerates skill in region with large variability



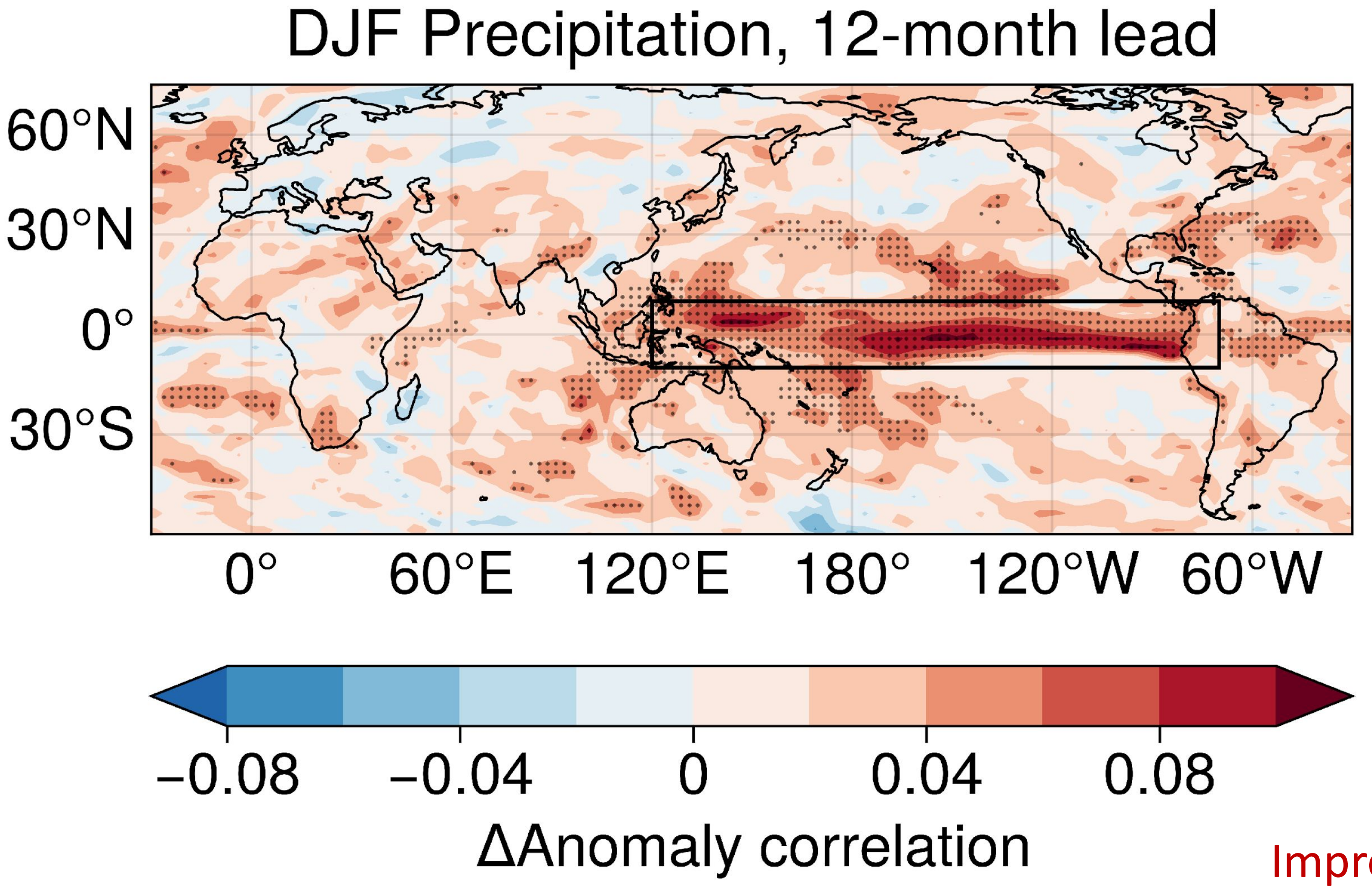
Seasonal skills



Significantly improves 6-18 months forecasts

Improvements in precipitation forecasts

Once analogs are identified, forecasting can be extend to any field available.



Improvements

Application to observations

Perfect model

Training CESM2 → Validation CESM2 → Test CESM2 →

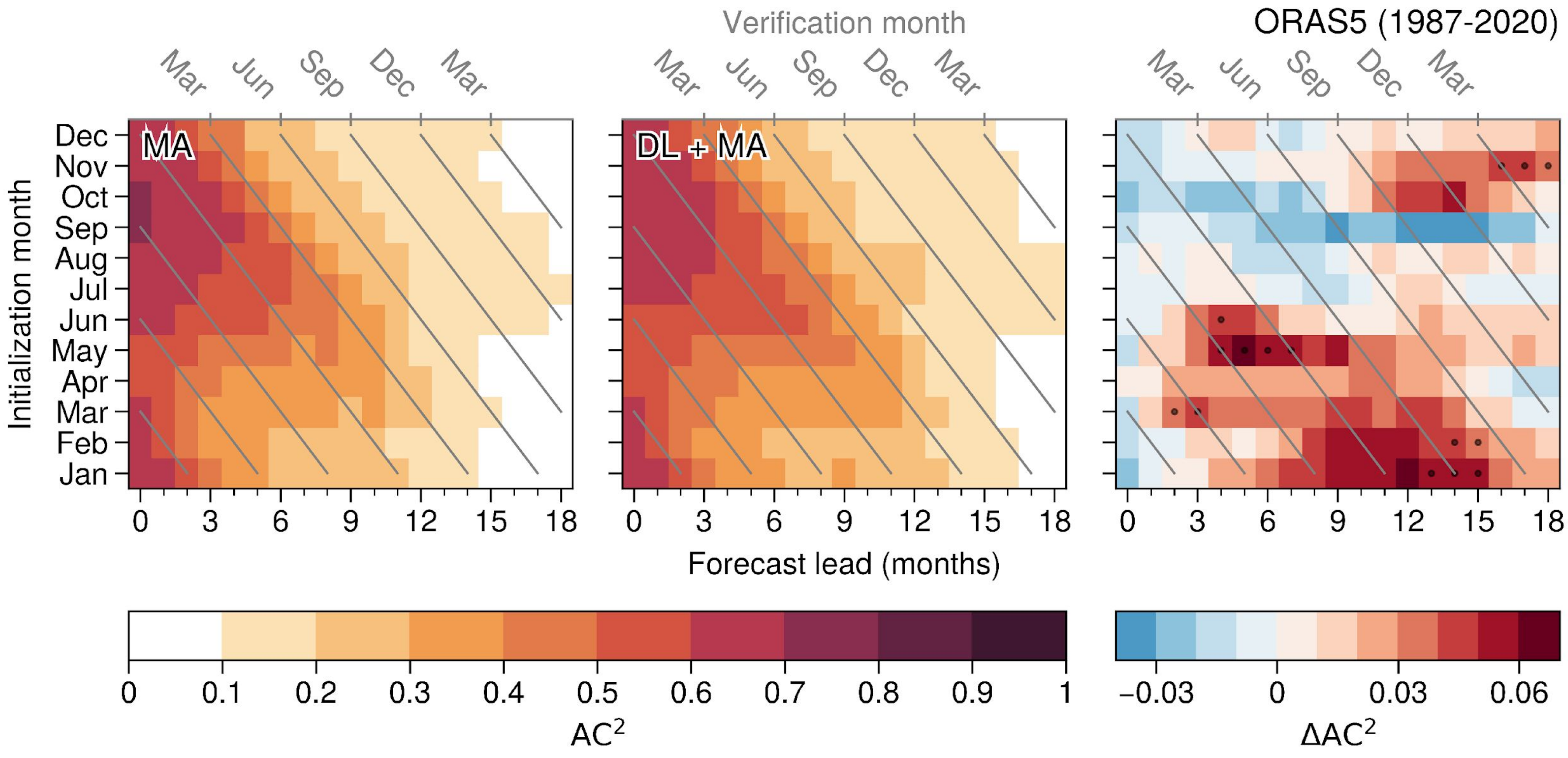
Hindcast

Test ORAS5

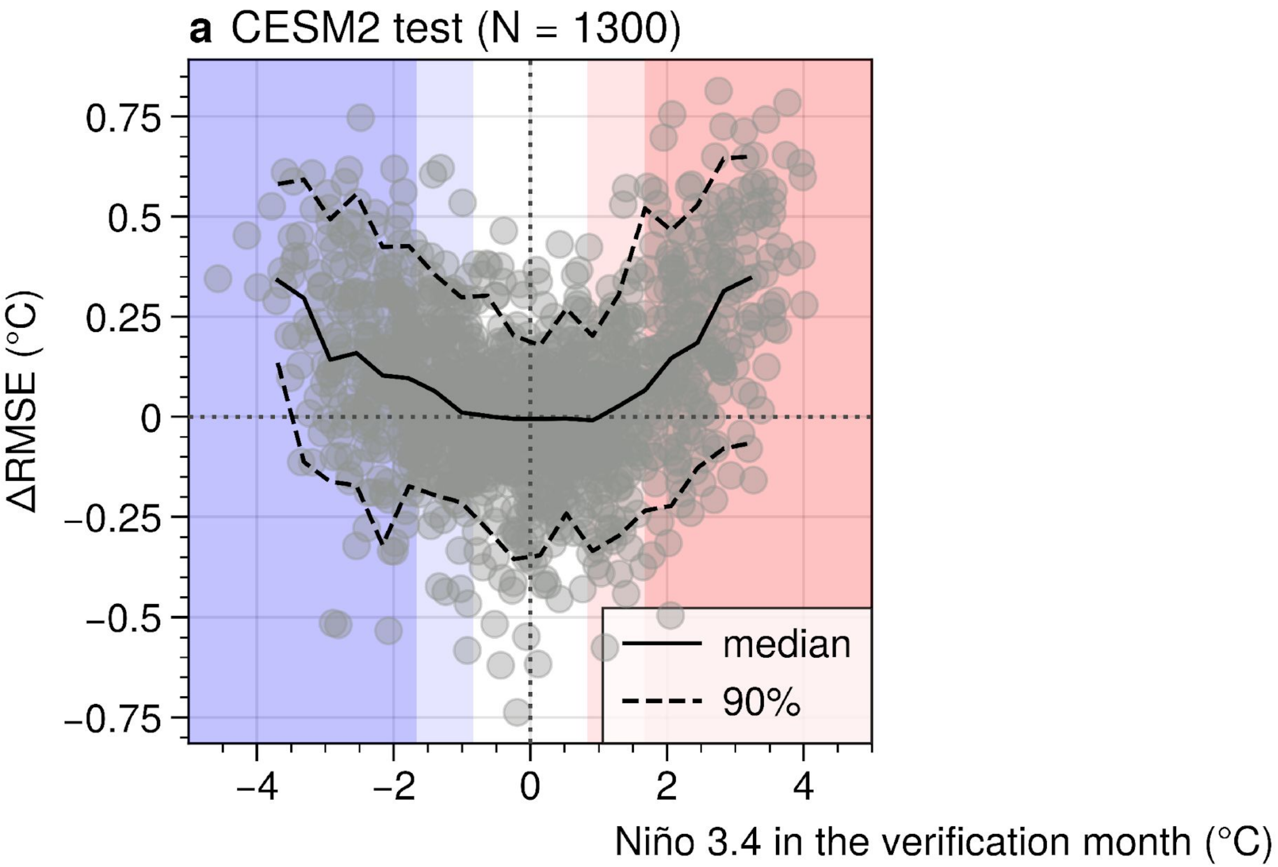
	Period	Sample size
Training (library)	1865-1958	94 y × 100 (70%)
Validation	1959-1985	27 y × 100 (20%)
Test	1986-1998	13 y × 100 (10%)

Period	Sample size
1987-2020	34 y

Hindcast results



Better improvements for extreme events

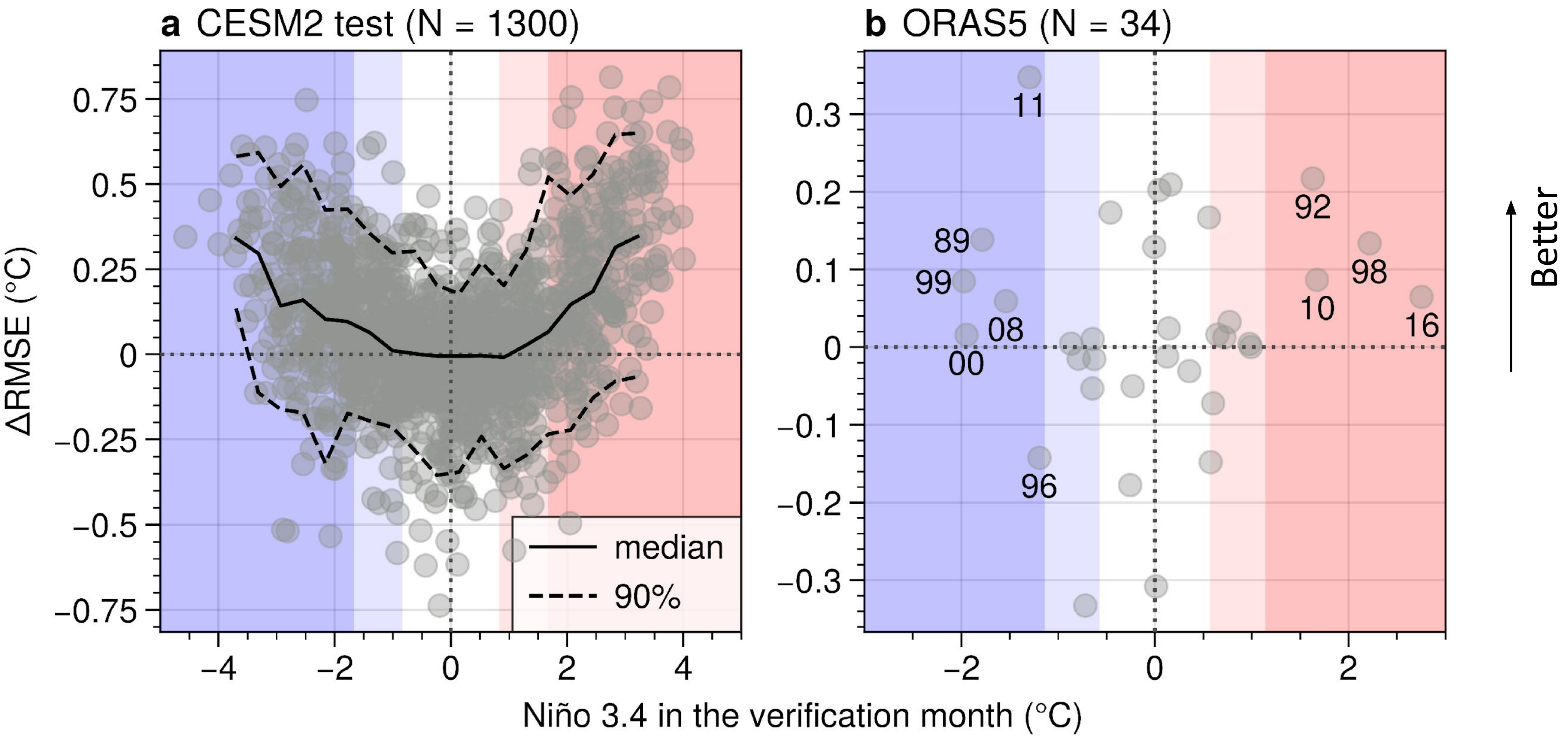


Better

Light background: > 0.5 σ
Dark background: > 1 σ

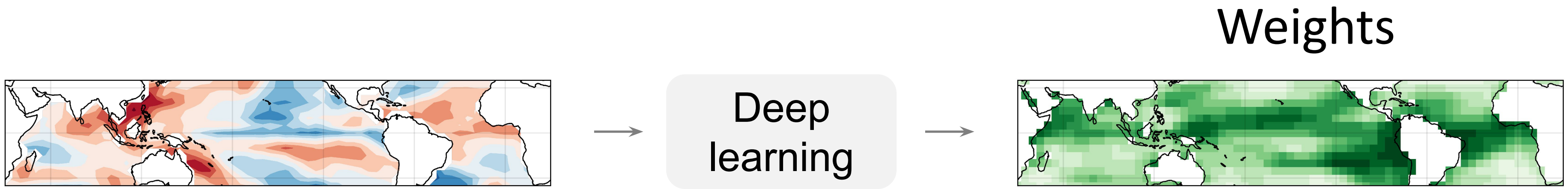
Better improvements for extreme events

Application to observations



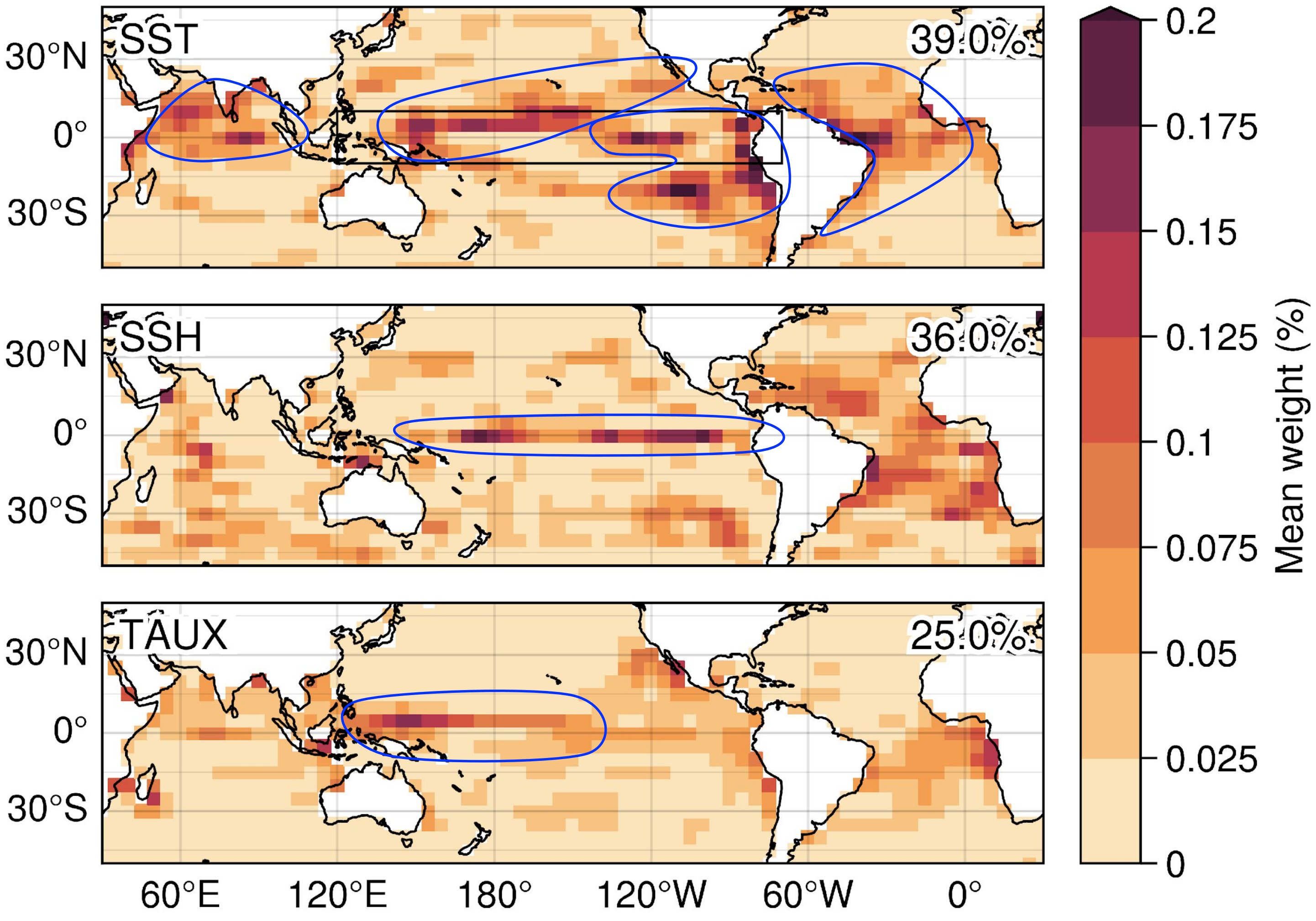
Light background: > 0.5 σ
Dark background: > 1 σ

Analyzing “sensitive regions”



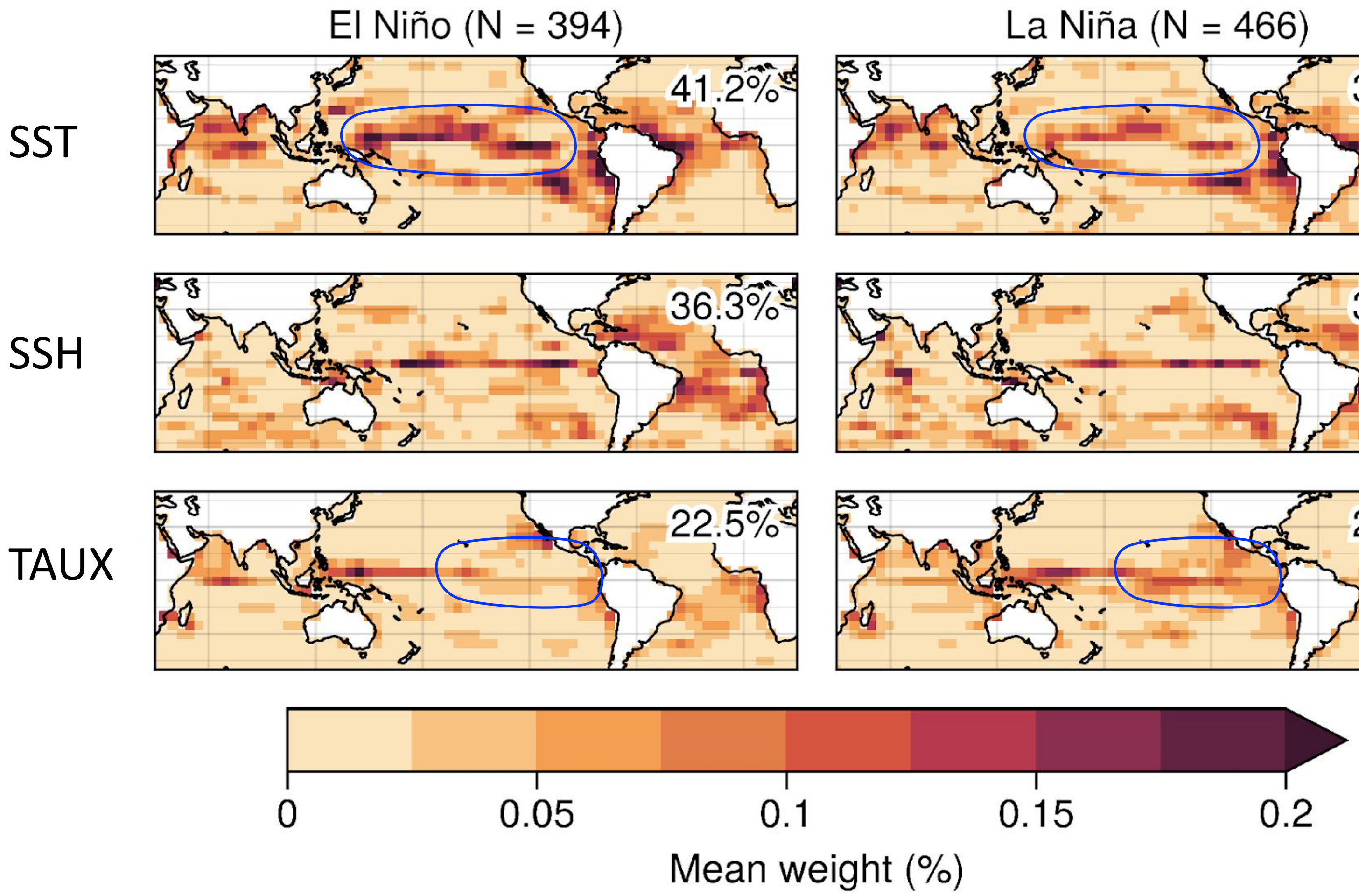
“Sensitive regions” are linked to various physical processes

Mean weights of all events (n = 1300)



- SST ~ SSH > TAUX
- SST: Off-equatorial weights
  Pacific meridional modes
- SSH: Thermocline slope
  Recharge-discharge state
- TAUX: Westerly wind event

Asymmetry in El Niño and La Niña forecasts



Conclusions

- Deep learning improves analog ENSO forecasting by 10%.
    - Better improvements for forecasting extreme events.

- This approach provides interpretability to deep learning.
    - For El Niño forecast: Pacific SST is more sensitive.
    - For La Niña forecast: Pacific wind stress is more sensitive.

- Broad implications for forecasting diverse climate phenomena.

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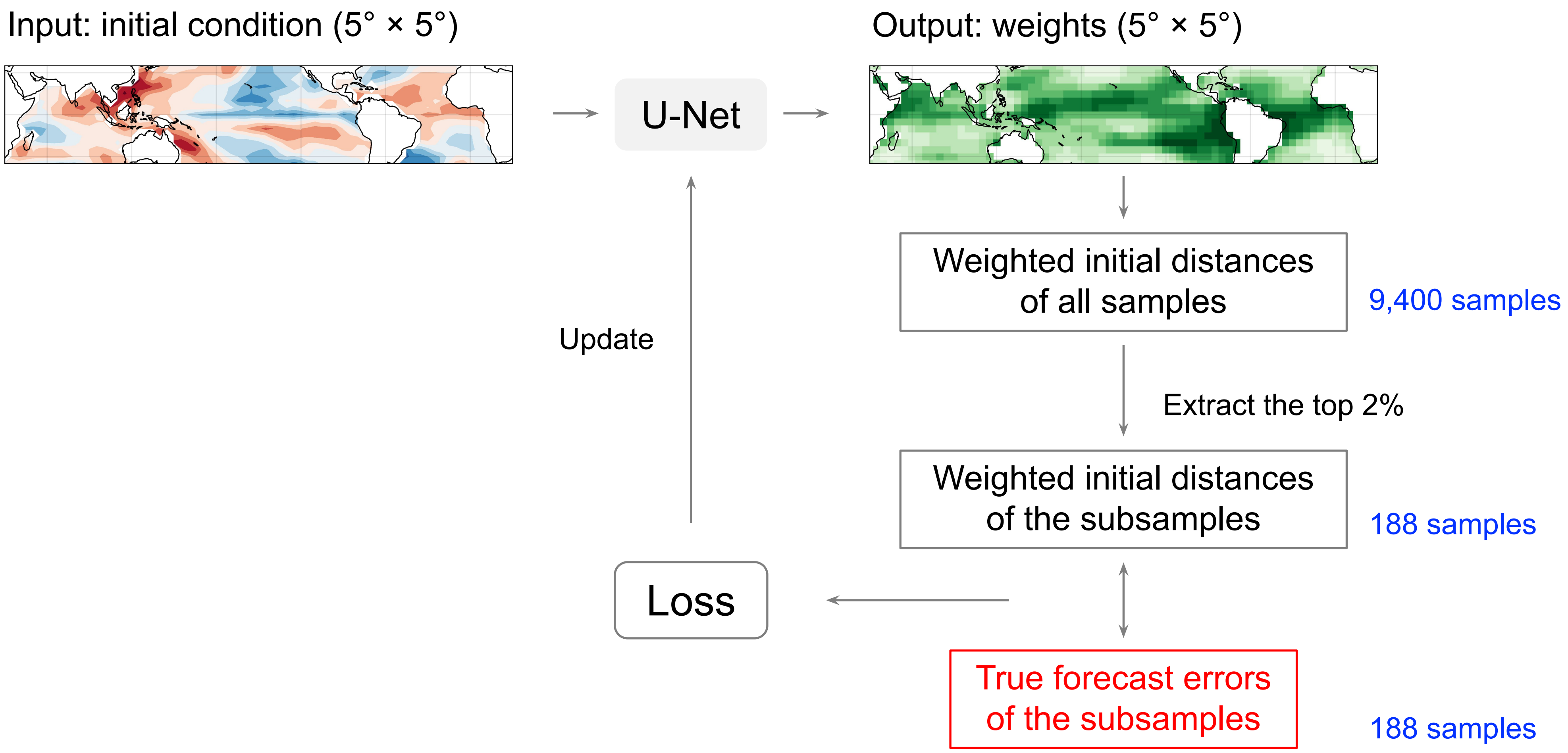
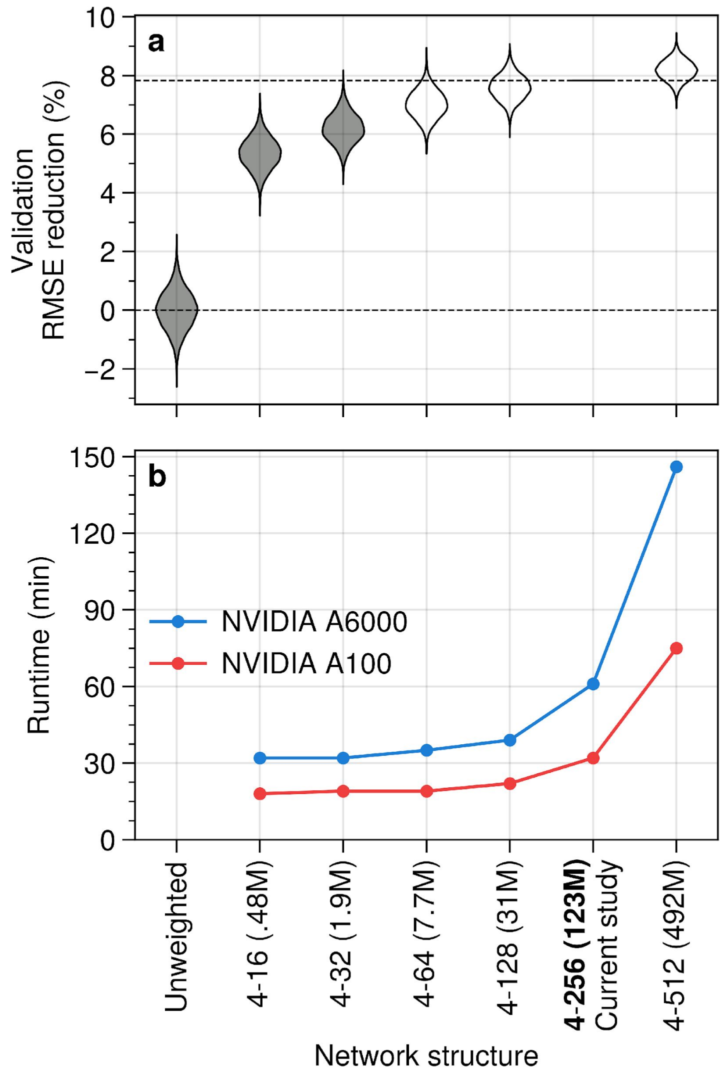
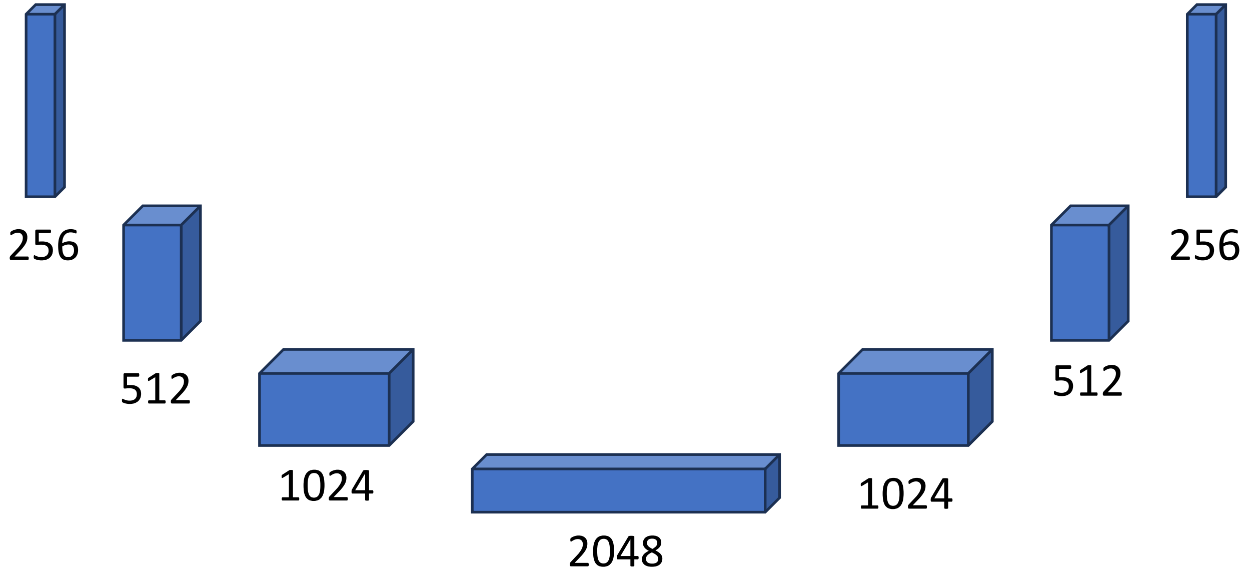
Network architecture



Network size



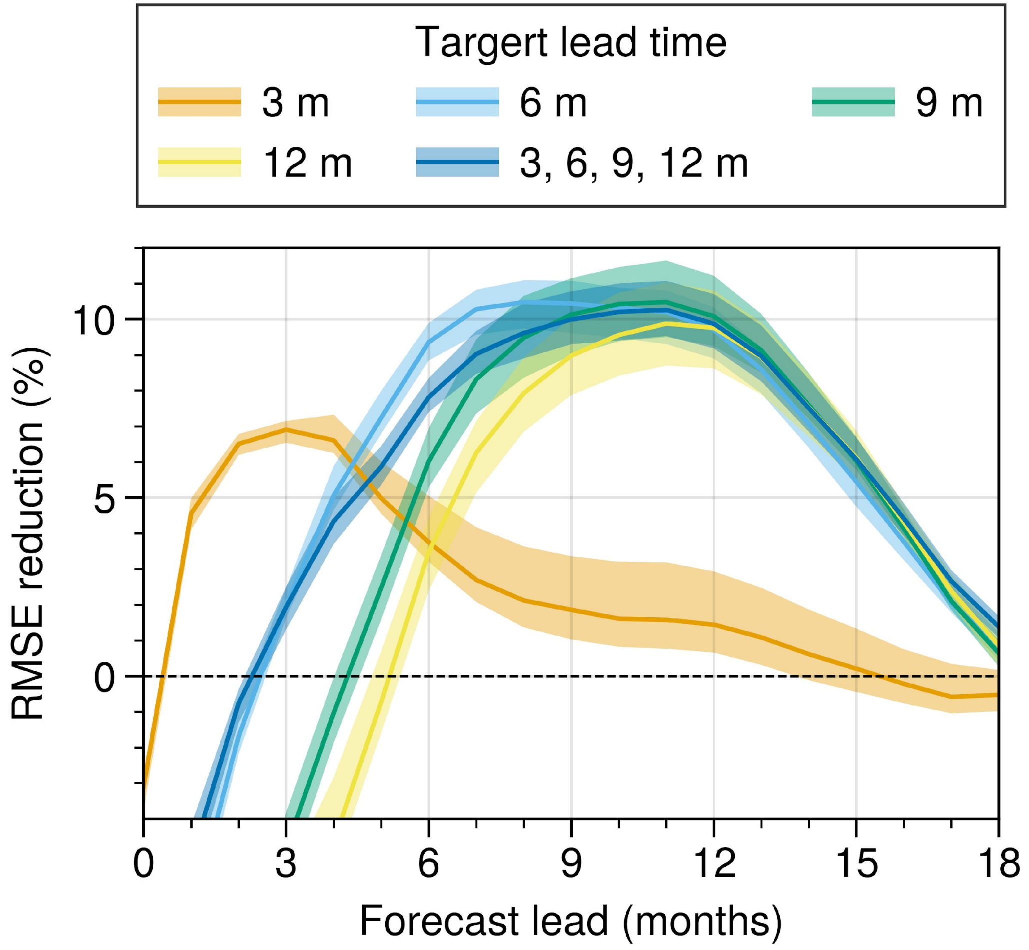
UNet: 4-layer with initial channel size of 256



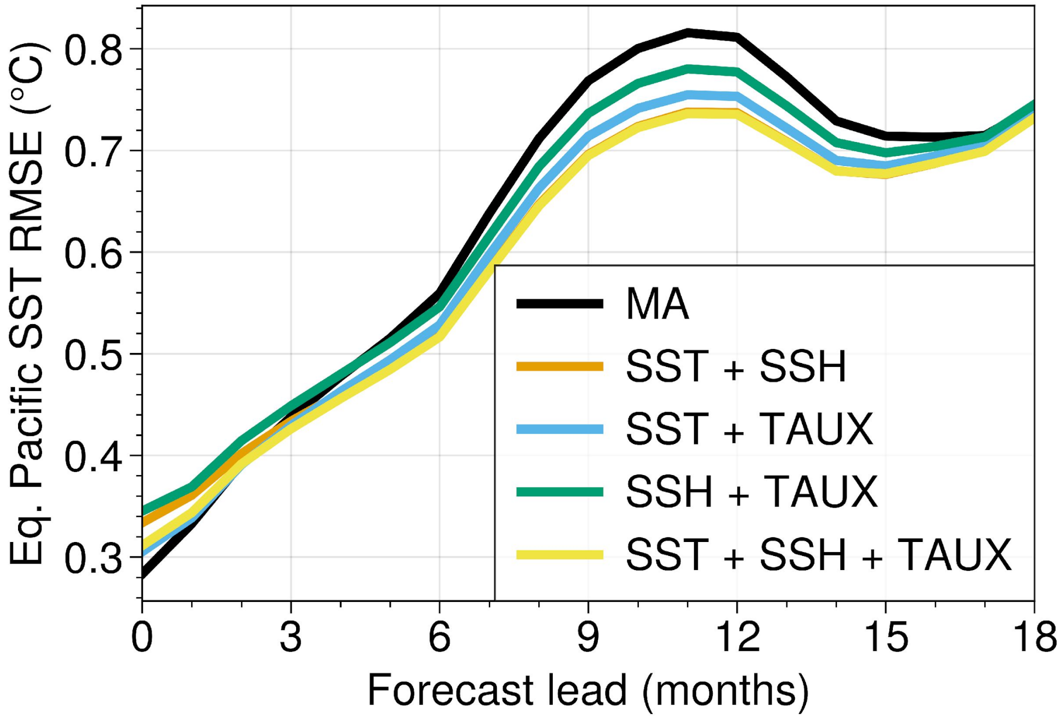
Channel = number of kernels used in convolution

e.g.) a color image has 3 channels (RGB)

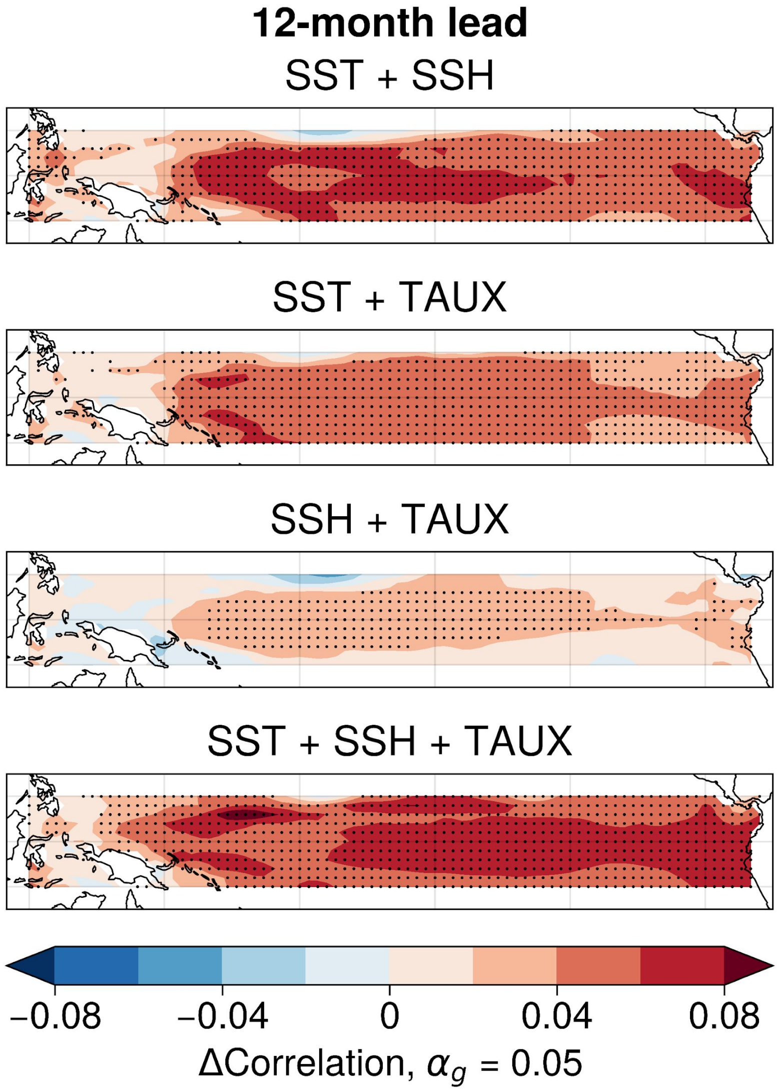
Do we need to train the model for each lead time?



Variable decomposition



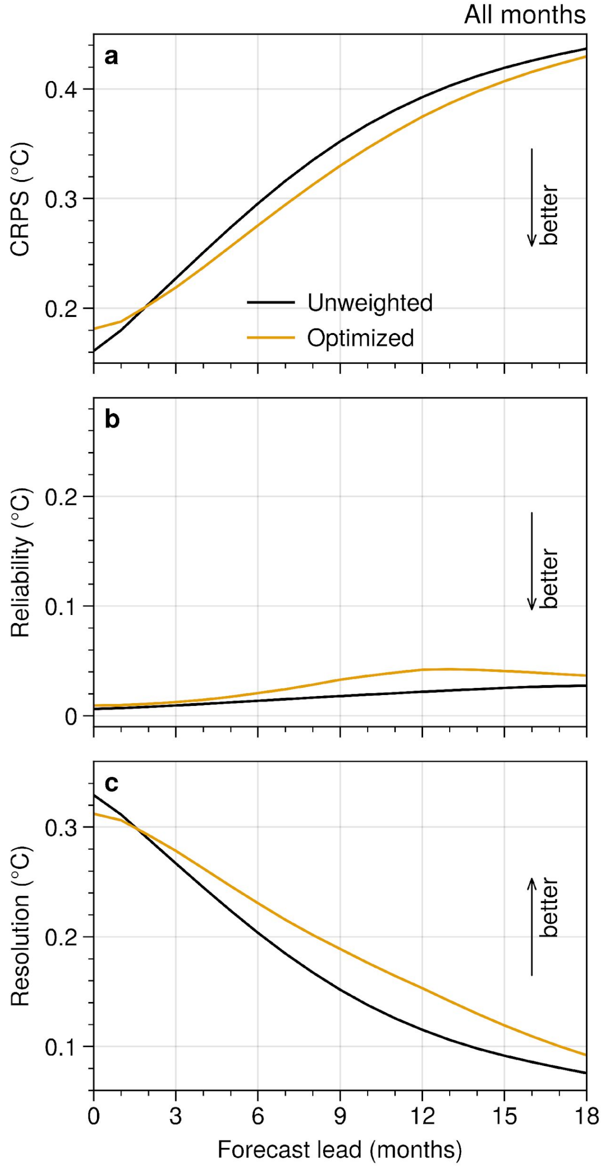
SST > SSH > TAUX



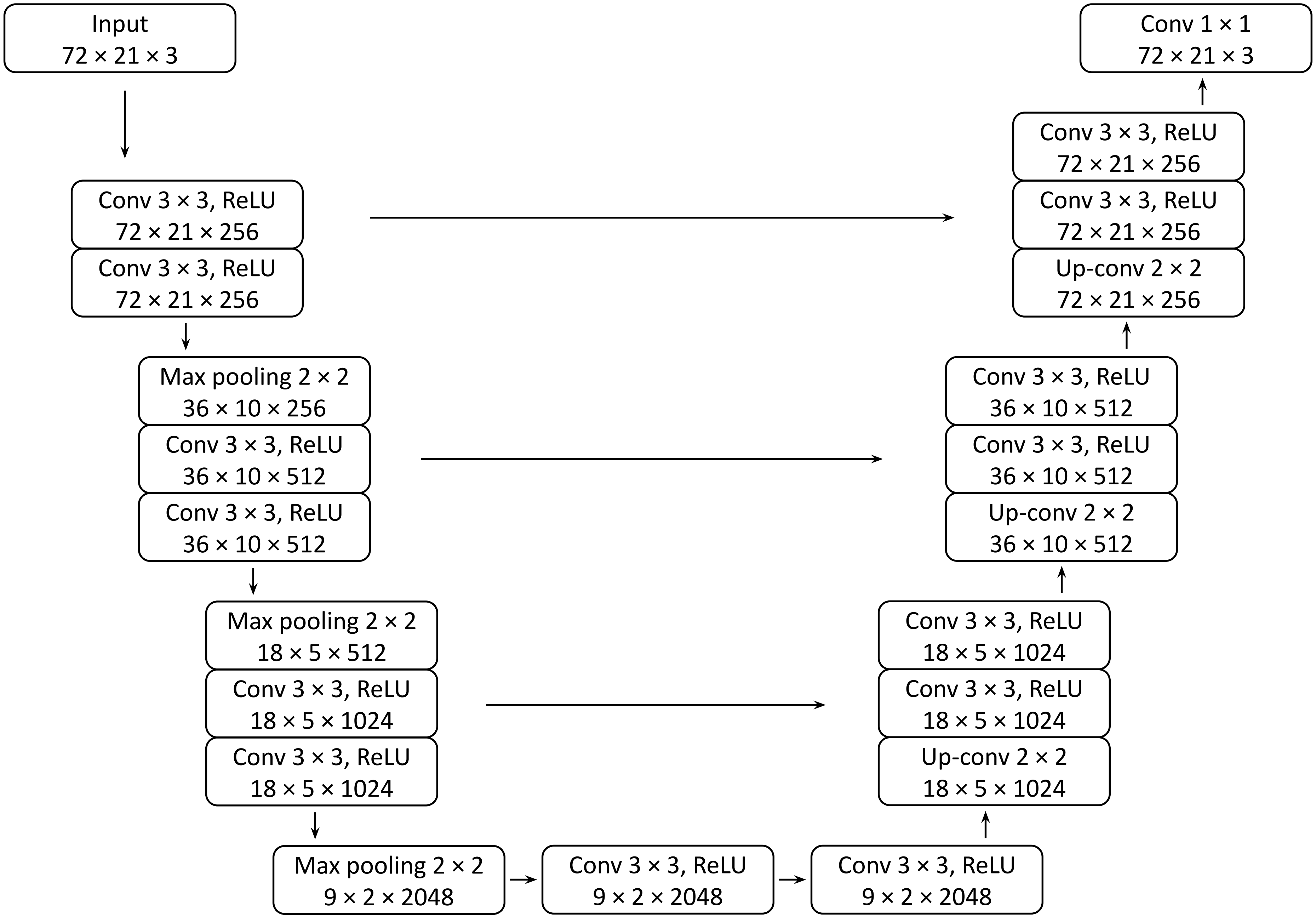
Probabilistic skill

<u>Decomposition of CRPS (Hershbach 2000)</u>

Reliability = flatness of the rank histogram
Resolution = spreads



4-layer U-Net



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