Optimizing Seasonal-to-Decadal Analog Forecasts with an Interpretable Neural Network

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What I’ve been thinking about the last four years…

How can we use machine learning to improve forecasts on climate timescales?

Interpretable Machine Learning

The machine learning algorithm provides its own explanations.

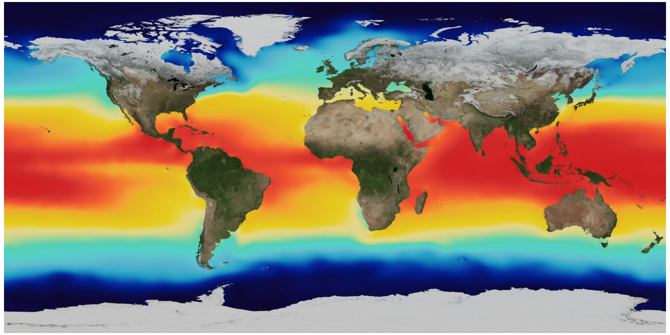
How can we use machine learning to improve our understanding of the climate system?

Optimizing Seasonal-to-Decadal Analog Forecasts with a Learned Spatially-Weighted Mask.

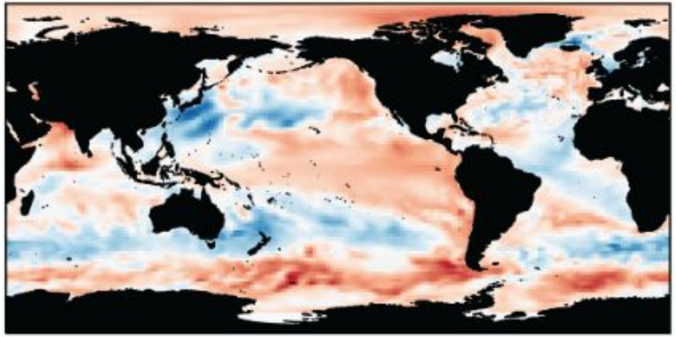
Jamin K. Rader, Elizabeth A. Barnes

Initialized Seasonal-to-Decadal Forecasting

Initialized Climate Prediction Systems



Initialize a climate model with observations



Make a prediction using the model's final state

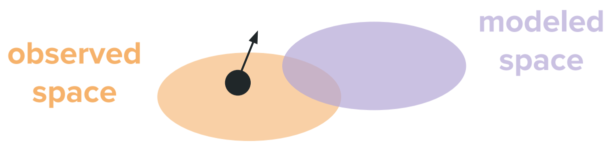
Iterate the model forward in time

Initialized Seasonal-to-Decadal Forecasting

Two issues:

Initialization Shock

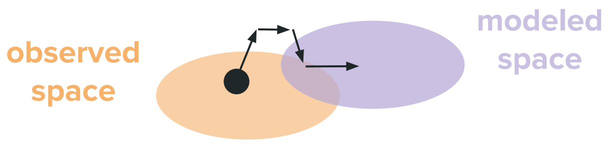
The initialized state may not fall within the model's "phase space"



The ocean/atmosphere initializations may not be consistent with each other

Climate Model Drift

As the model moves forward in time, it will pull the observations back to its mean state



A data-driven approach would avoid these issues

Analog Forecasting: An Intuitive Approach to Prediction

"A poor man's initialized prediction system" [1]

Premise: Two climate states that look similar initially will continue to look similar.

Application: Find a state in a climate simulation that looks like the climate state you are forecasting for (an analog). Make a forecast based on how the analog evolved.

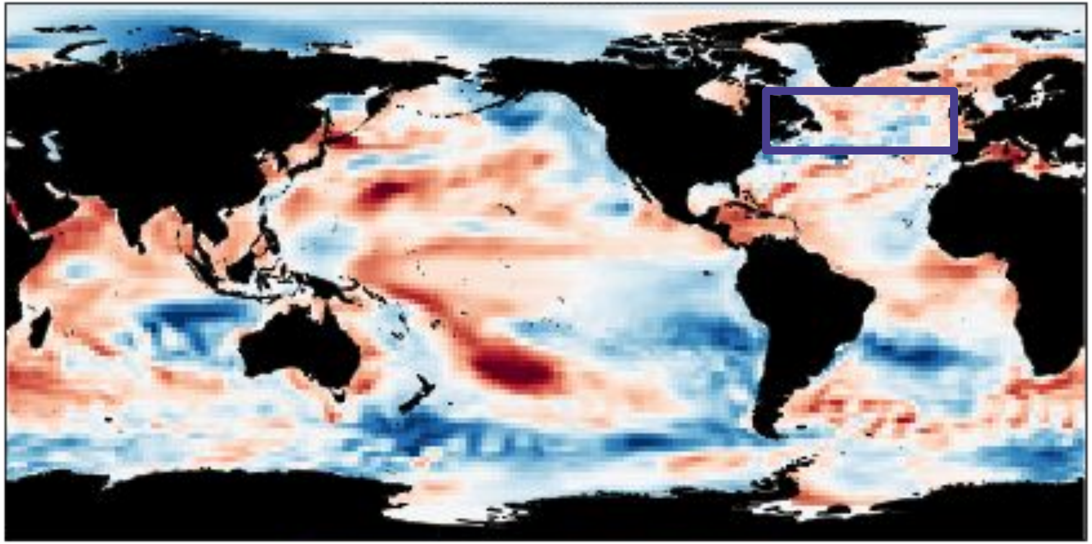
March 20, 1948: *Tornado hits Tinker AFB*

March 25: *Conditions looked similar to March 20*

Thus they forecasted that, like March 20, a tornado would hit the base.

They were right! A tornado hit the base.

North Atlantic SST Multi-Year Analog Forecasts



North Atlantic sea surface temperatures exhibit decadal variability.

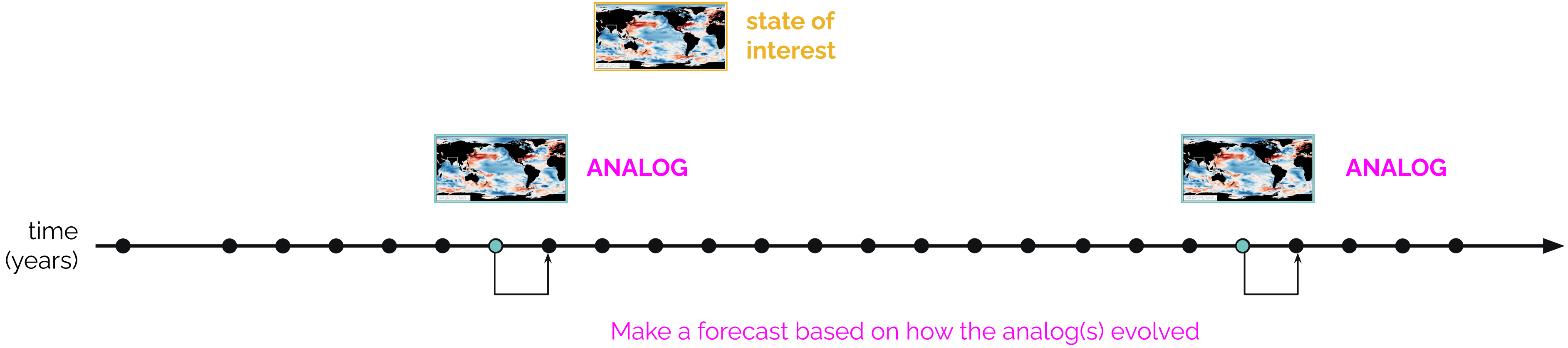
Associated with Asian summer monsoon strength, Atlantic hurricane frequency and intensity, Northern hemisphere extreme precipitation and drought. [2,3,4,5]

Task: *Given an initial global map of SST, predict what the average North Atlantic SST will be over the next 1-5 years.*

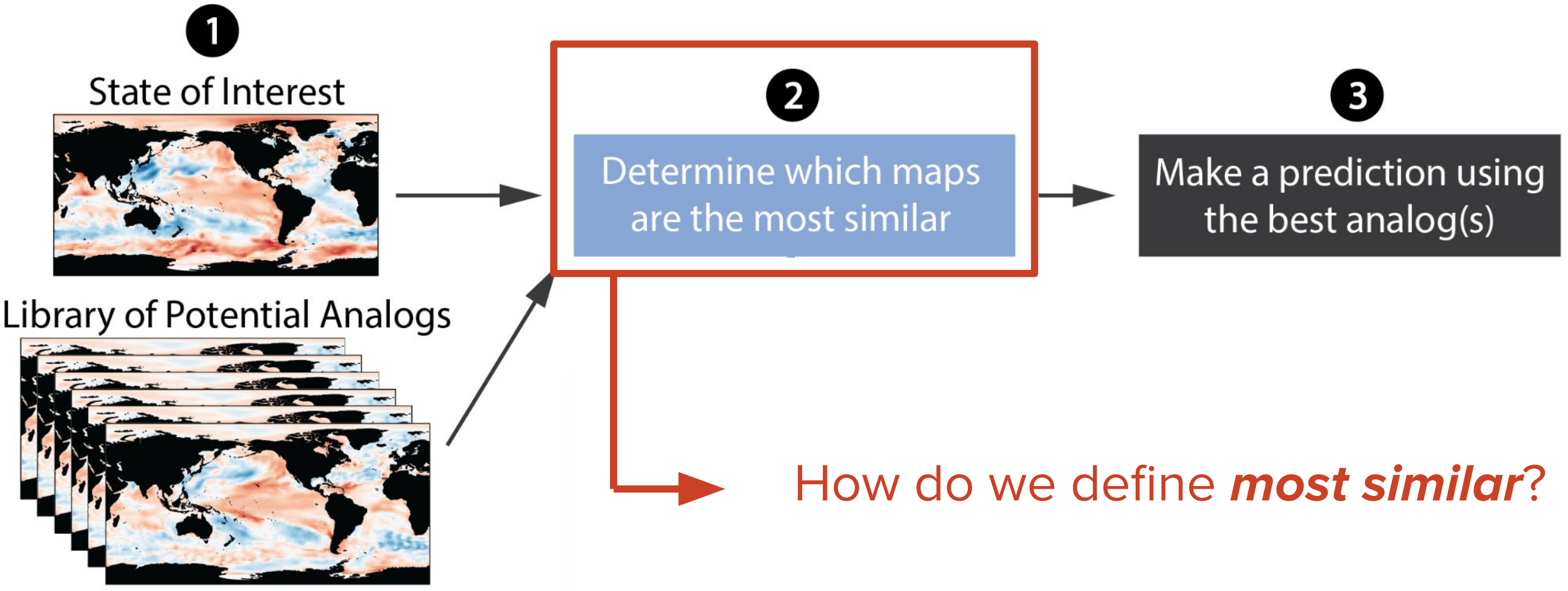
North Atlantic Multi-Year Analog Forecasts

Using the Max Planck Institute for Meteorology Grand Ensemble

Treat some of the 100 ensemble members as “observations,” use the rest to find analogs



Analog Forecasting: An Interpretable Approach



How do we define ***most similar***?

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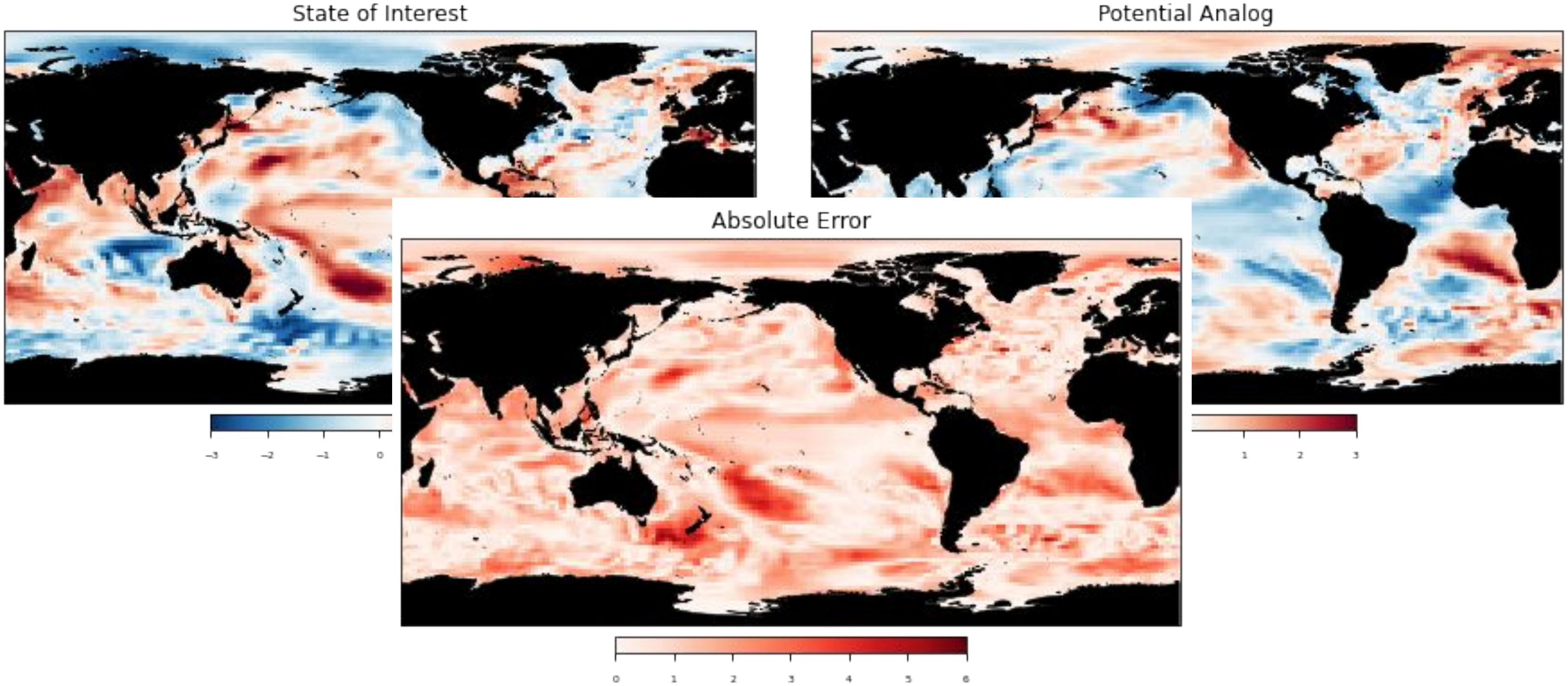
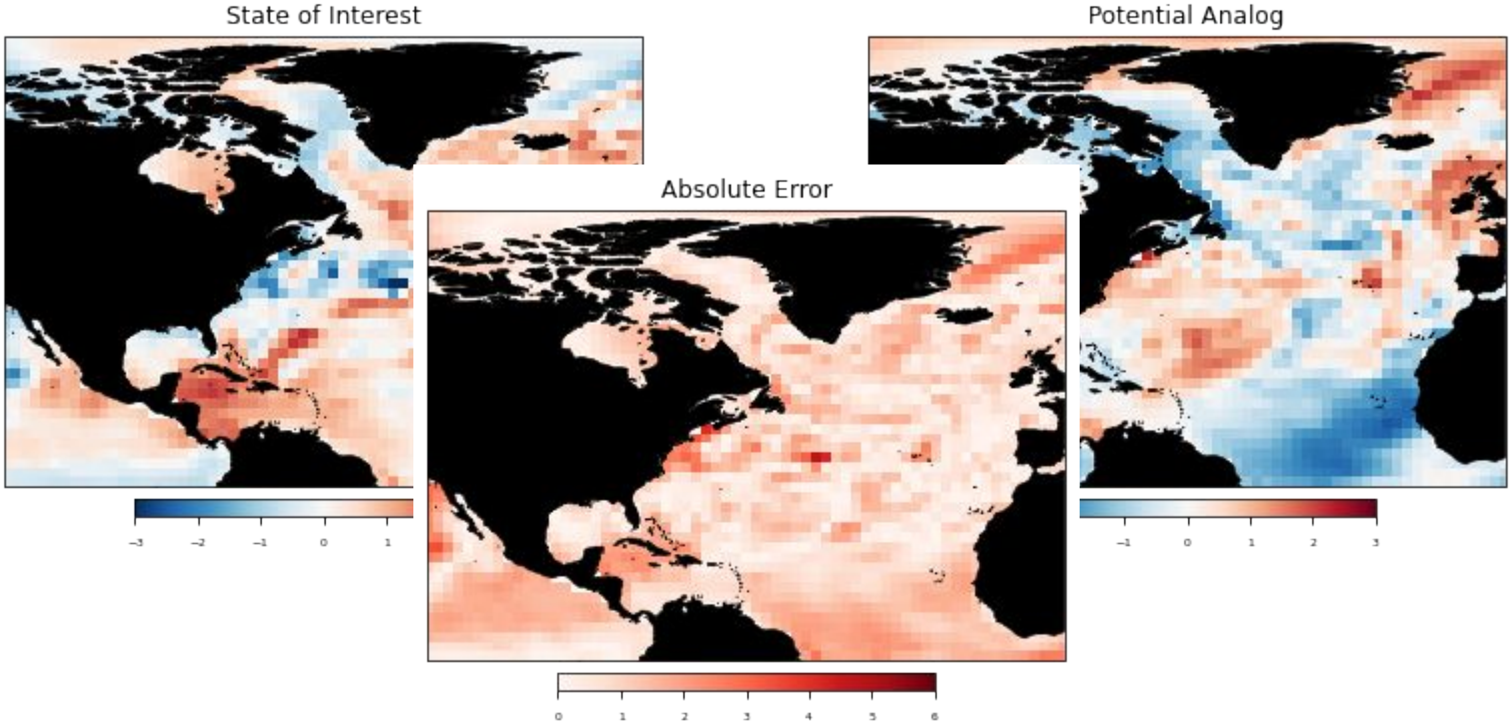
Option 1: Compute a Global Mean-Squared Error (MSE)



Not all points across the globe are important for determining whether the North Atlantic will evolve similarly between the two maps.

How do we define ***most similar***?

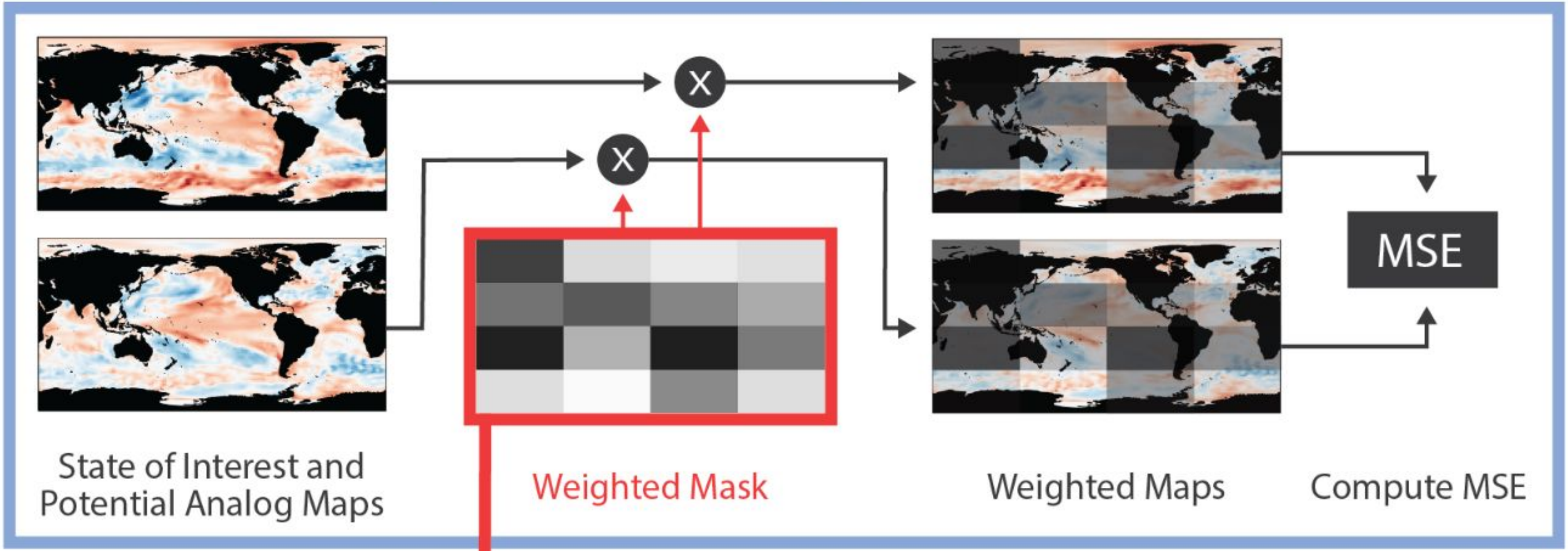
Option 2: Compute a Regional MSE (over a known precursor region)



Requires that we know the precursor regions a priori, and assumes that all grid points within this region are equally important.

How do we define ***most similar***?

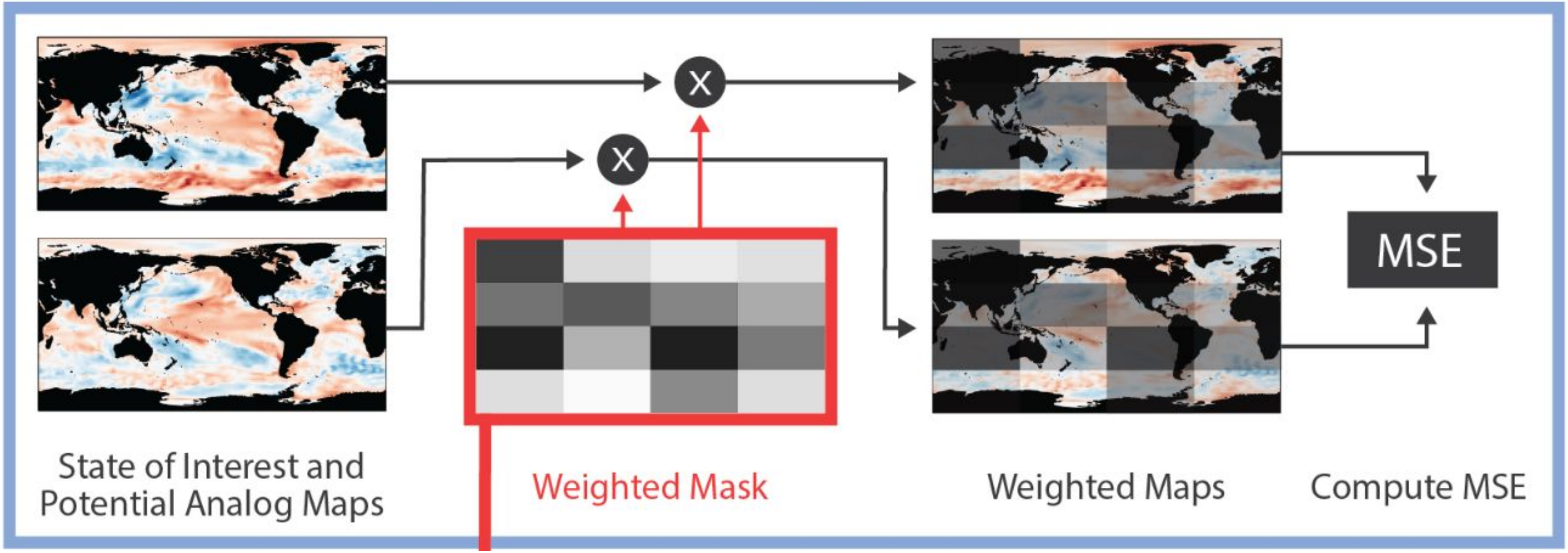
*Option 3: **We compute a spatially-weighted MSE***



The MSE will be low when the two maps agree in the regions where the mask weights are high, regardless of the differences between the maps where the mask weights are low.

The potential analog(s) with the lowest weighted MSE are used for forecasting.

Option 3: ***We compute a spatially-weighted MSE***



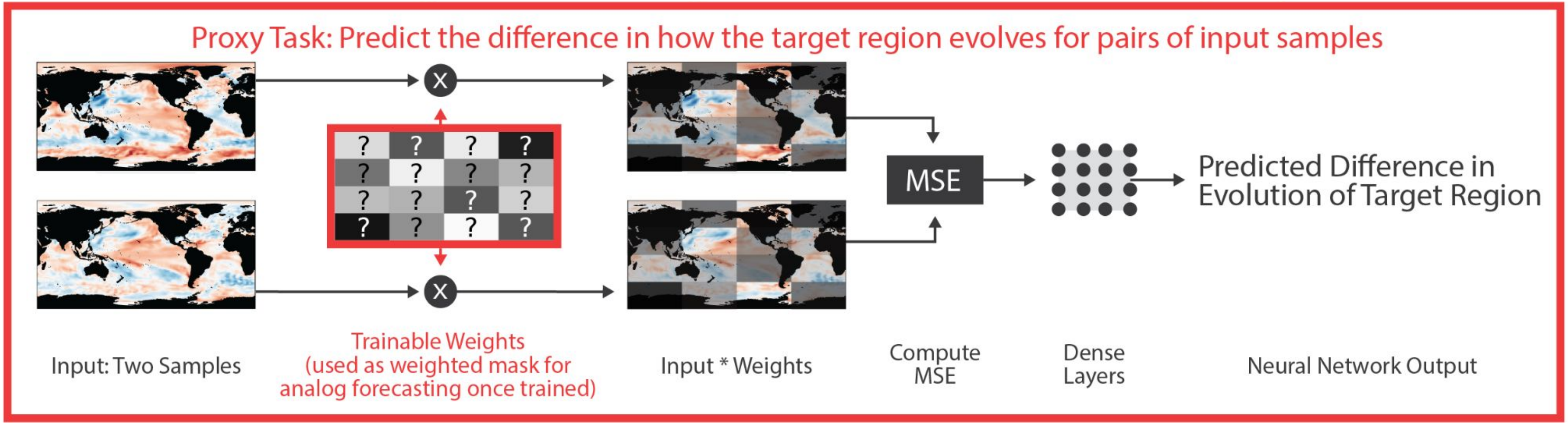
How do we obtain this ***weighted mask?***

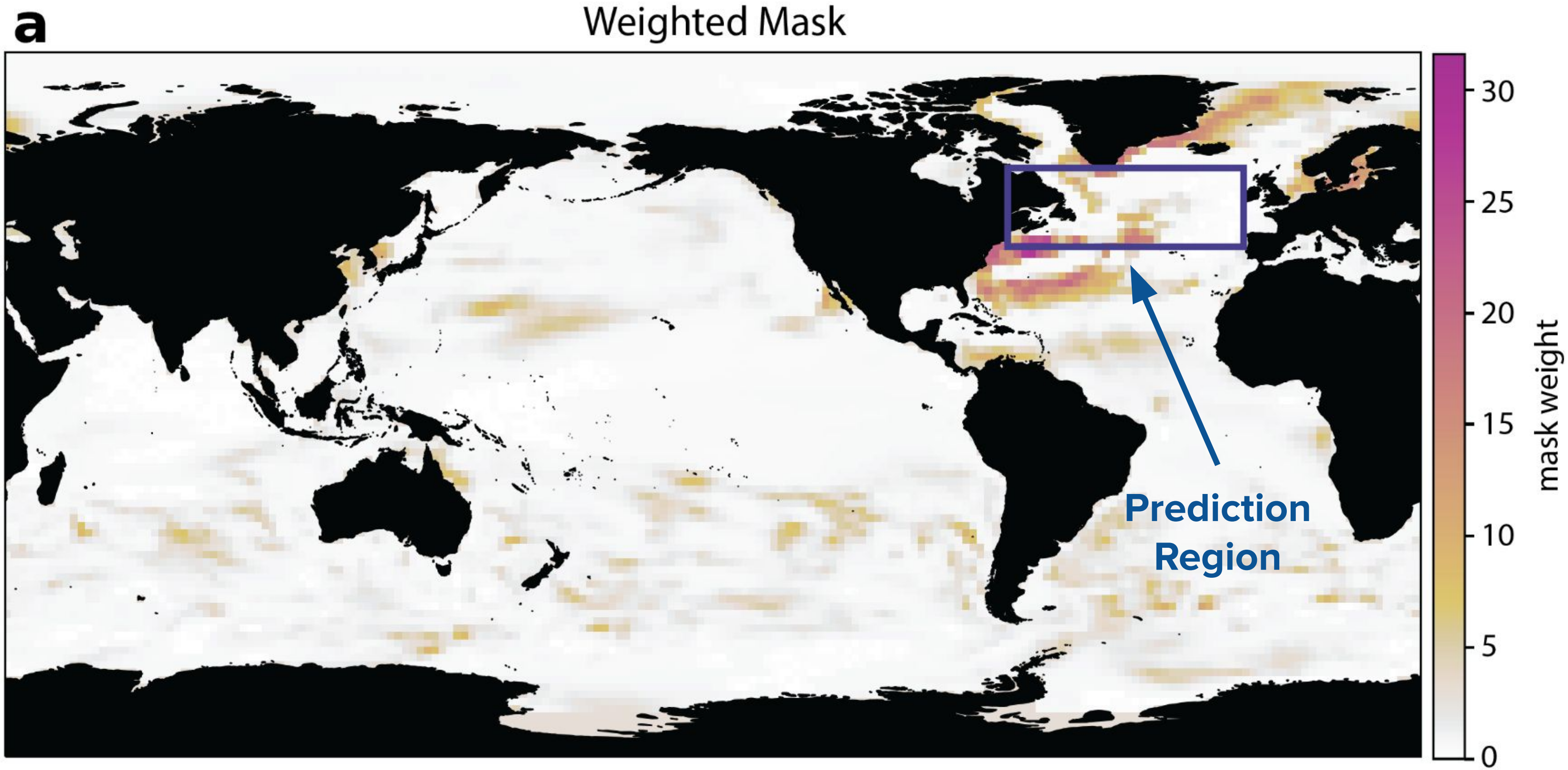
Learning the Weighted Mask through a Proxy Task

Directly using machine learning to determine the N-best analogs is difficult, so we train it on a proxy task.

This interpretable neural network is tasked to predict the difference in the evolution of North Atlantic sea surface temperature for two initial climate states (which could be very similar, or very different).

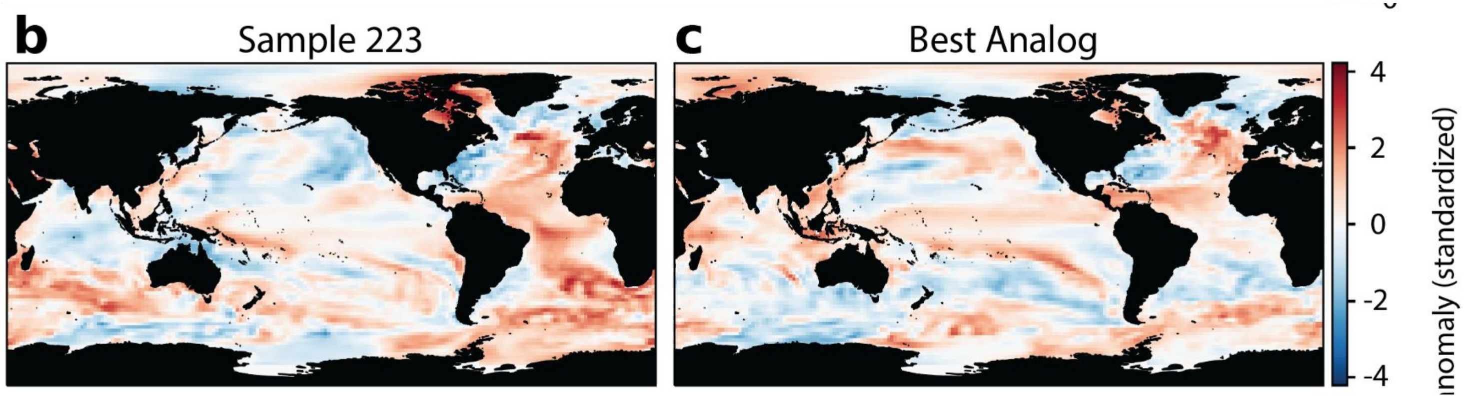
En route to making its prediction, it must learn an optimal spatially-weighted mask.



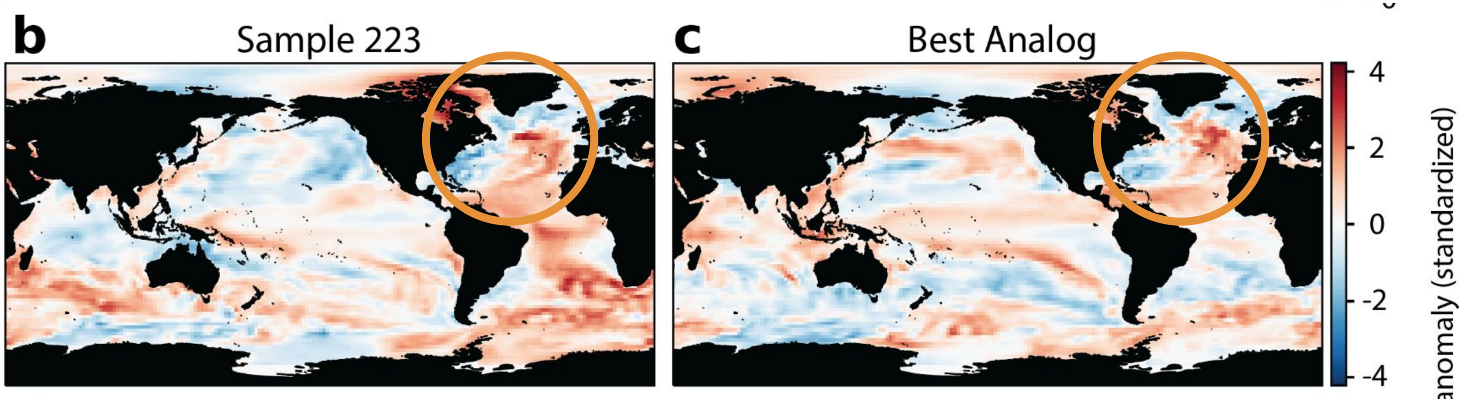


The weighted mask can be used to improve our understanding of precursors for North Atlantic sea surface temperature on multi-year timescales

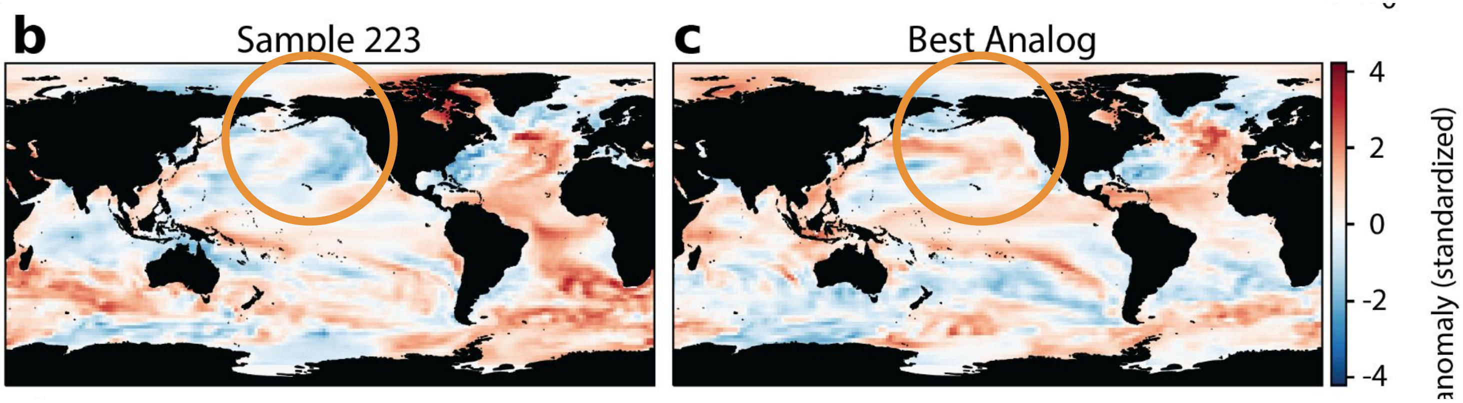
(in addition to improving analog forecasting skill)



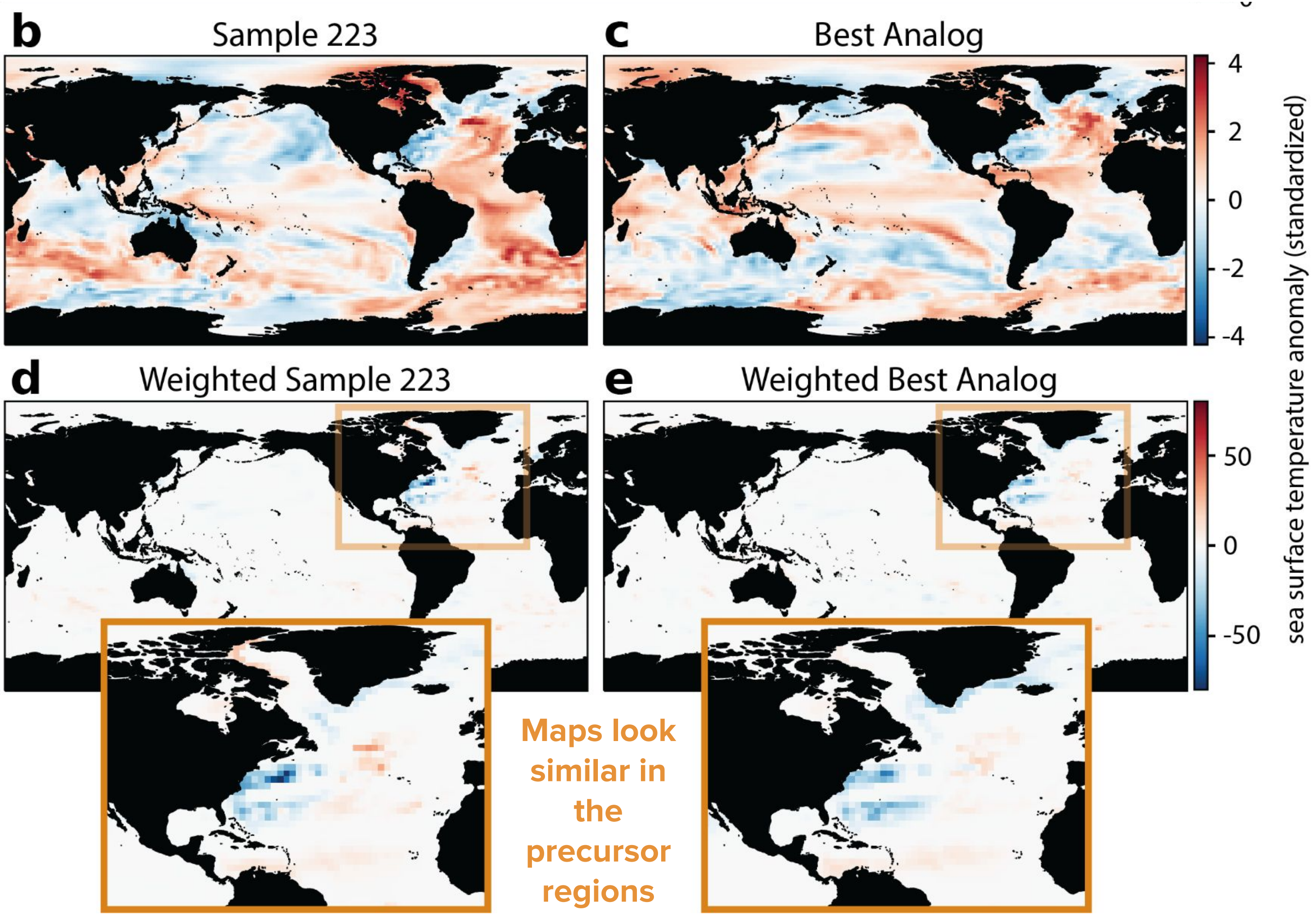
An example of the best analog for one sample state of interest



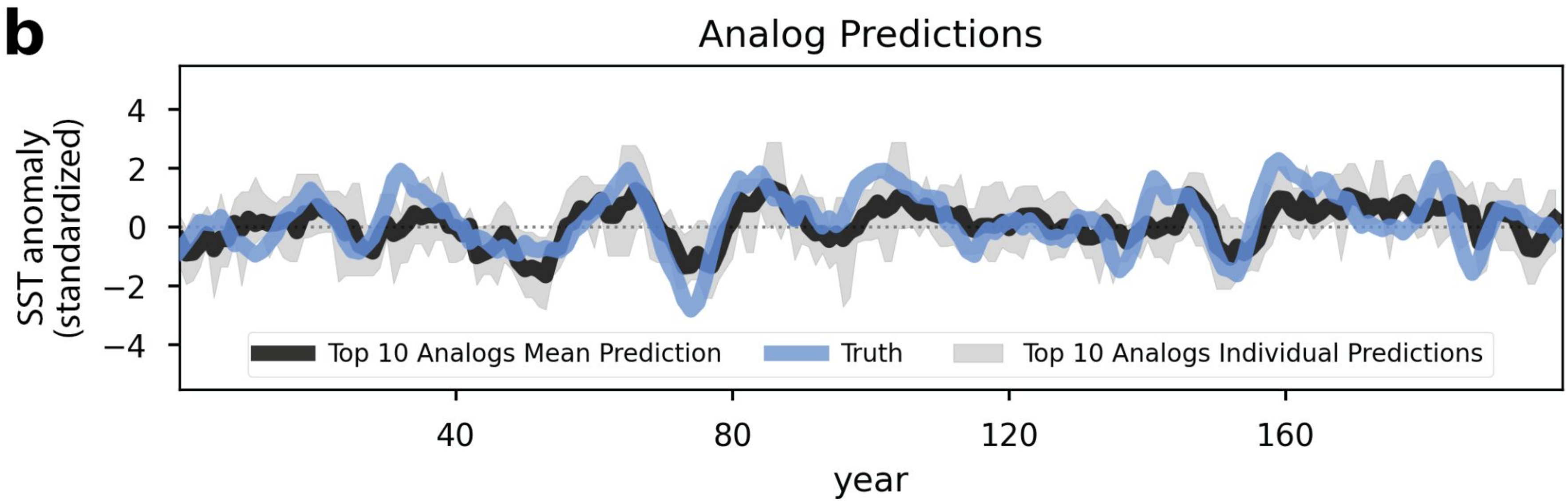
Some regions in the two maps look very similar



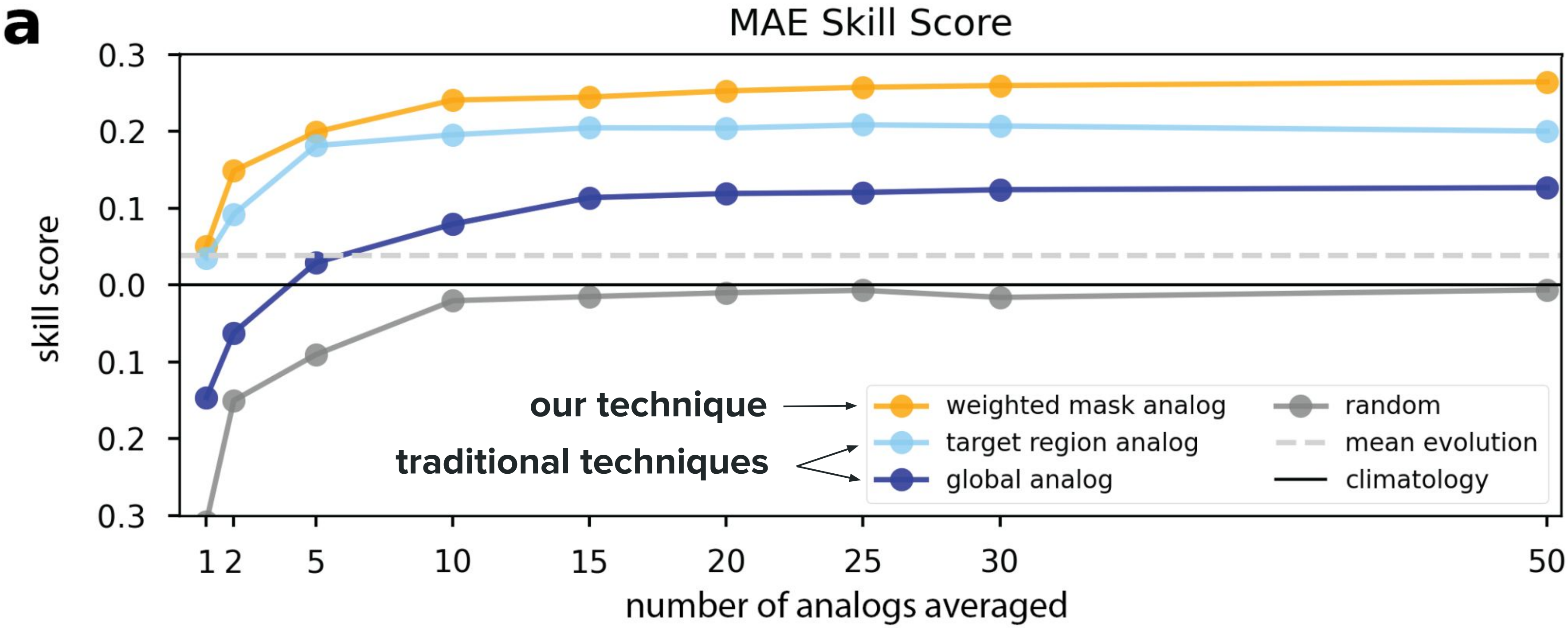
Some regions in the two maps look very different


b
Sample 223
c
Best Analog
4
2
0
-2
-4
d
Weighted Sample 223
e
Weighted Best Analog
50
0
-50
sea surface temperature anomaly (standardized)
Maps look similar in the precursor regions

The mean prediction from the 10-best analogs can predict North Atlantic sea surface temperature



This approach significantly improves analog forecasts of North Atlantic sea surface temperature



An Embarrassingly Parallel Problem

The most computationally intensive step in this work is **computing the weighted MSE** between the state of interest and all the potential analogs, to determining which should be used as analogs.

This step is **embarrassingly parallel**.

When parallelized, this process takes about 1/7th the time.

Takeaways

Interpretable neural network architectures can be used in conjunction with traditional prediction methods to **improve climate forecasts**.

In addition to improving forecasting skill, these methods can **highlight precursor regions** for climate variability.

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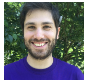
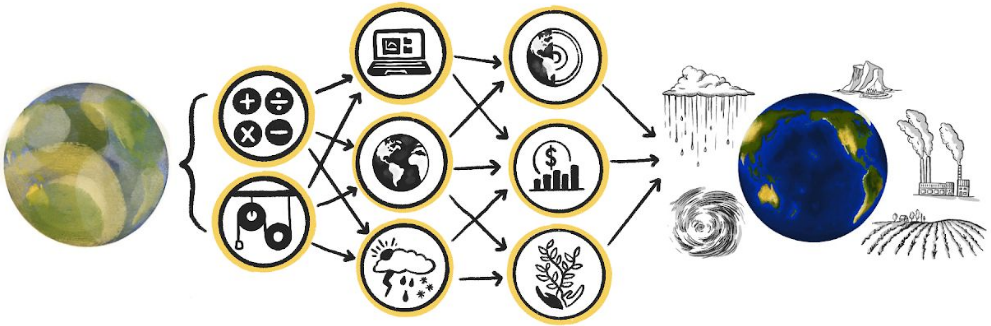
Looking Ahead

Can we apply this method to **observations** to make real-time seasonal-to-decadal forecasts? *This may require data from many different climate models and some transfer learning.* 

Can we extend this method to **subseasonal timescales**? *This will require significantly more data to identify "sufficiently similar" analogs.* 



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