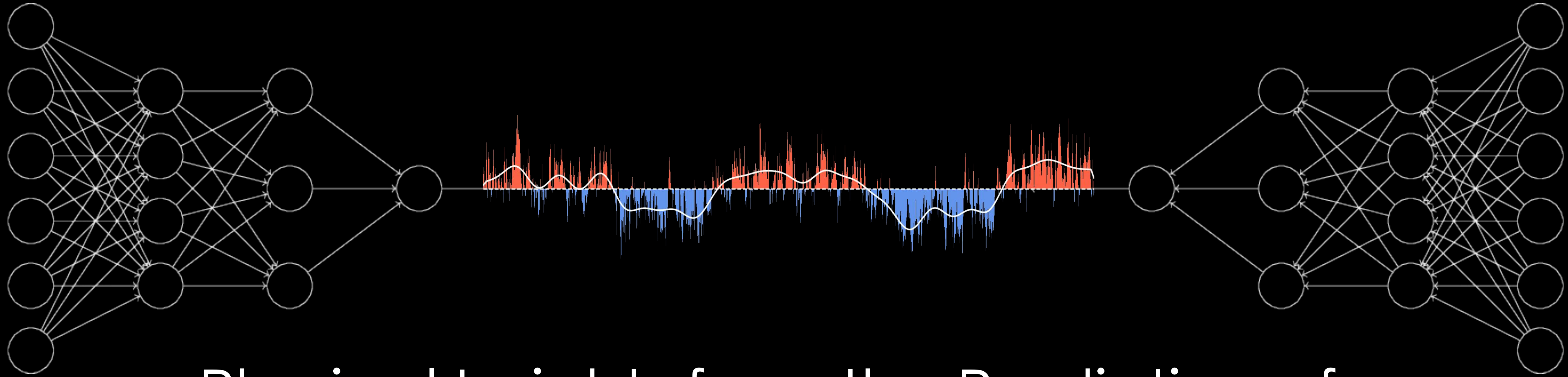

Physical Insights from the Prediction of Atlantic Multidecadal Variability using Explainable Deep Neural Networks

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2023 CESM Earth System Prediction Winter Working Group Meeting

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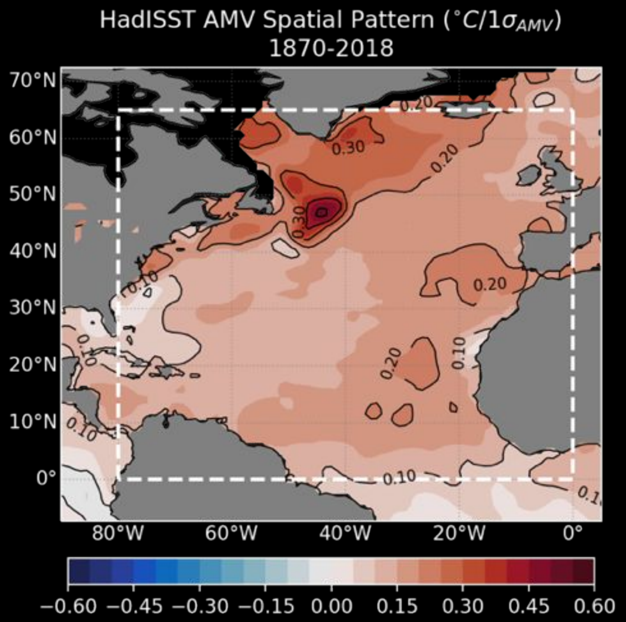
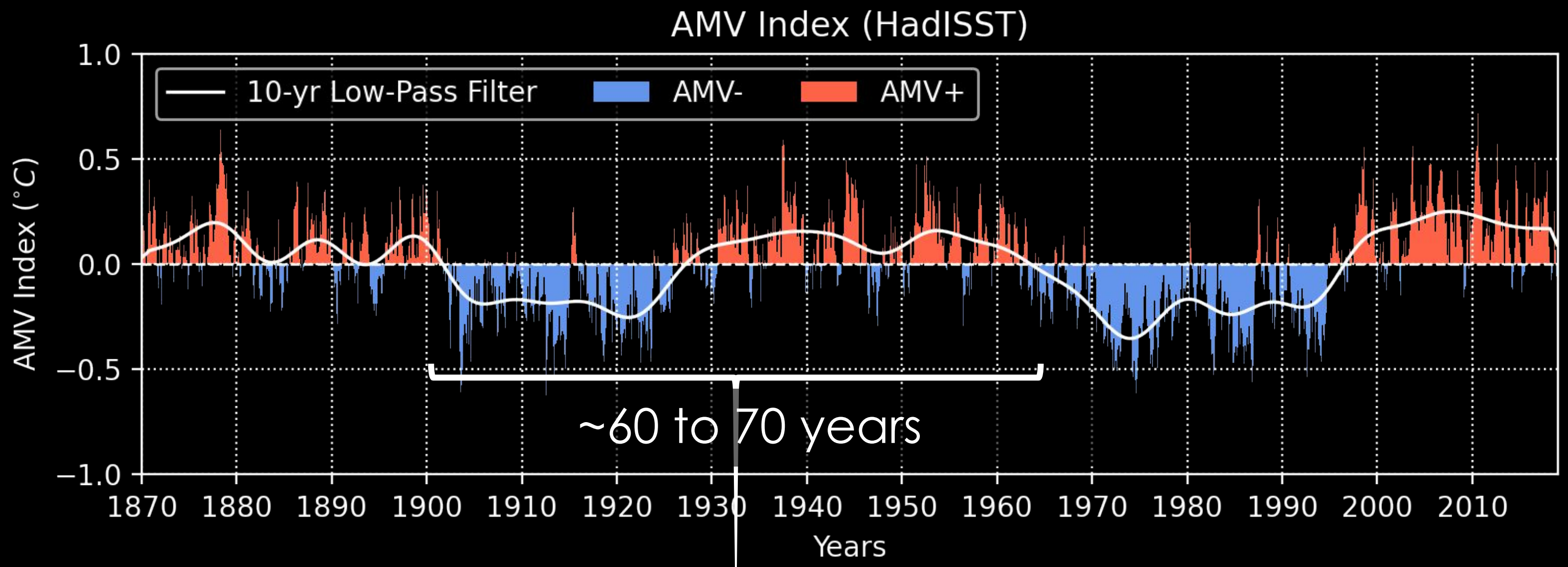
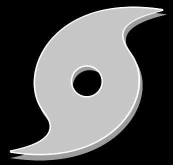
Atlantic Multidecadal Variability (AMV)



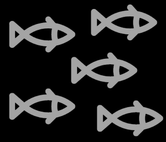


Why it's important:



Atlantic Hurricane Activity

Extreme Temperature and Precipitation

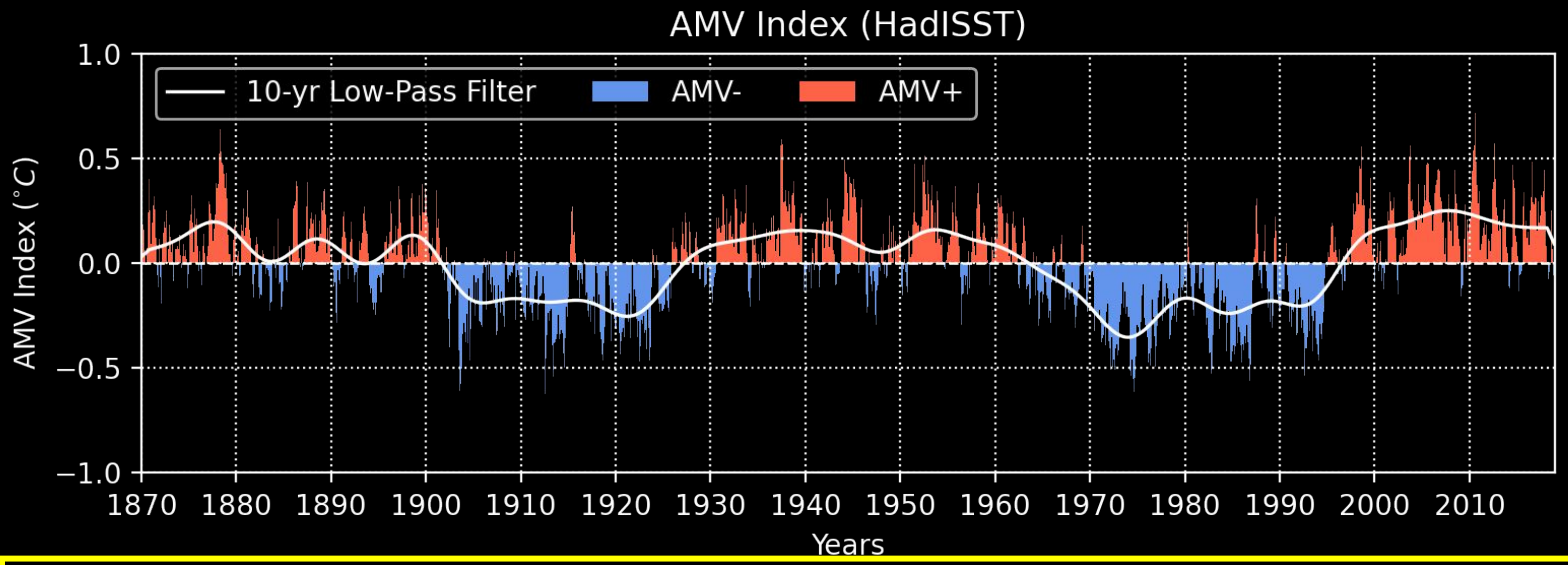


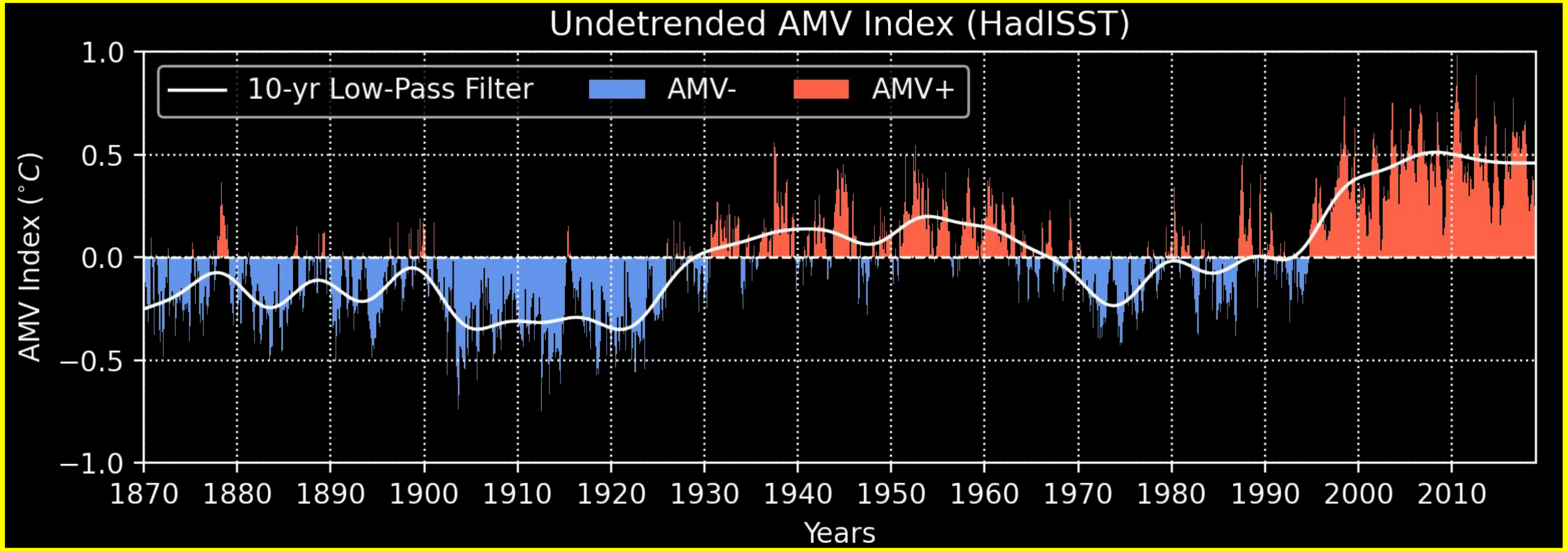
Ecosystem Regime Shifts

Relative importance of ocean vs. atmospheric dynamics?

AMV and the External Trend

We focus on predicting the undetrended and unsmoothed AMV Index



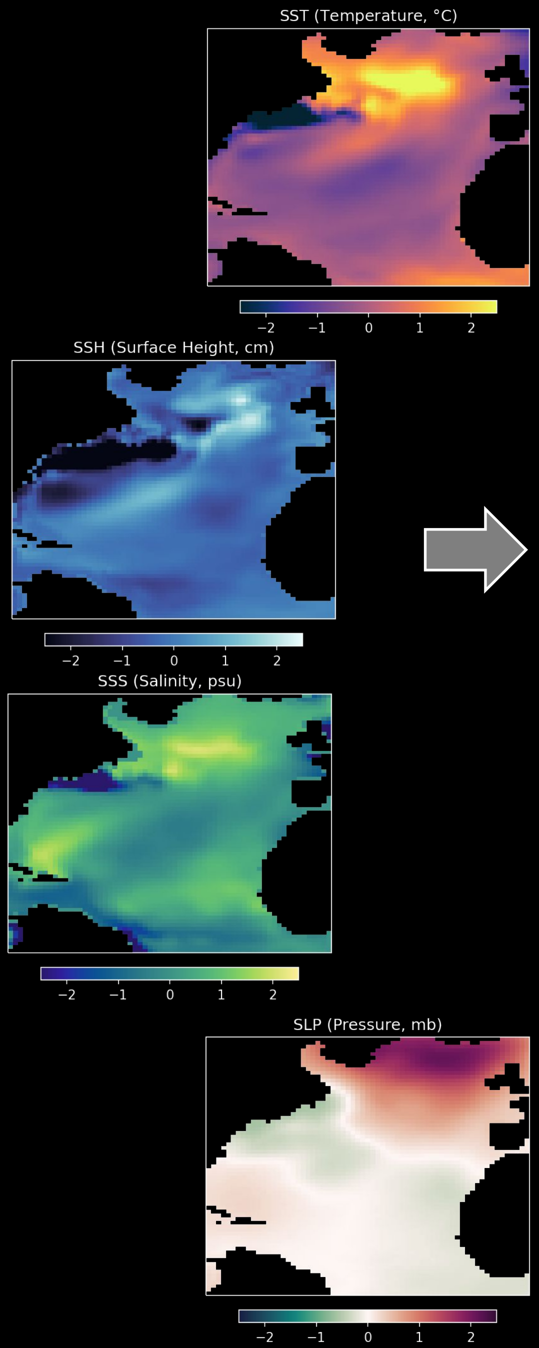


- Q: Do oceanic or atmospheric variables contribute to accurate prediction of the AMV state?

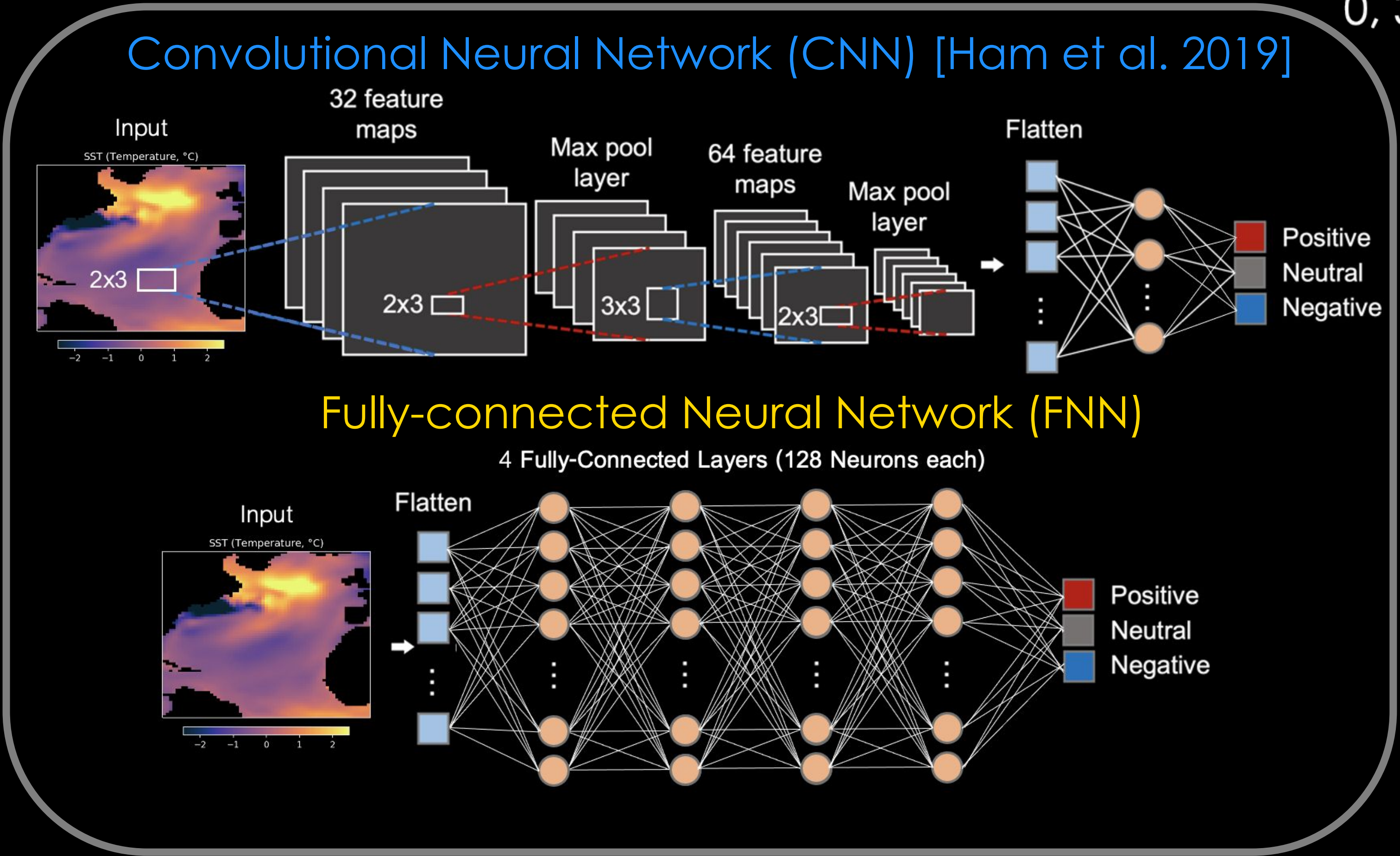
Neural networks have shown promise at *interannual* climate prediction → Are neural networks capable of making skillful predictions at longer timescales?

Insufficient data in observations 1870-2022 (~150 years) → Community Earth System Model 1.1 (CESM1) 40-member Large Ensemble Simulations 40 x (1920-2015) = 3,440 Years

The "Black Box" of machine learning/deep neural networks → Investigate sources /patterns of predictability using Layer-wise Relevance Propagation (LRP) (Toms et al. 2020, Mamalakis et al. 2022, …)



Neural Network

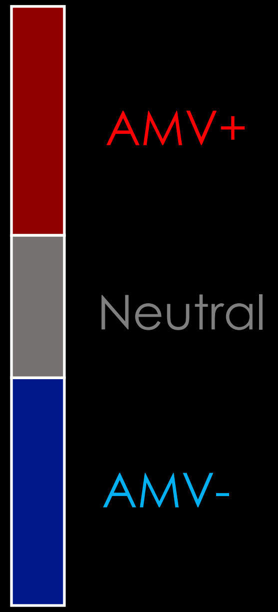


4 Predictors x 50 networks x 9 lead times = *1,800 networks*

AMV State

0, 3, …, 24 years later

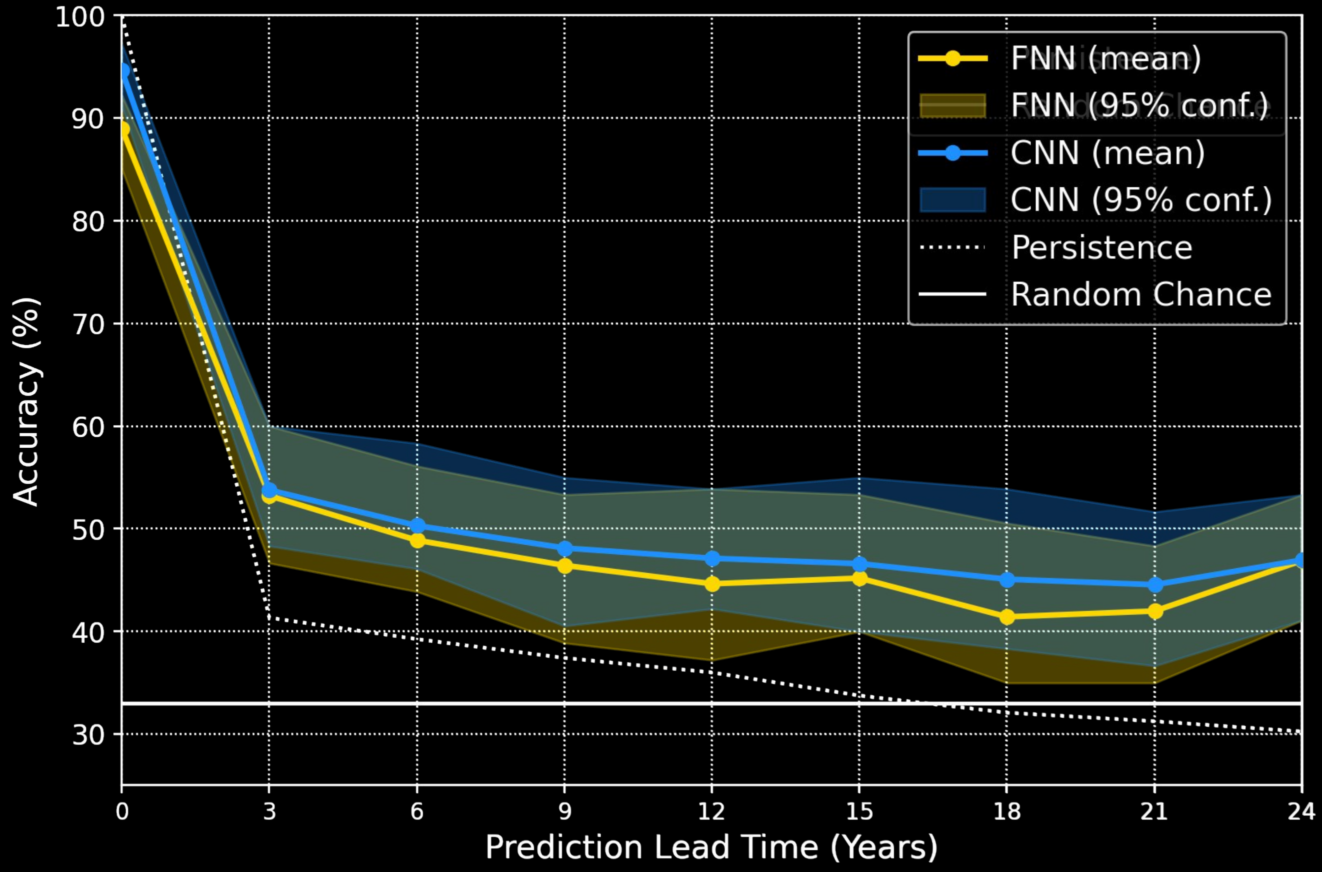
1σ Threshold



Do Convolutional Neural Networks (CNNs) outperform Fully-connected Neural Networks (FNNs)?

SST as a predictor | Persistence Baseline: AMV state will remain the same

Both CNN and FNN outperform the baselines, and exhibit *comparable accuracy*



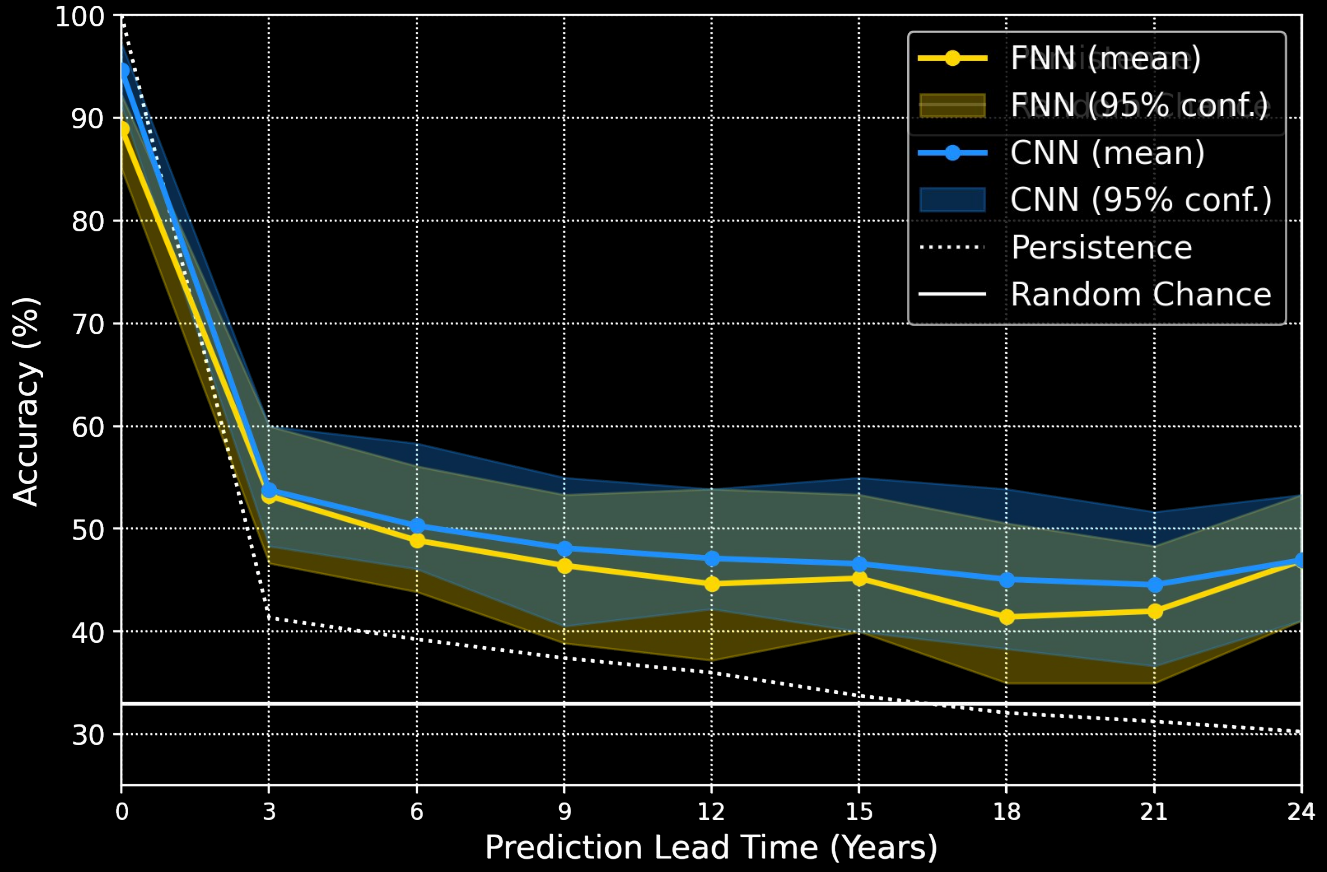
Shading: 95% confidence

Do Convolutional Neural Networks (CNNs) outperform Fully-connected Neural Networks (FNNs)?

SST as a predictor | Persistence Baseline: AMV state will remain the same

CNNs and translation invariance

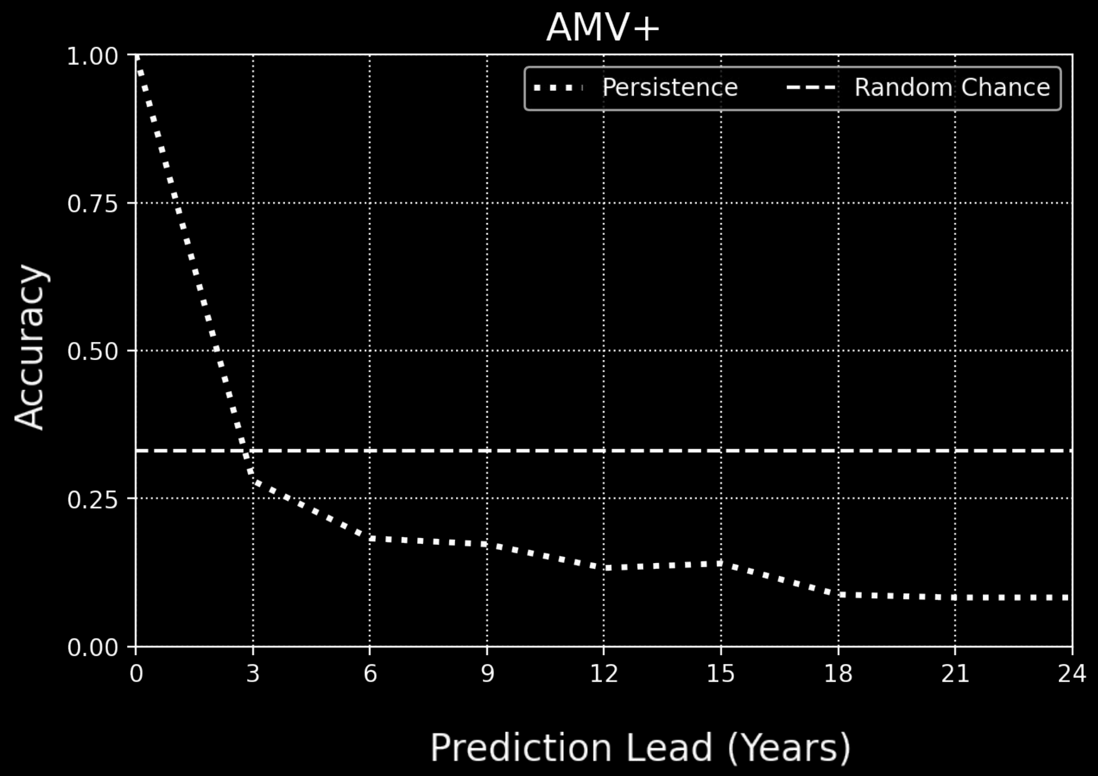
Source: Zhou et al 2015



Shading: 95% confidence

From this point onwards, we focus on results for the simpler FNN

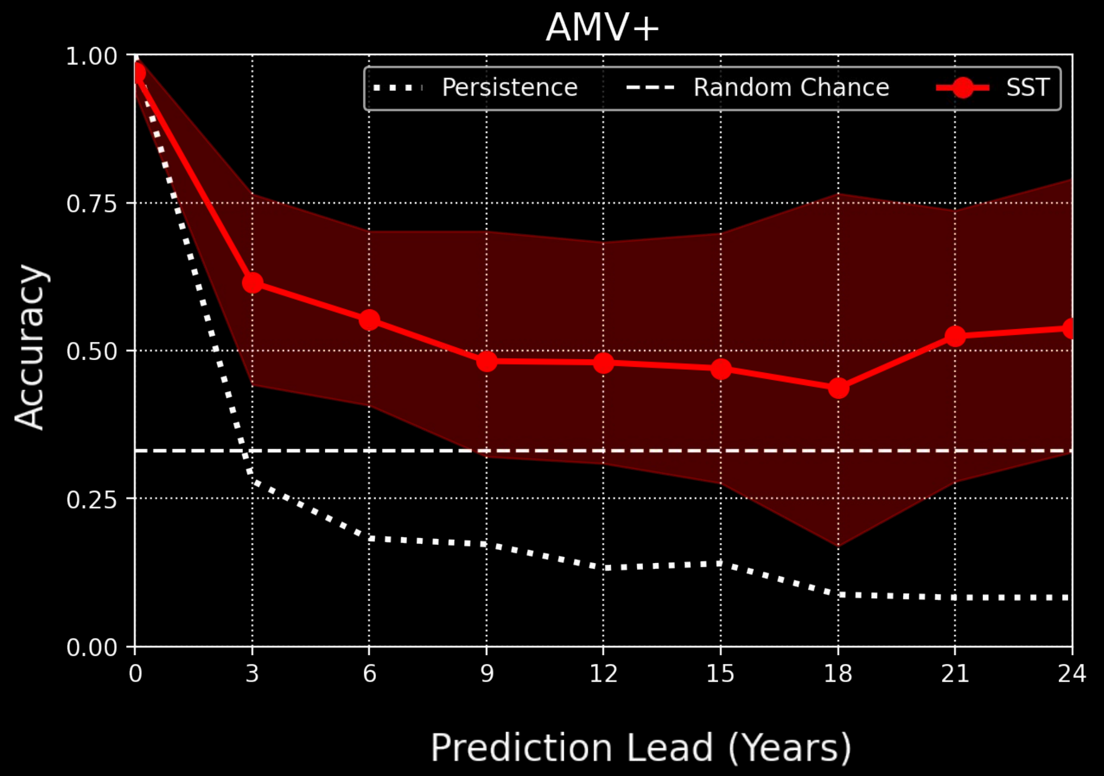
Differences in Skill by Predictor: AMV+, Baselines



Predictors Evaluated:
SST: Sea Surface Temperature
SLP: Pressure at Sea Level
SSH: Sea Surface Height
SSS: Sea Surface Salinity

First, we examine the accuracy of AMV+ predictions for FNNs trained with a given predictor.

Differences in Skill by Predictor: AMV+, SST

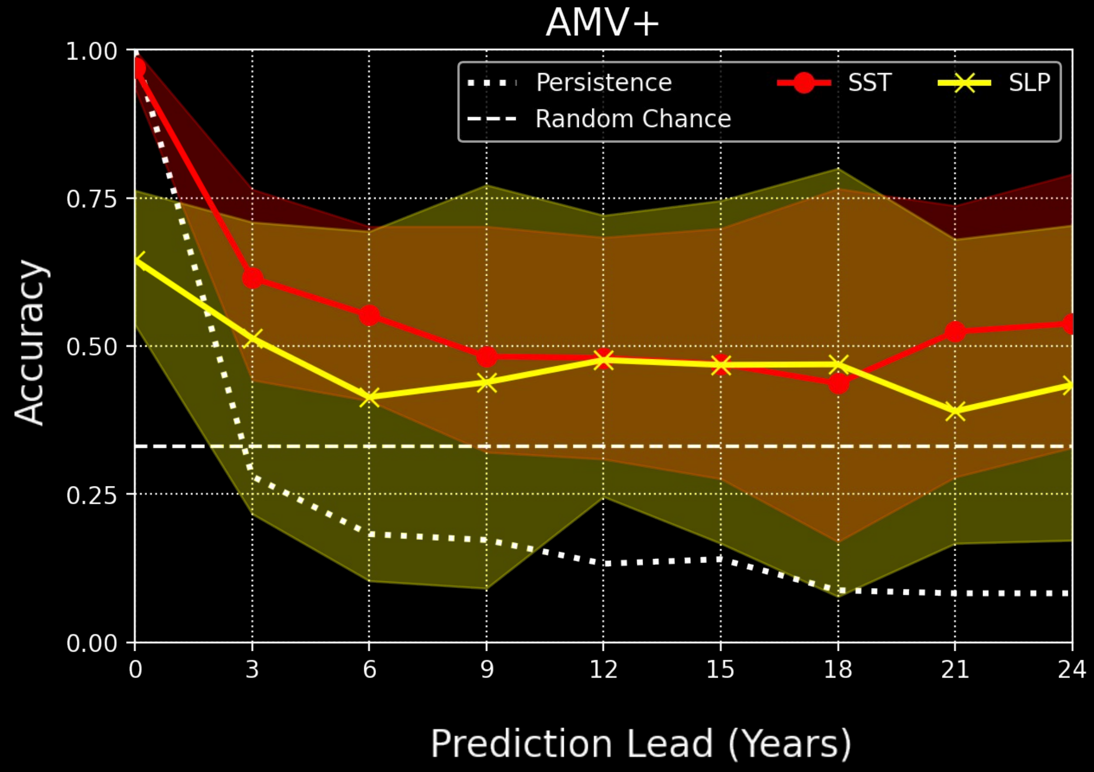


Shading: 95% confidence

Predictors Evaluated:
SST: Sea Surface Temperature
SLP: Pressure at Sea Level
SSH: Sea Surface Height
SSS: Sea Surface Salinity

SST is a useful predictor in the first 3-6
The FNN is outperforming the persistence baseline

Differences in Skill by Predictor: AMV+, SLP

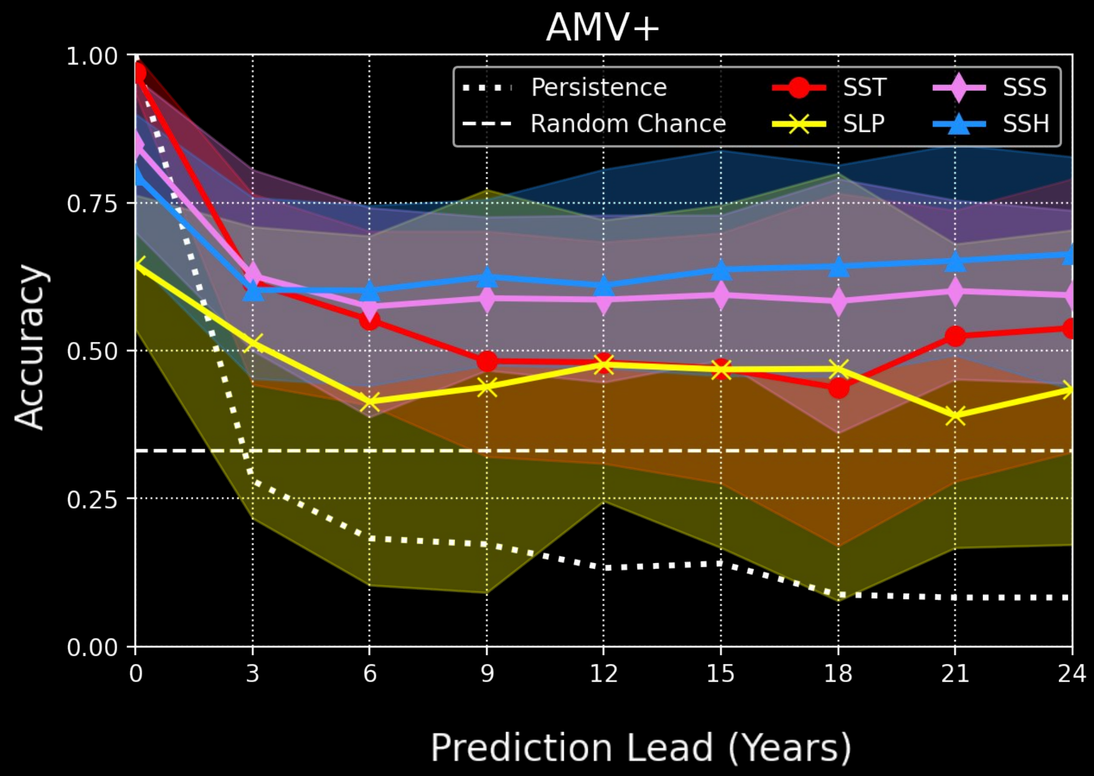


Shading: 95% confidence

Predictors Evaluated:
SST: Sea Surface Temperature
SLP: Pressure at Sea Level
SSH: Sea Surface Height
SSS: Sea Surface Salinity

SLP performs worse than SST in predictions <12 years, but has comparable skill at later leads.

Differences in Skill by Predictor: AMV+, SSS & SSH



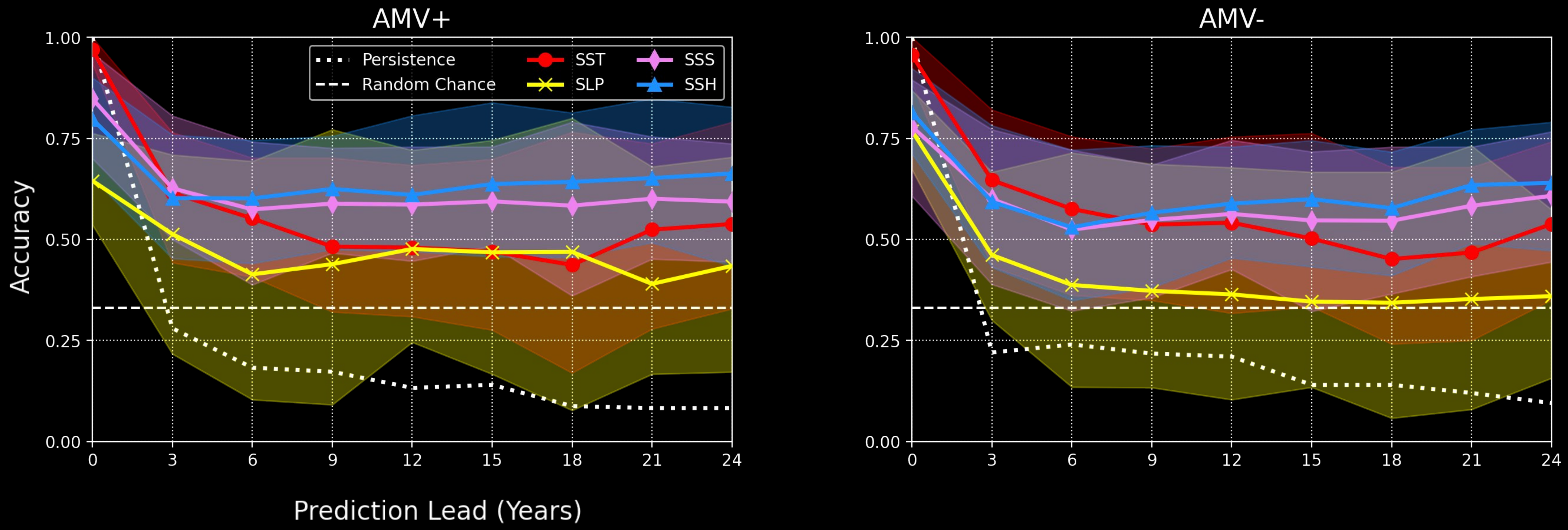
Shading: 95% confidence

Predictors Evaluated:
SST: Sea Surface Temperature
SLP: Pressure at Sea Level
SSH: Sea Surface Height
SSS: Sea Surface Salinity

SSS & SSH predictors result in consistently higher skill at predictions >6 years

Networks trained with *oceanic variables* exhibit higher accuracies at longer leadtimes

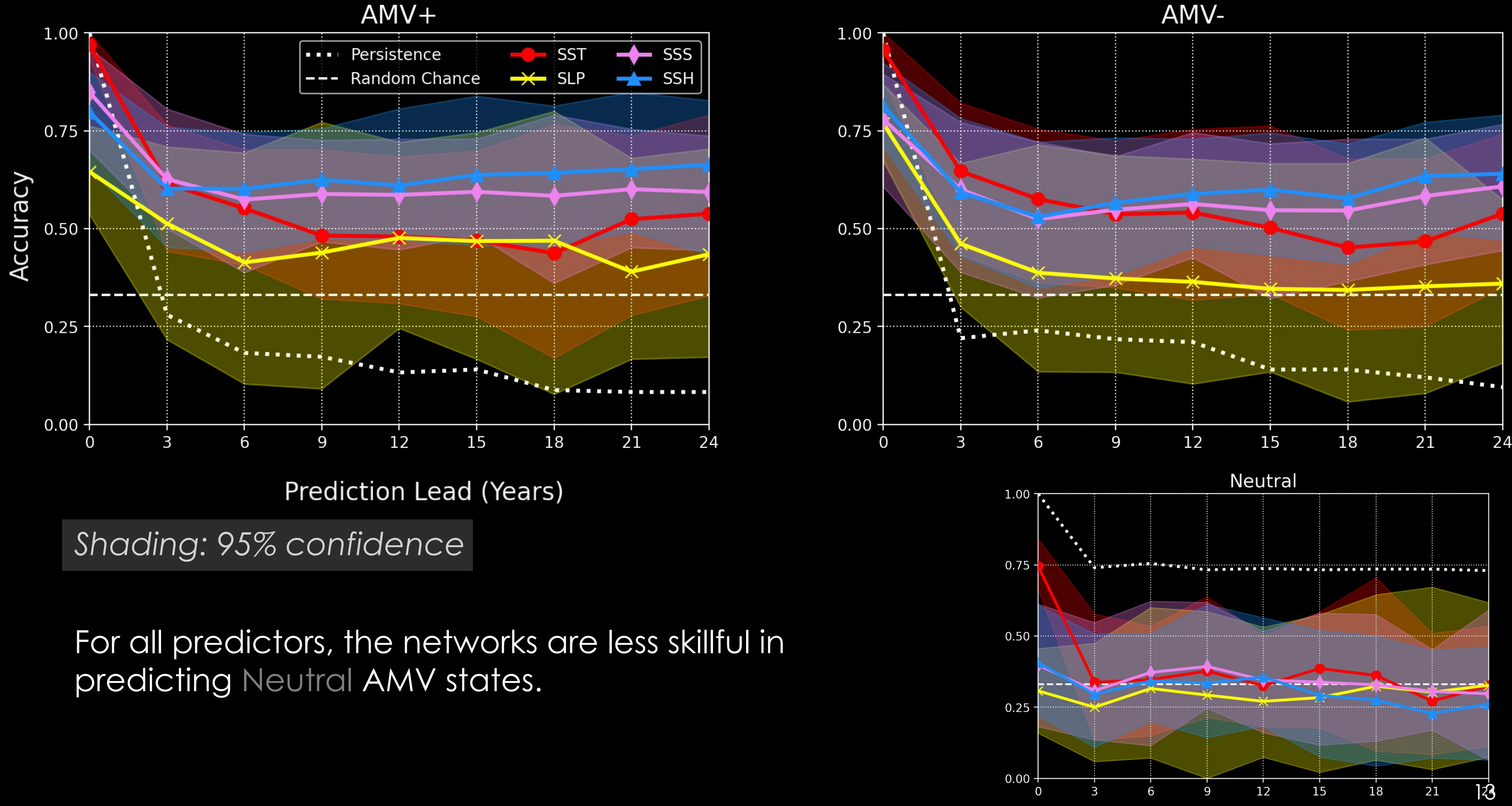
Differences in Skill by Predictor: AMV-



Shading: 95% confidence

The differences between the predictors are similar for AMV-
The gap in skill between SST and the oceanic predictors is smaller.

Differences in Skill by Predictor: Neutral



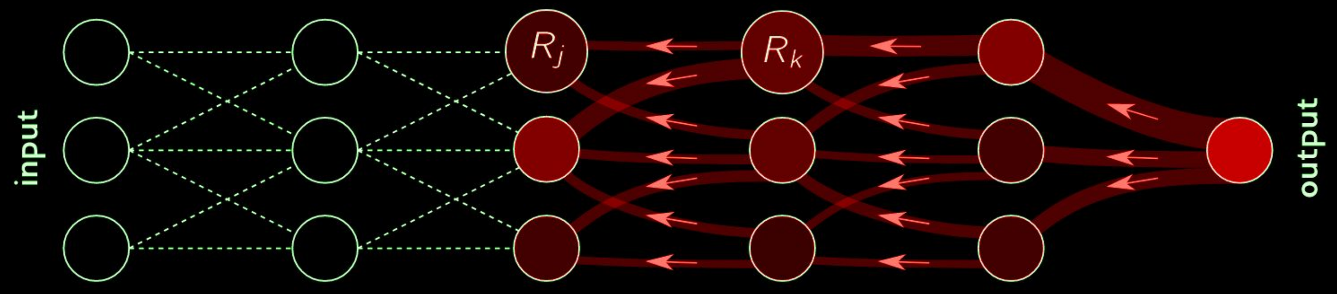
Shading: 95% confidence

For all predictors, the networks are less skillful in predicting Neutral AMV states.

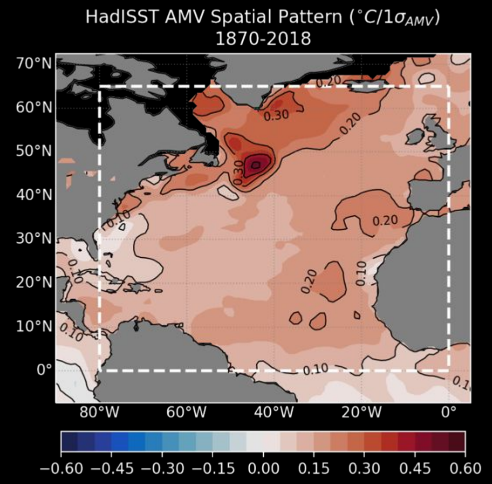
Where are the sources of predictability?

(Preliminary results)

Layerwise Relevance Propagation (LRP)



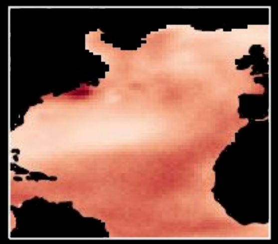
Schematic from Montavon et al. 2019



Mean relevance composites of *correct* AMV+ predictions for the Top 25 networks

Lead 24 Lead 18 Lead 12 Lead 6 Lead 0

SST

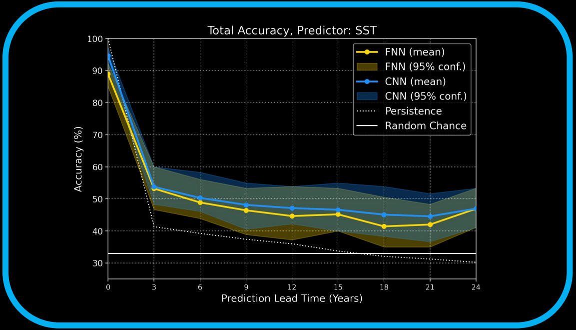


Gulf Stream/North Atlantic Regions have high relevance for long term prediction

Takeaways, Future Directions

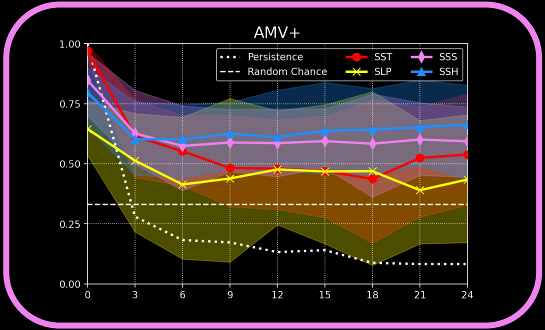
1

Complex architectures (CNN) do not necessarily lead to more accurate AMV prediction.



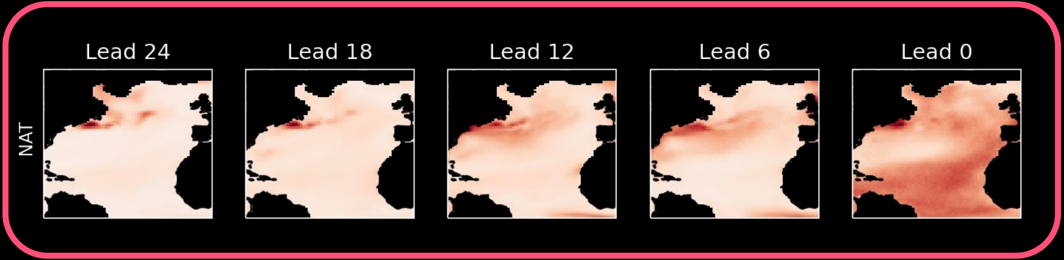
2

Oceanic variables (SSH, SSS) offer more predictive skill on long (>6 year) lead times



3

Gulf Stream / North Atlantic Current emerge as important regions for long term predictability



***Future Work*:**

- Investigate dynamics/causality behind predictability in high relevance regions for SSH, SSS
- Explore how the presence of the external trend contributes to predictability
- Examine sensitivity of relevance maps to other explainability methods
- Applicability and transfer learning to observations/reanalyses, and other models

Thanks for listening! Questions? Email: glennliu@mit.edu