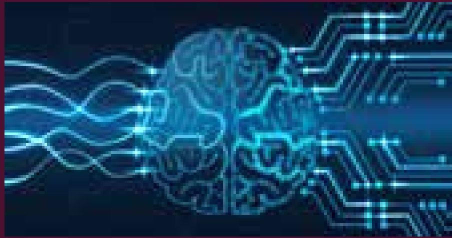
Assessing Decadal Variability of Subseasonal Predictability using Artificial Neural Networks

Marybeth Arcodia

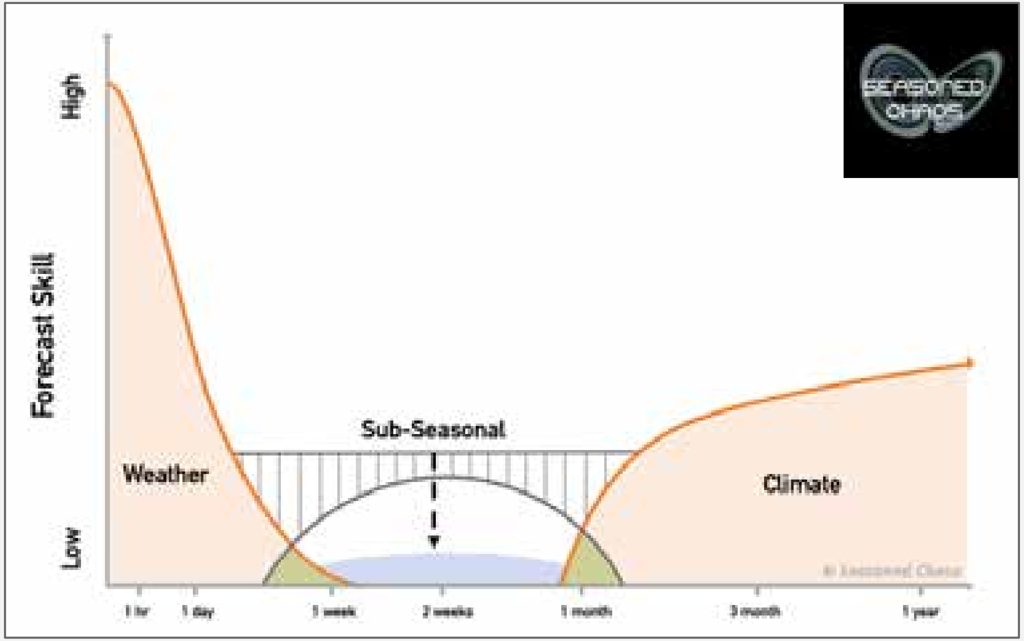
Elizabeth Barnes, Kirsten Mayer,
Jiwoo Lee, Min-Seop Ahn, Ana Ordonez



47th CDP Workshop
October 27, 2022

Subseasonal desert of predictability

Vitart et al. 2012, 2017; Marriott et al., 2020



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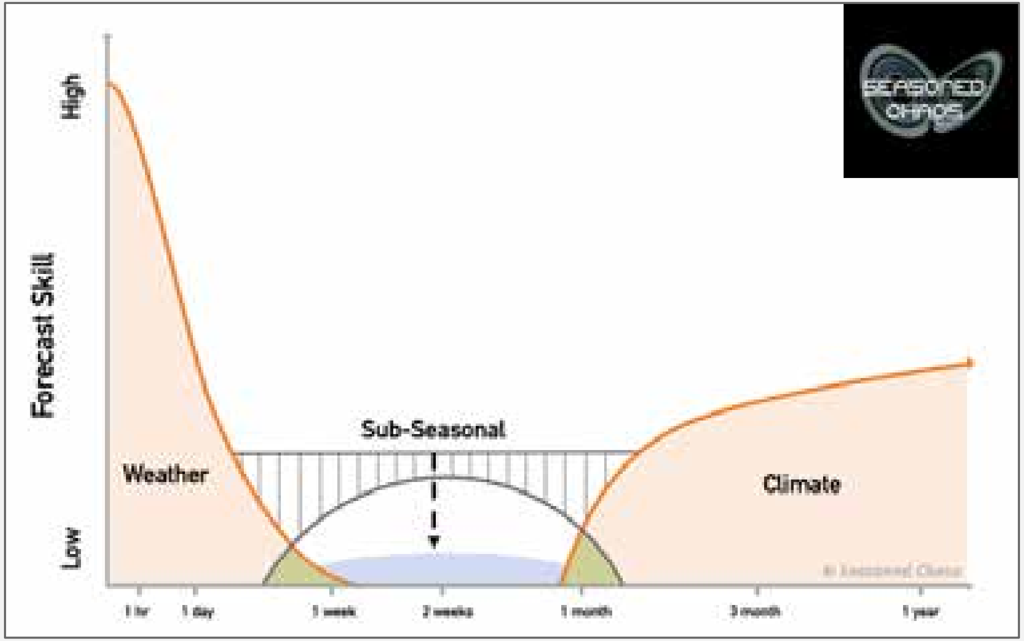
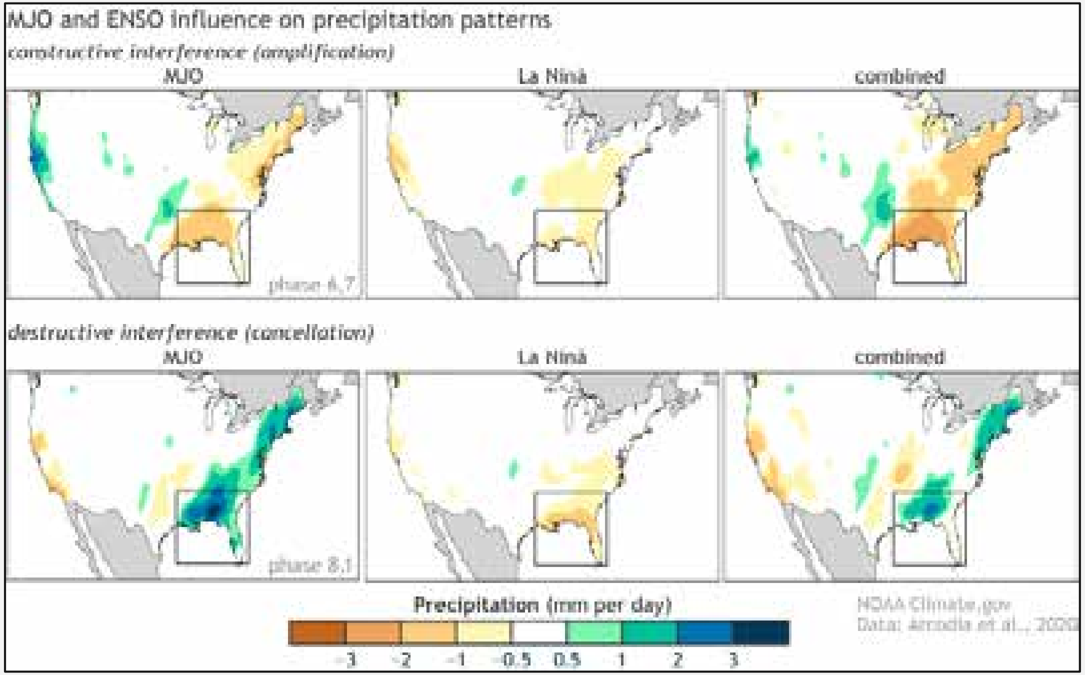


We rely on predictable states of the climate system to improve subseasonal forecasts, aka ***forecasts of opportunity***

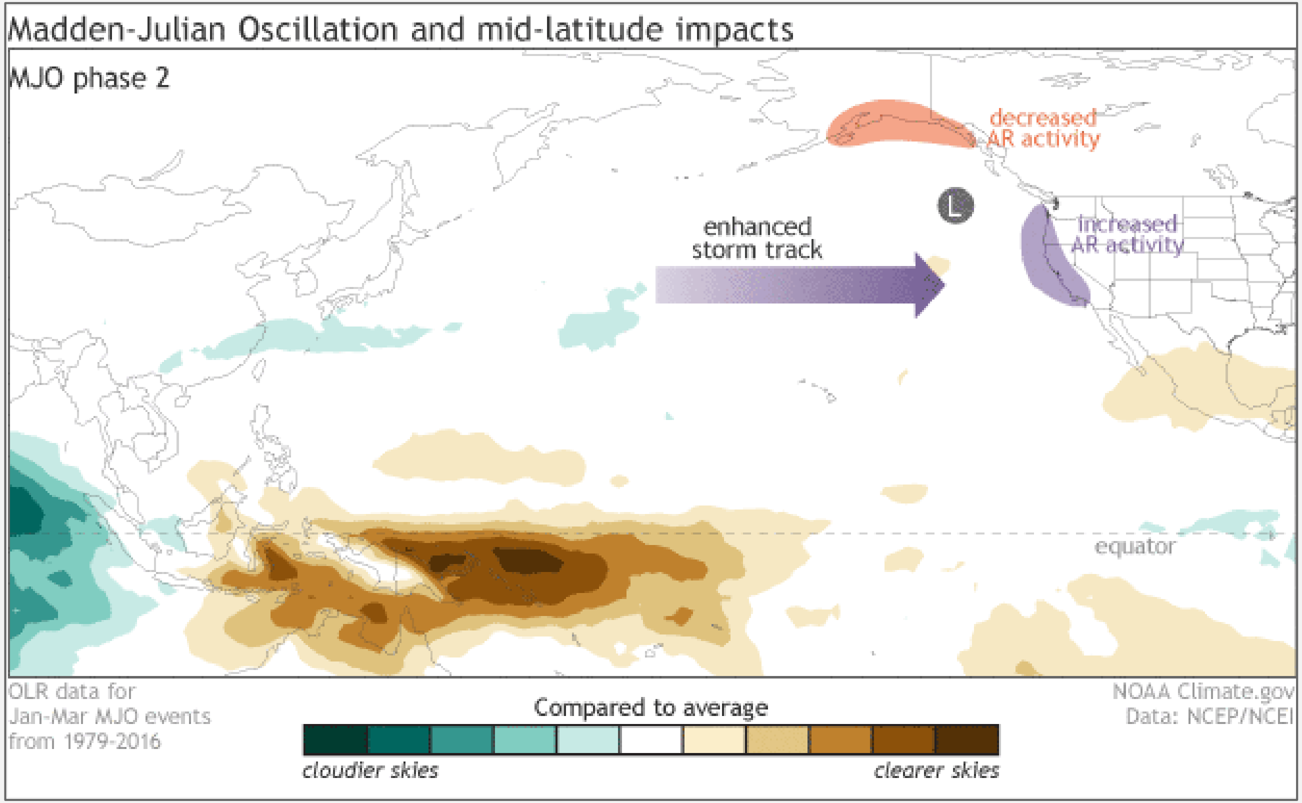
Connection of tropical conditions to S2S North American West Coast precipitation

Connection of tropical conditions to S2S North American West Coast precipitation

- MJO, ENSO largest sources of subseasonal and interannual predictability (Diaz et al., 2001; Lau and Waliser, 2011)
- Combined influence of MJO and ENSO lead to ***forecasts of opportunity***



Arcodia, Kirtman, Siqueira (2020)



Colorado State University

Low Frequency Modulators of North American West Coast precipitation

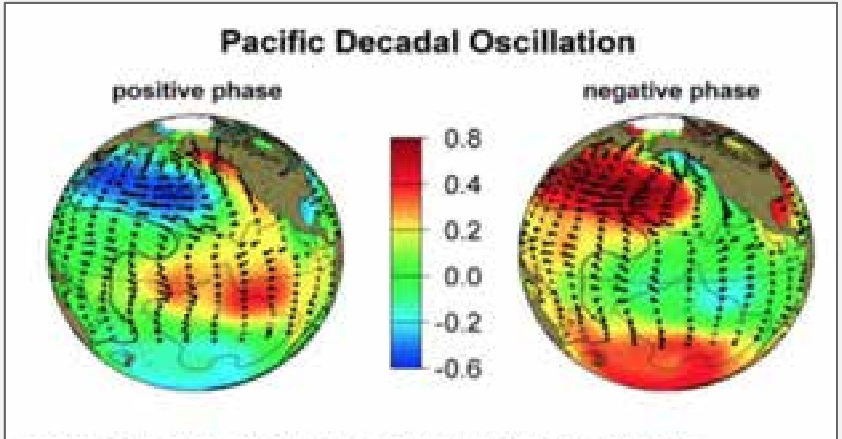
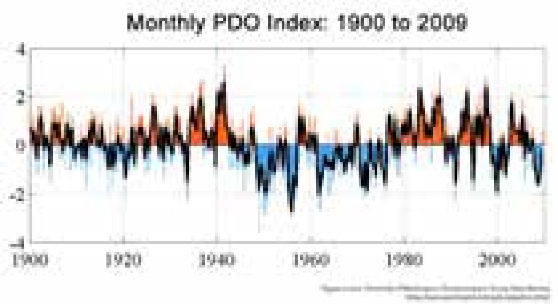
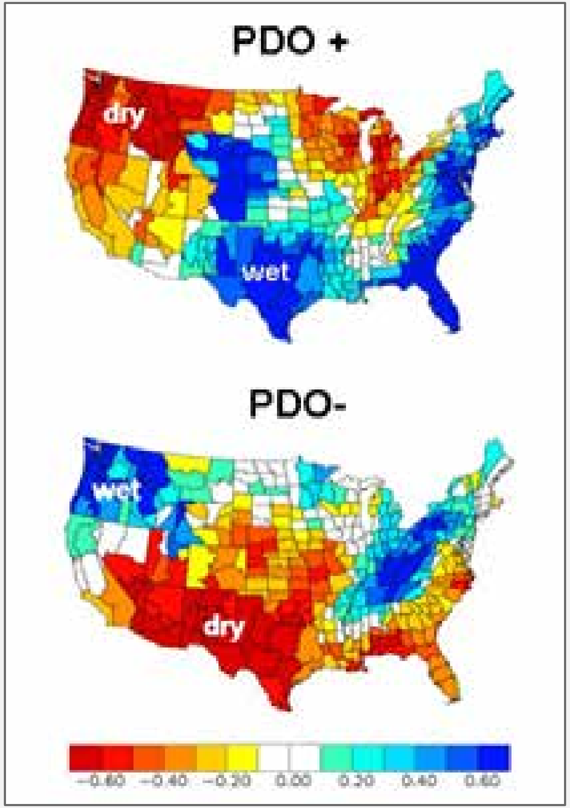


Image courtesy of Stepen Hare and Nathan Mantua, University of Washington, units are degrees Celsius





Given that…

- The tropics can provide a source of mid-latitude subseasonal predictability for precipitation on the North American West Coast
- Pacific Decadal Oscillation modulates rainfall variability along the West Coast on low frequency timescales

How does subseasonal predictability provided by the tropics vary on decadal timescales?

Artificial Neural Network (ANN)

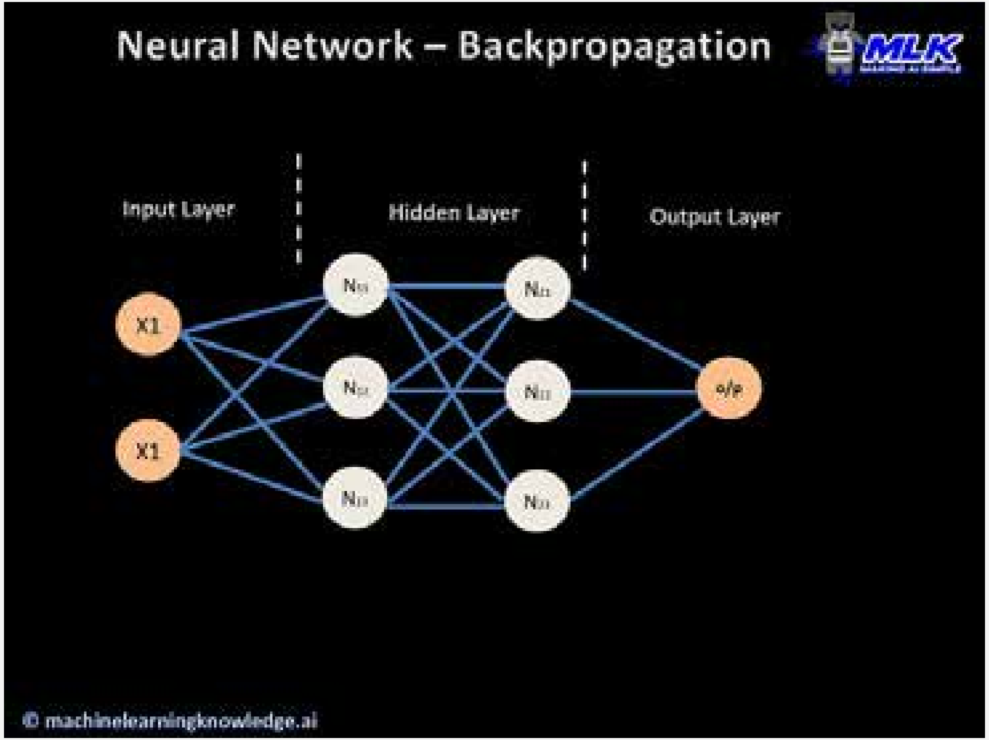
Artificial Neural Network (ANN)

data/ input → 

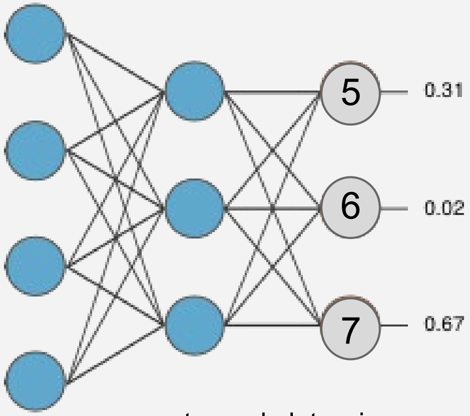
→ prediction/ output

Hidden layers

Artificial Neural Network (ANN)



Leveraging Machine Learning



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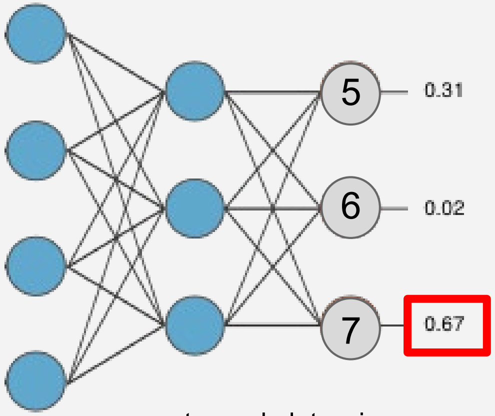
Leveraging Machine Learning



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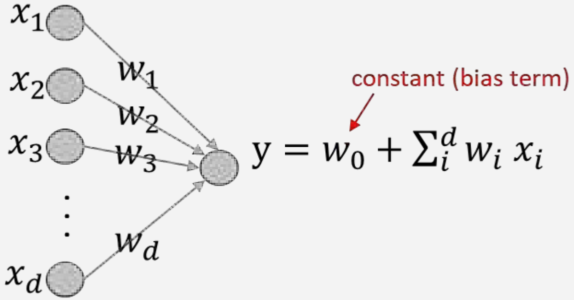
We can quantify the confidence in the probability of the predicted output

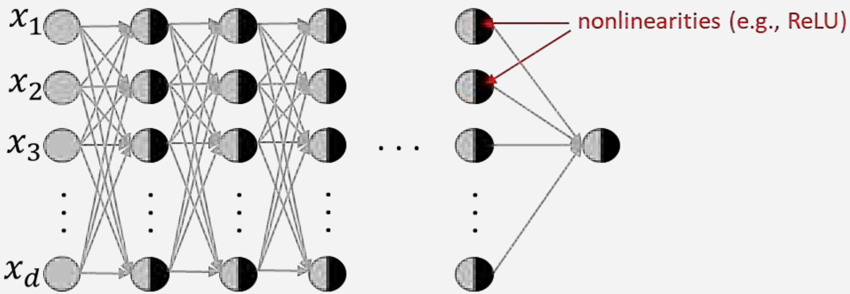
What did the neural network learn?

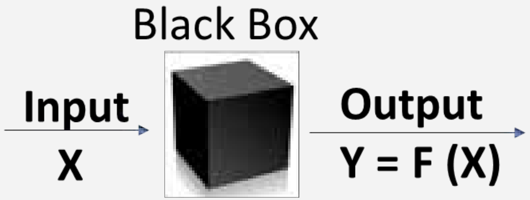
What did the neural network learn?

Linear model: inherently interpretable



Neural Network: not inherently interpretable

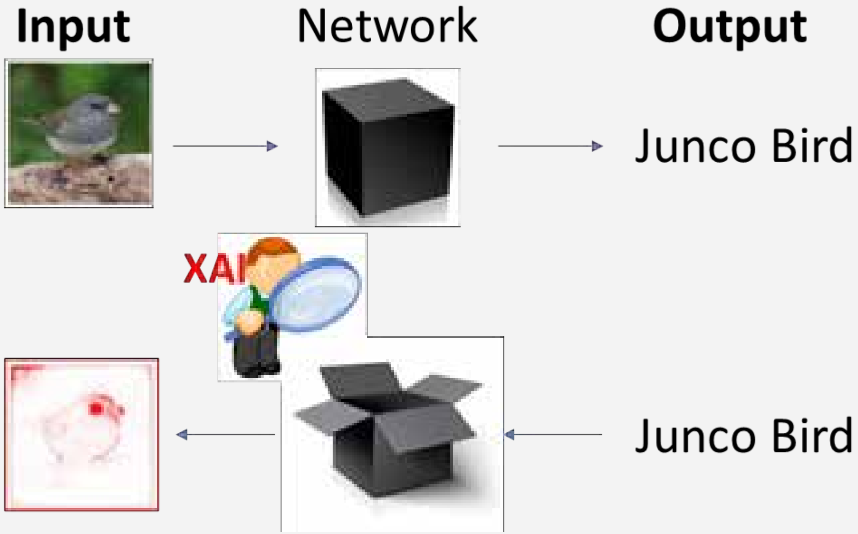




Credit: Tony Mamalakis

eXplainable Artificial Intelligence (XAI) aims to explain how a Neural Network makes predictions, i.e., what the *decision strategy* is.

XAI methods highlight which features in the input space are important for the prediction



Explanation/ relevance Heatmap

From *Adebayo et al. (2020);* Credit: Tony Mamalakis

Integrated Gradients (attribution)

- ***Attribution*** refers to the relative contribution of a specific input feature to the output. **[units output]**

Relevance of feature i for prediction n

Input

Gradient

$$R_{i,n} = x_{i,n} * \left.\frac{\partial \hat{F}}{\partial \mathrm{X}_i}\right|_{\mathrm{X}_i = x_{i,n}}$$

Mamalakis et al. 2022; Ancona et al. 2018

Artificial Neural Network (ANN)

data/ input →

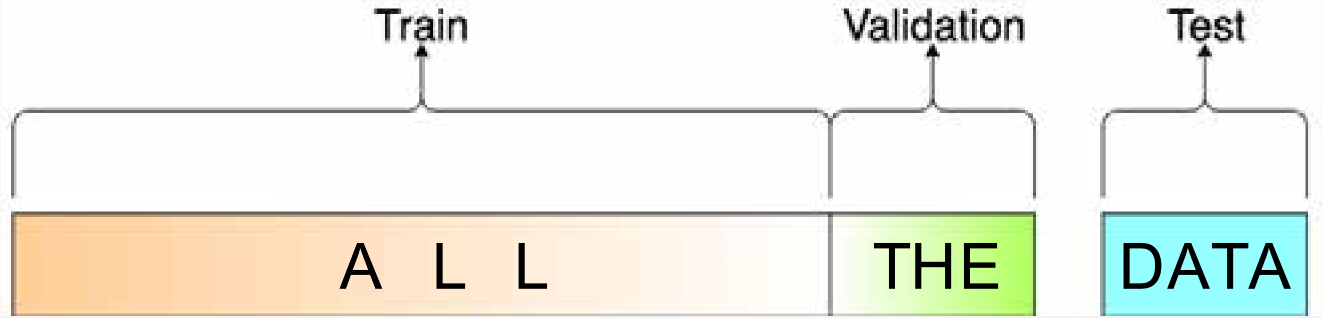
→ prediction/ output

Hidden layers

Pre-processing Data

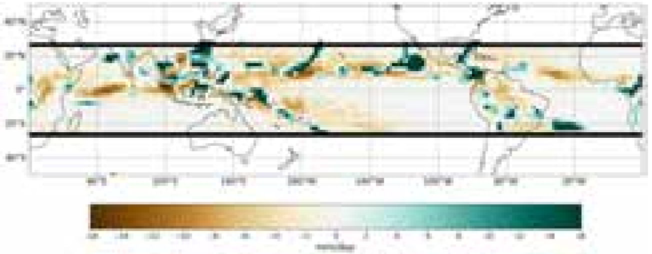
- CESM-2 Large Ensemble Dataset (10 members)
  - Daily data; 1850-1950; November - March
  - Daily anomalies calculated via subtraction of the ensemble mean and detrending
    - Calculate daily climatology from the ensemble mean

Neural Network Setup



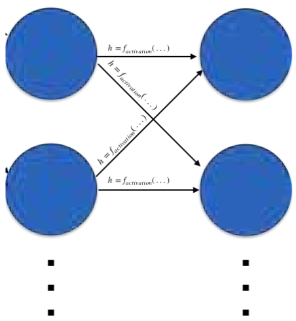
- Training: Ensembles 0-7; Validation: Ensemble 8; Testing: Ensemble 9
- Next:
  - Training: Ensembles 1-8; Validation: Ensemble 9; Testing: Ensemble 0
  - Training: Ensembles 2-9; Validation: Ensemble 0; Testing: Ensemble 1
  - Etc…

Artificial Neural Network (ANN)

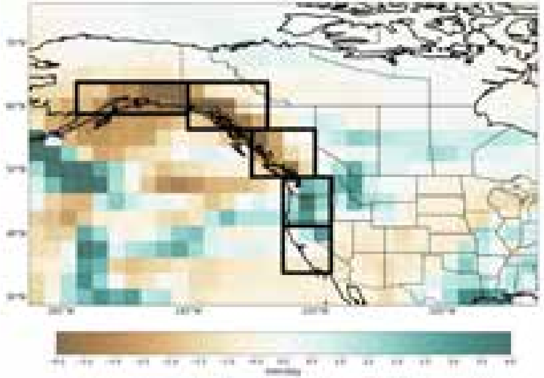


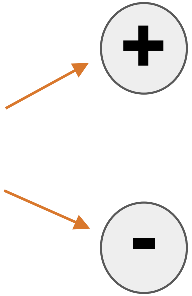
Input:
Daily Tropical Precipitation Anomaly

hidden layers



[128 x 32]

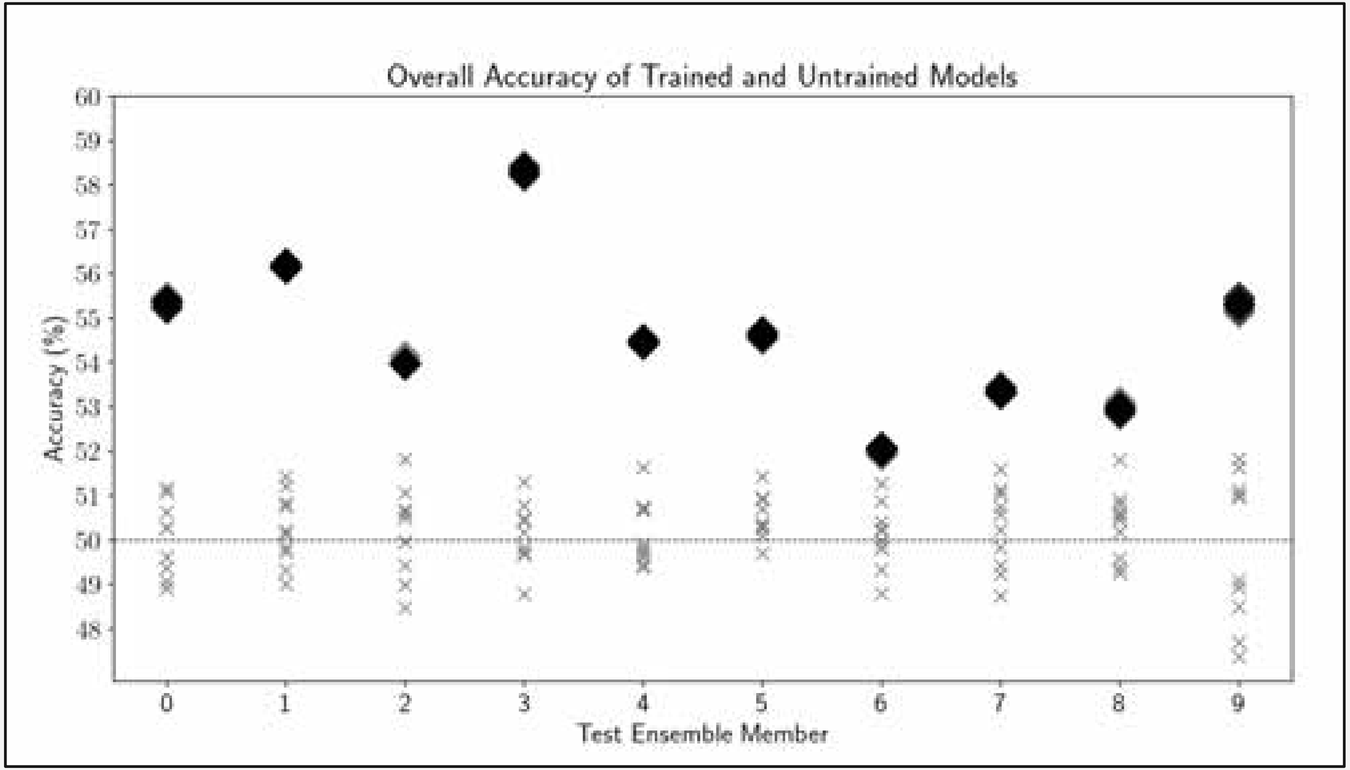




Output:
Week 3-4 Precipitation Anomaly

Goal: Predict sign of precipitation anomaly for averaged Week 3-4 in 5 regions along the North American West Coast

Determine if accuracy >50% is due to random chance



◆ Trained
X Untrained

Does the subseasonal predictability from the tropics vary on decadal timescales?

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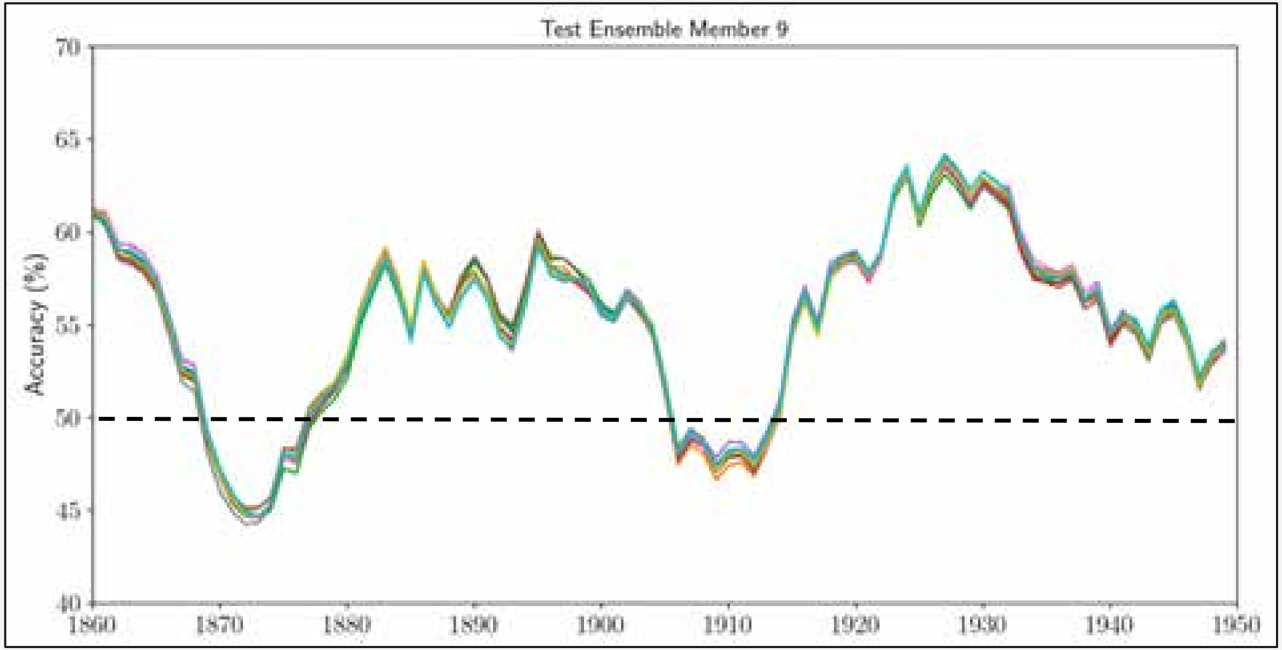
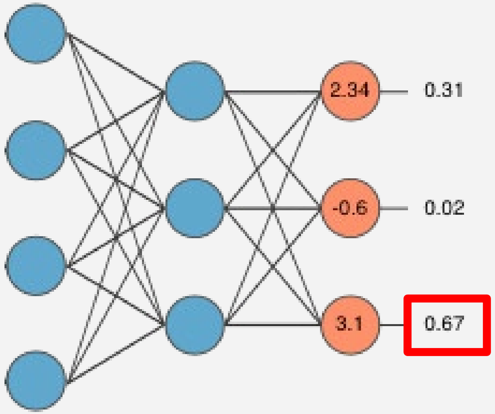
10-yr running window of prediction accuracy
Alaskan Week 3-4 precip
One testing ensemble member, 10 random seeds



Quantify Confidence of the Neural Network's Predictions



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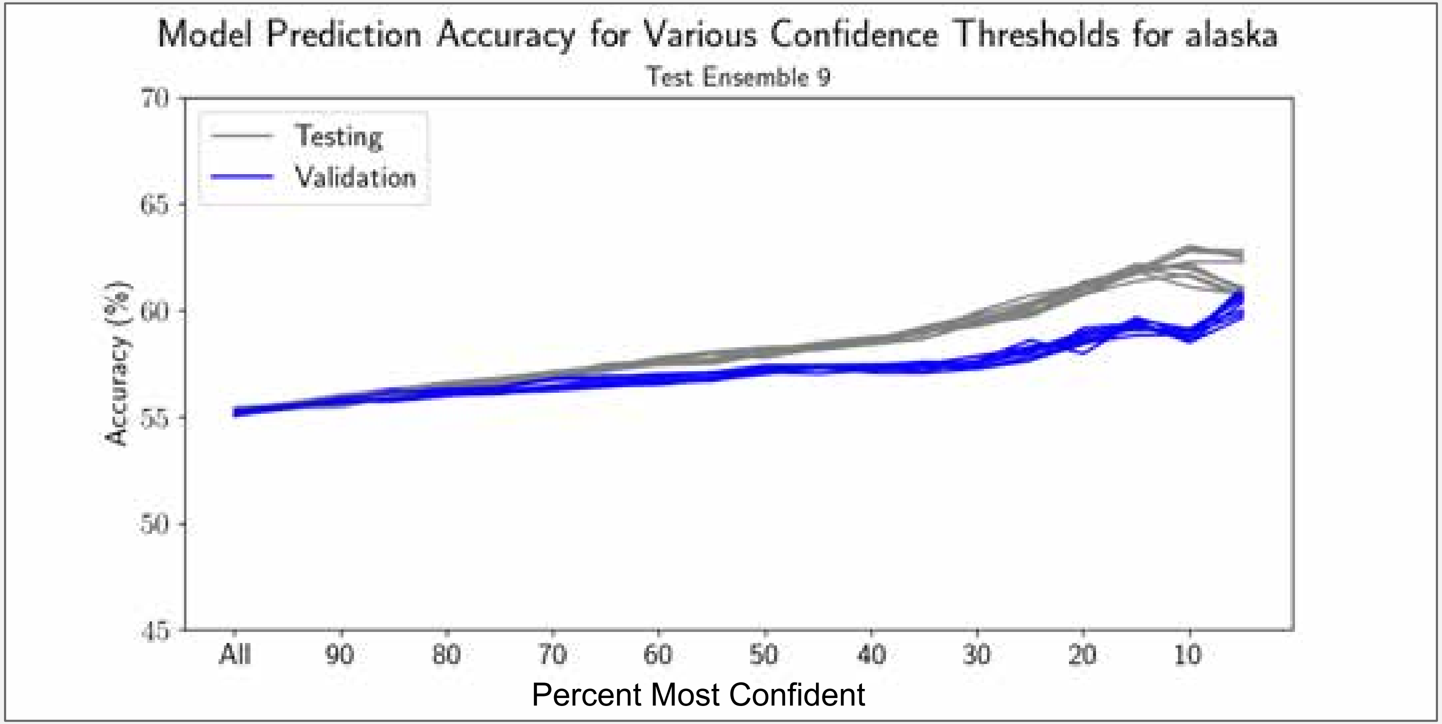
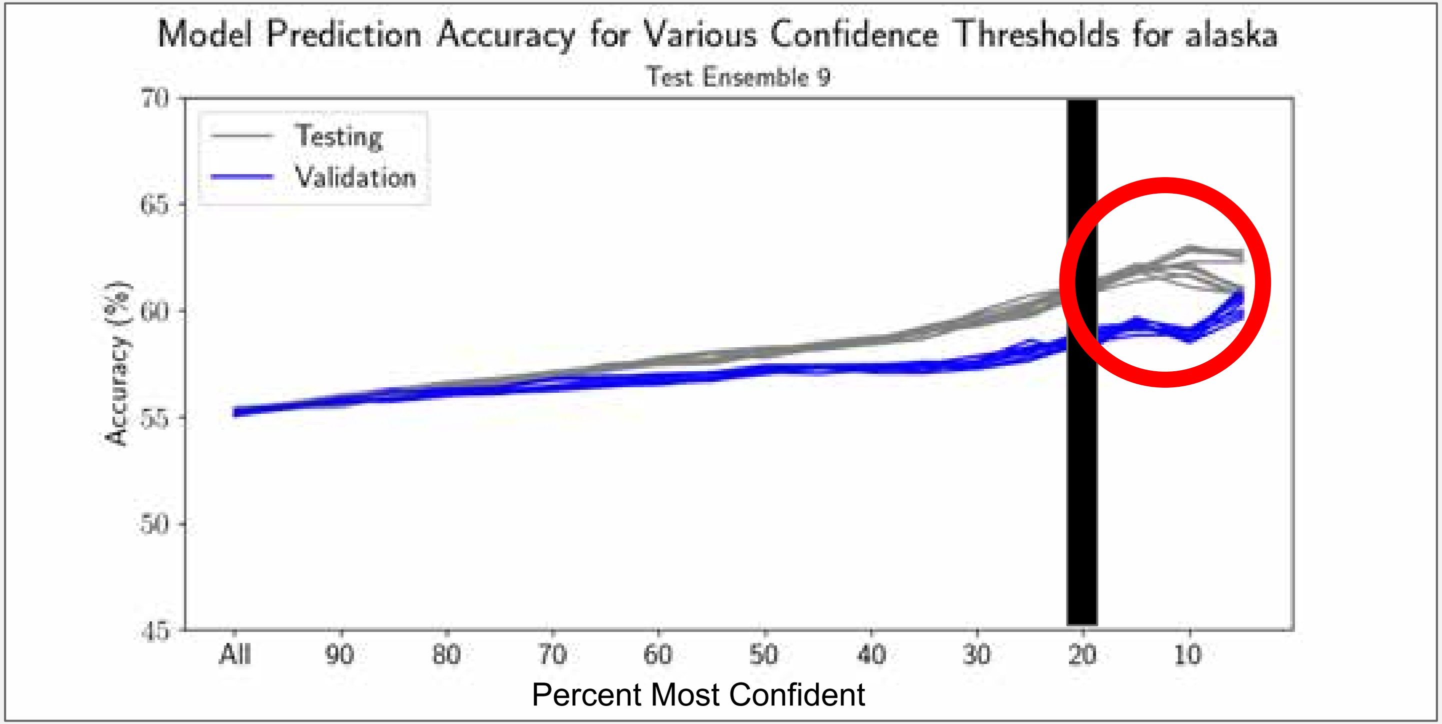
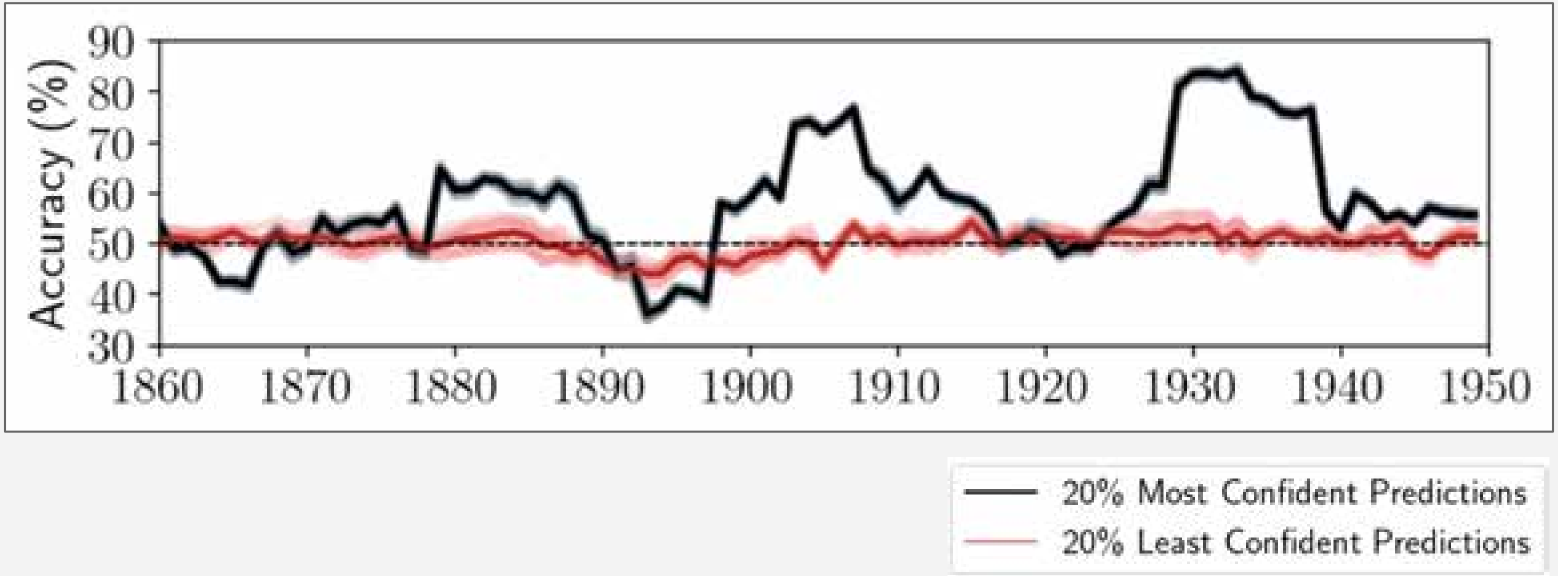


Forecasts of Opportunity



Accuracy improves with confidence ⇒ more predictable time periods

10-yr running window of prediction accuracy
Alaskan Week 3-4 precip



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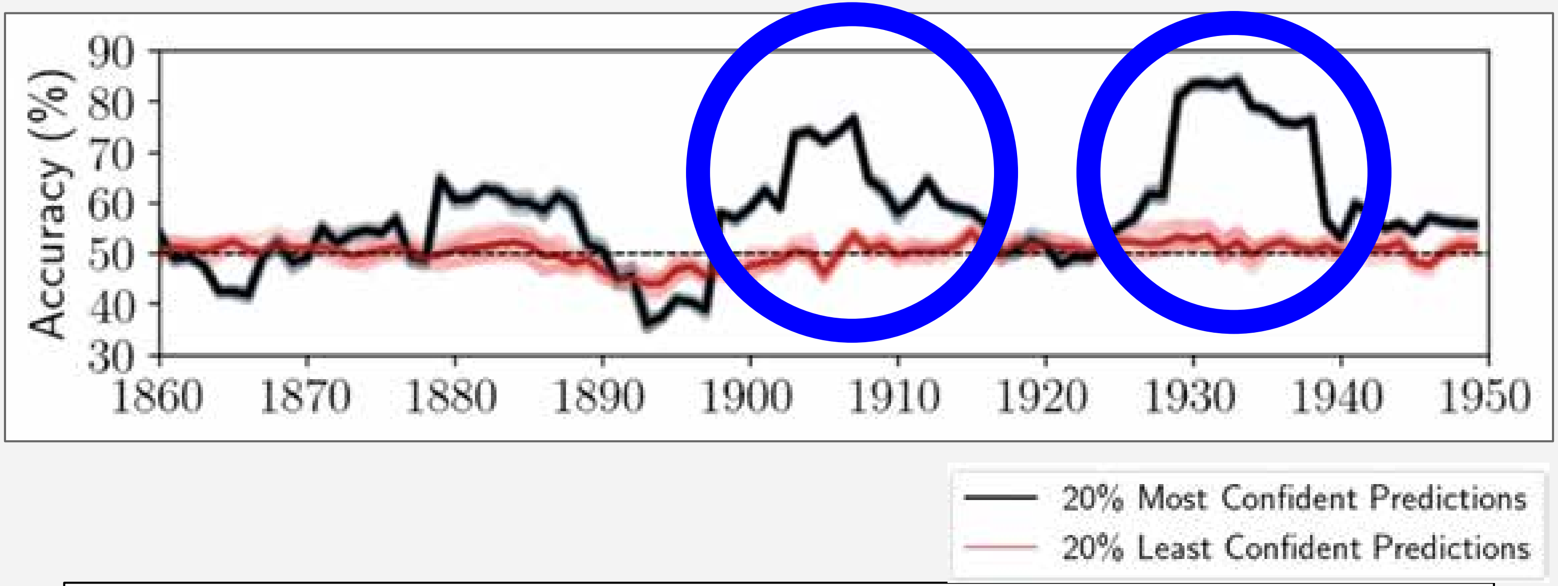
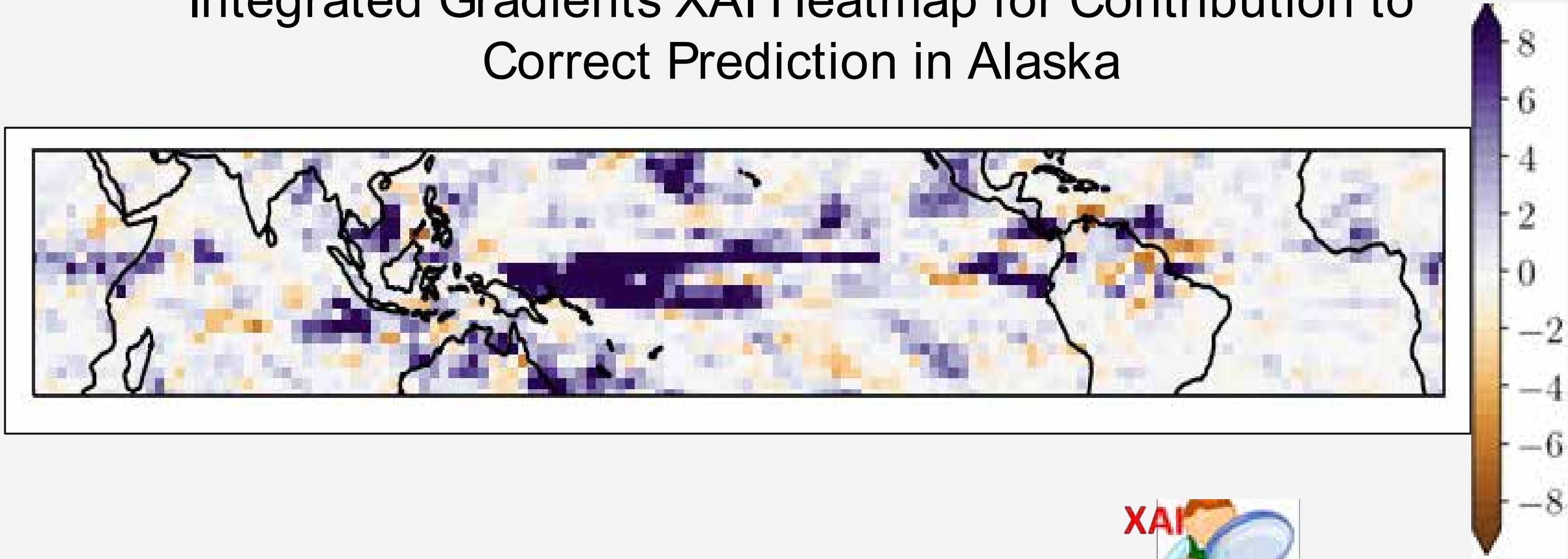


Certain low frequency time periods have higher predictive skill and forecast confidence …leads to increased predictability

Integrated Gradients XAI Heatmap for Contribution to Correct Prediction in Alaska



Investigate Low Frequency Drivers of Predictability Variability

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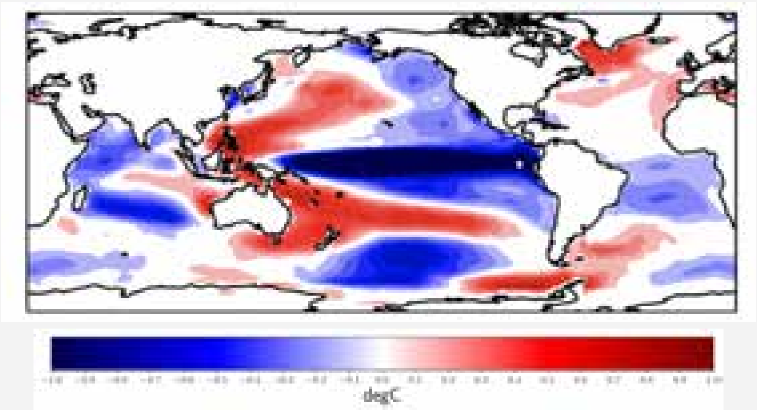
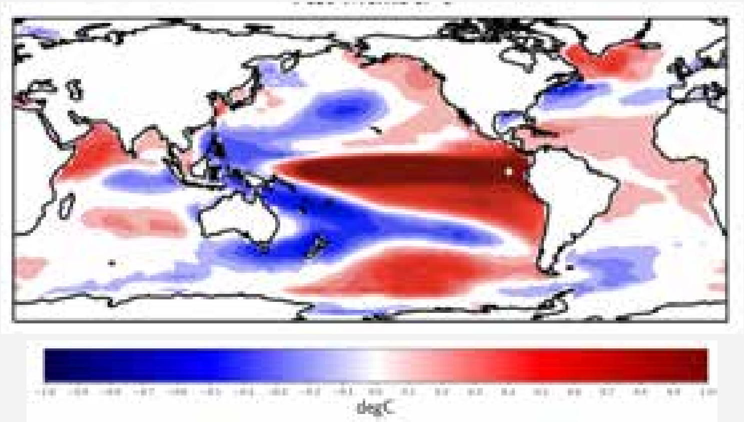
Correct, 20% Most Confident
Negative Anomaly Prediction



Correct, 20% Most Confident
Positive Anomaly Prediction



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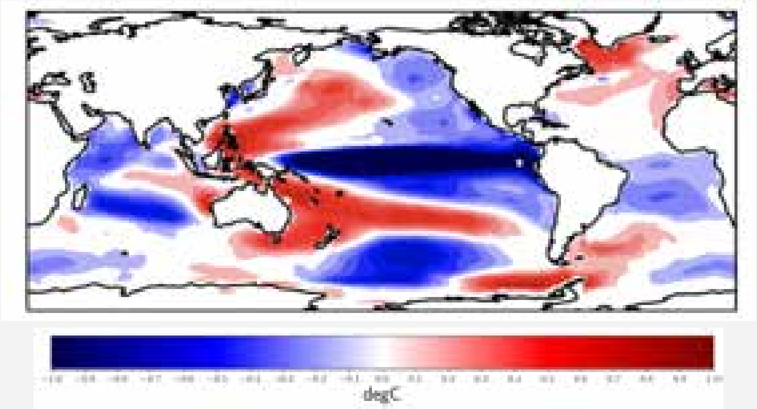

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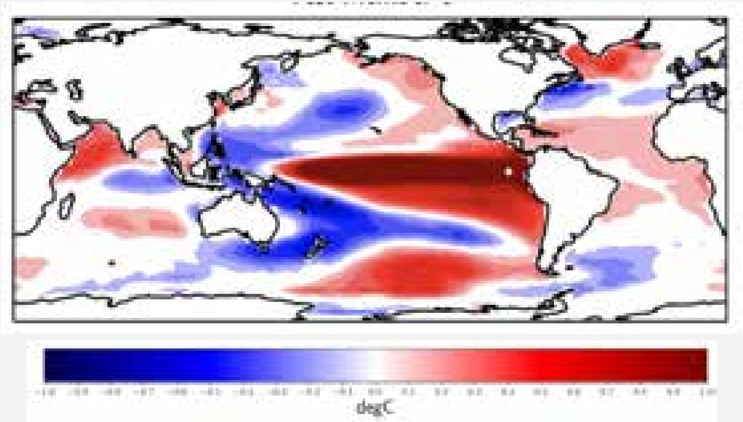

SST patterns in ENSO- and PDO-like states lead to forecasts of opportunity for Week 3-4 precip

Investigate Low Frequency Drivers of Predictability Variability

Using a binomial statistics approach, we calculate the number of confident and correct predictions for positive and negative PDO phases

Alaska Negative Precip Anomaly	Alaska Positive Precip Anomaly
68.56% Negative PDO Days	33.18% Negative PDO Days
31.09% Positive PDO Days	66.64% Positive PDO Days

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- When ENSO and the PDO are in phase, the NN is both confident and accurate in its prediction
- Not a deterministic predictor, but highlights low frequency predictable states of the climate system
    - The PDO amplifies ENSO teleconnections when they are in phase (Maher et al., 2022)

NEXT STEPS

- Perform additional analyses on phase combinations of climate modes
- Test how this low frequency variability of subseasonal predictability will hold under future climates

SUMMARY

- Used an artificial neural network to quantify predictability of daily tropical precipitation as a predictor for Week 3-4 North American West Coast precipitation anomalies

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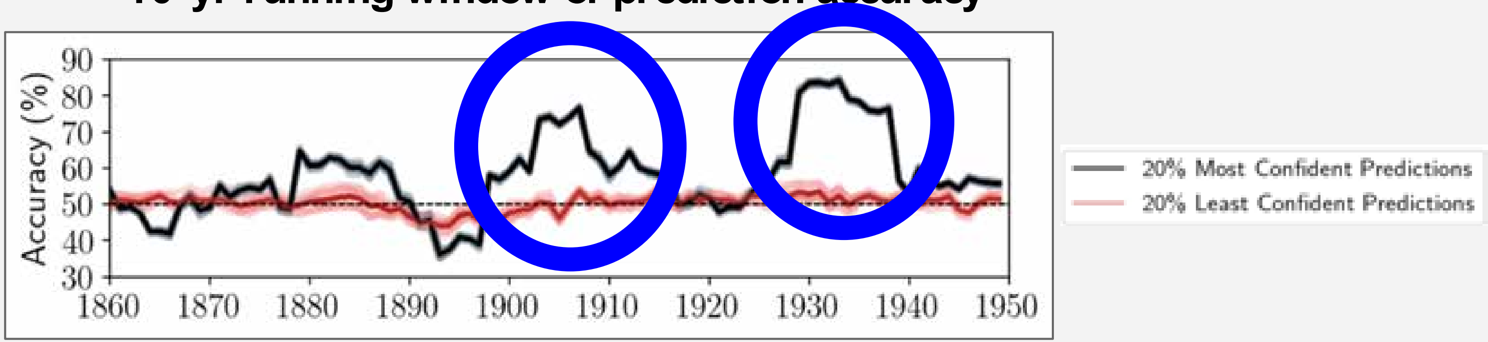
    - Highlights forecasts of opportunity

10-yr running window of prediction accuracy



SUMMARY

- Used an artificial neural network to quantify predictability of daily tropical precipitation as a predictor for Week 3-4 North American West Coast precipitation anomalies
- Found there is decadal variability in subseasonal predictive skill
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- Certain ENSO and PDO-like states of tropical precip and global SST result in confident and correct predictions

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- Used an artificial neural network to quantify predictability of daily tropical precipitation as a predictor for Week 3-4 North American West Coast precipitation anomalies
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  - Highlights forecasts of opportunity
- Certain ENSO and PDO-like states of tropical precip and global SST result in confident and correct predictions
  - Not a deterministic predictor, but highlights subseasonal predictable states on low frequency timescales

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EXTRA SLIDES

Alaska

Correct 20% Most Confident Predictions

Negative Anomaly Prediction

Positive Anomaly Prediction

Alaska

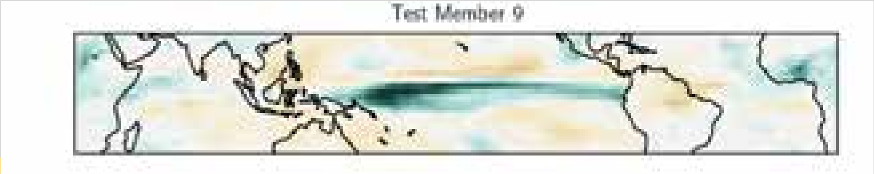
Correct 20% Most Confident Predictions

Negative Anomaly Prediction

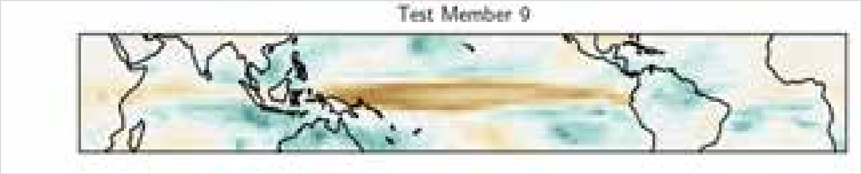
Positive Anomaly Prediction

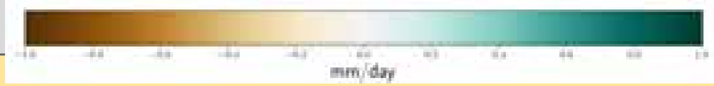
Incorrect 20% Most Confident Predictions

Negative Anomaly Prediction



Positive Anomaly Prediction





Alaska

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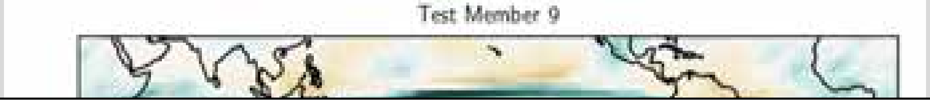
Positive Anomaly Prediction



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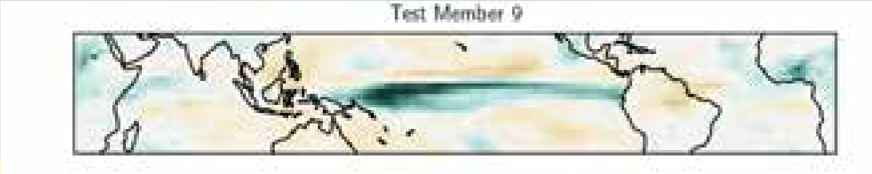
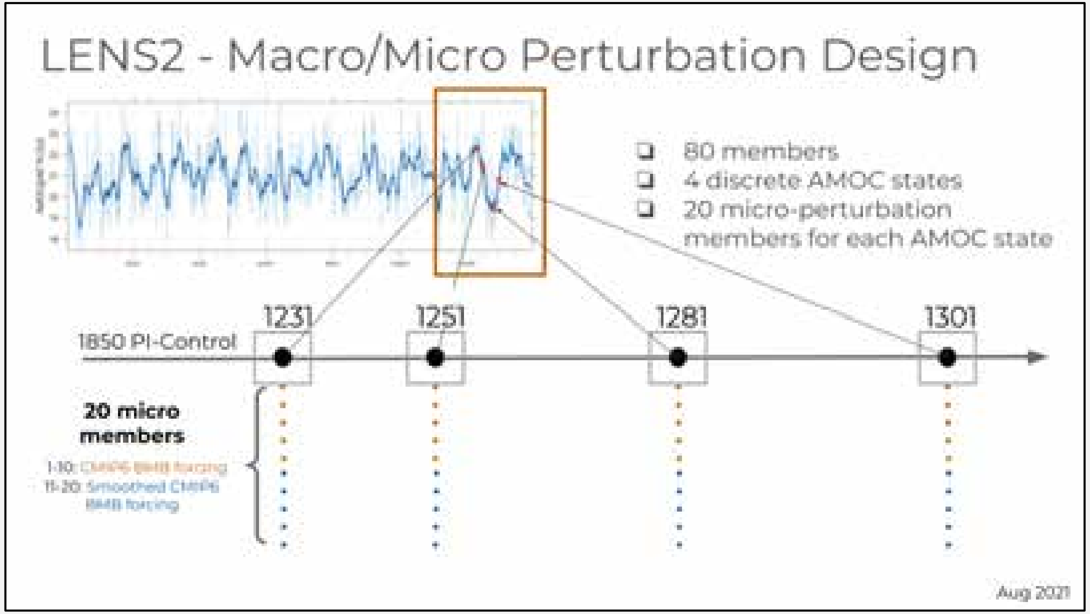


Positive Anomaly Prediction

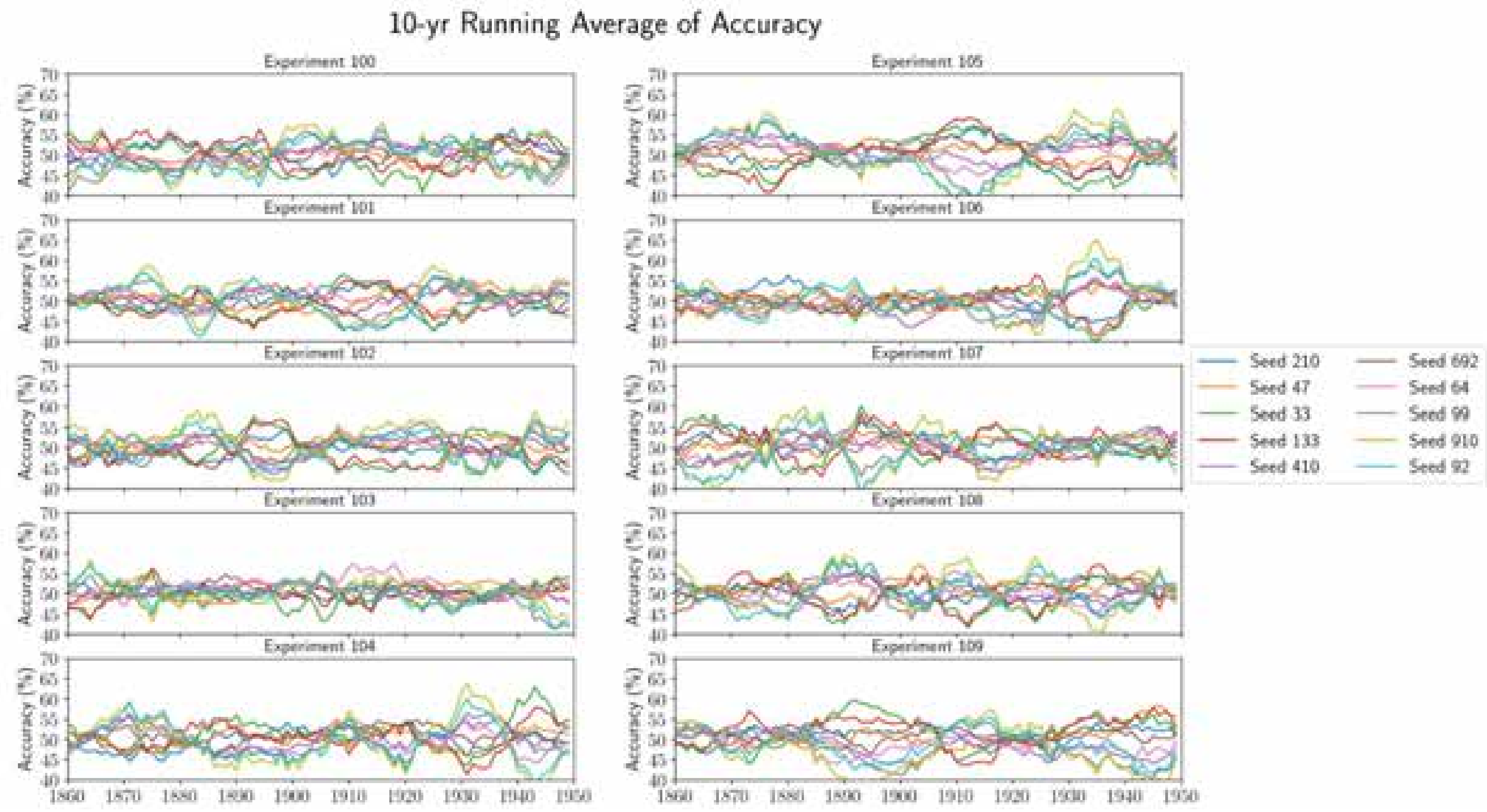
Network uses ENSO-like state of precip to make correct and confident predictions, i.e. forecasts of opportunity

Data

- CESM-2 Large Ensemble Dataset
  - 1850-1950 SMBB (smoothed biomass forcing), daily anomalies
  - Ensembles from each of the 4 initialized AMOC states



Untrained models



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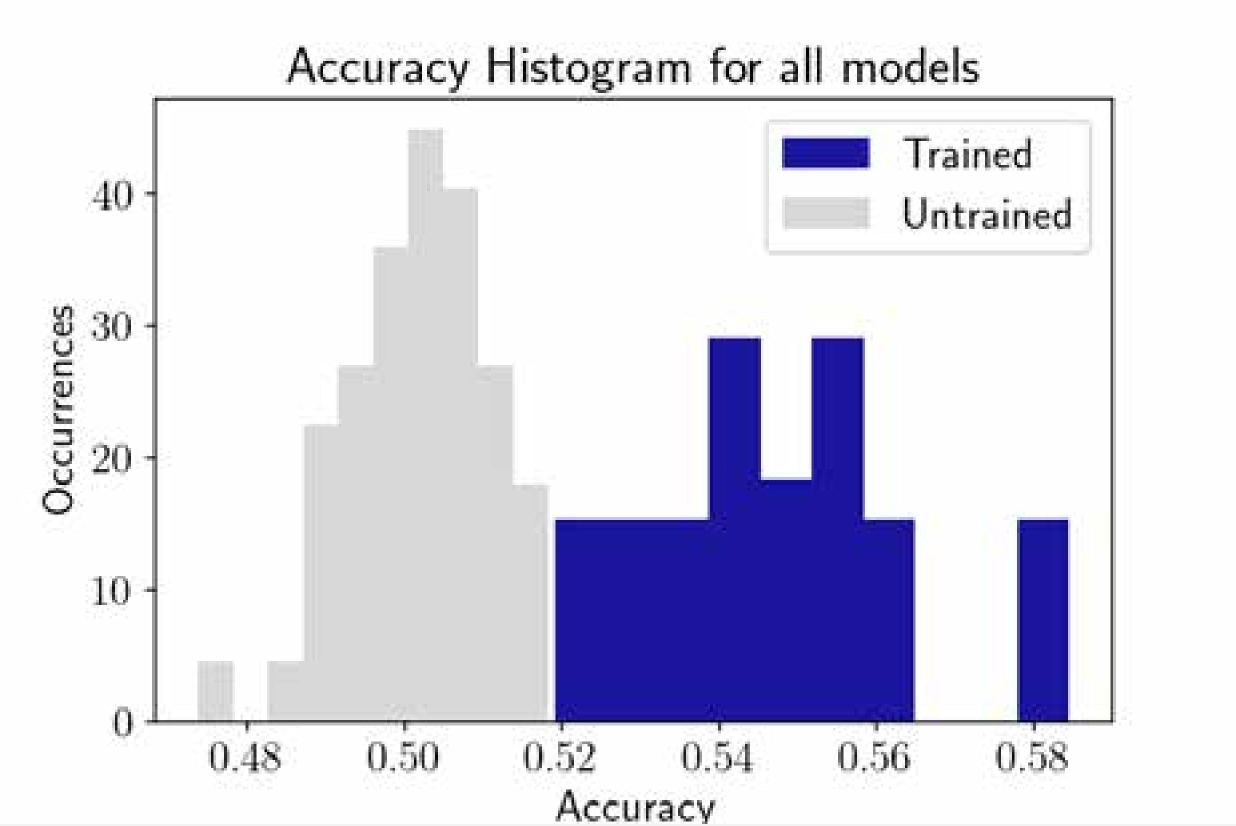

Alaska

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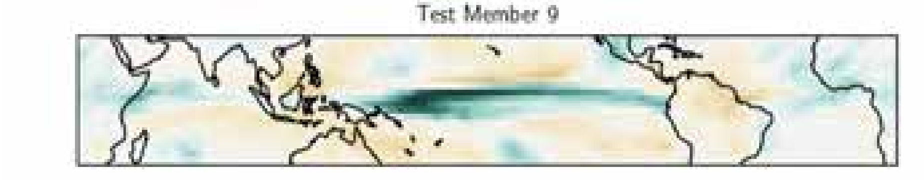

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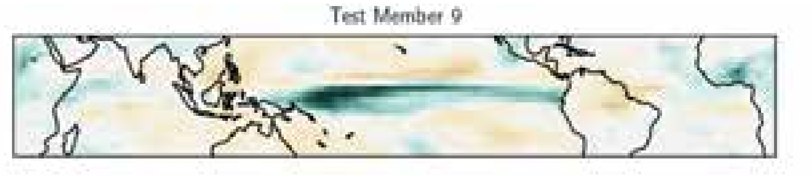
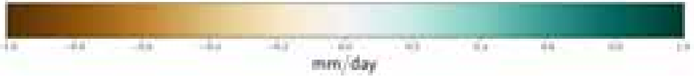


Positive Anomaly Prediction



California

Correct 20% Most Confident Predictions

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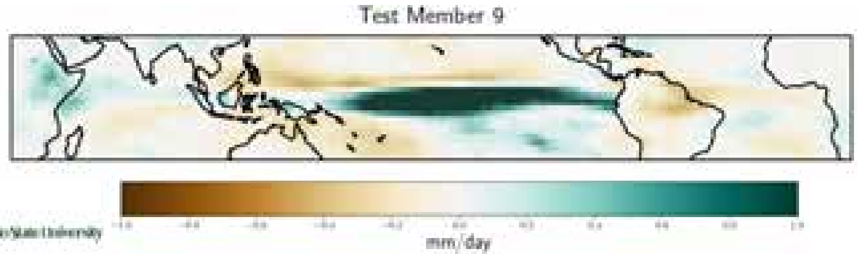
Positive Anomaly Prediction



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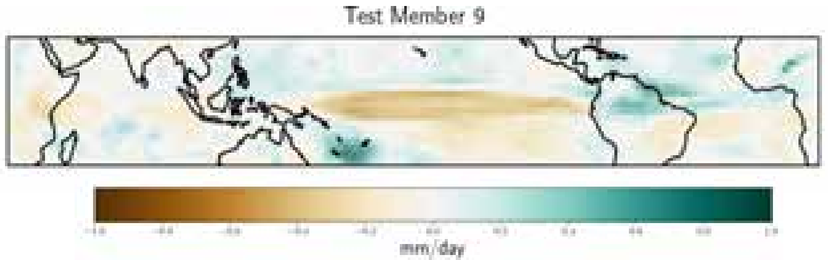
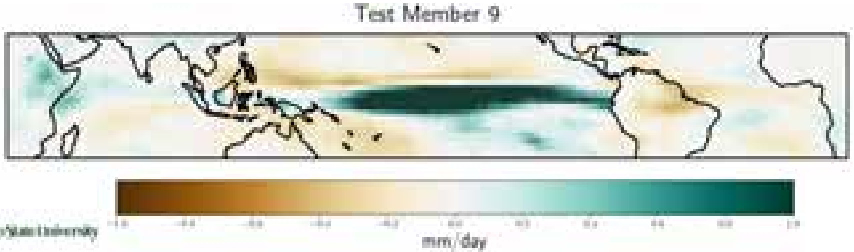


California

Correct 20% Most Confident Predictions

Negative Anomaly Prediction

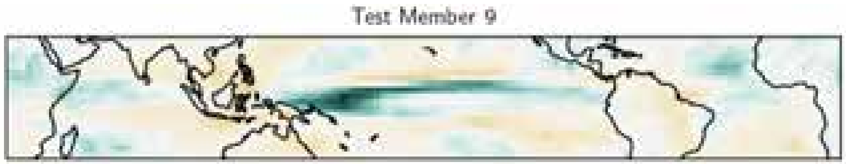
Positive Anomaly Prediction



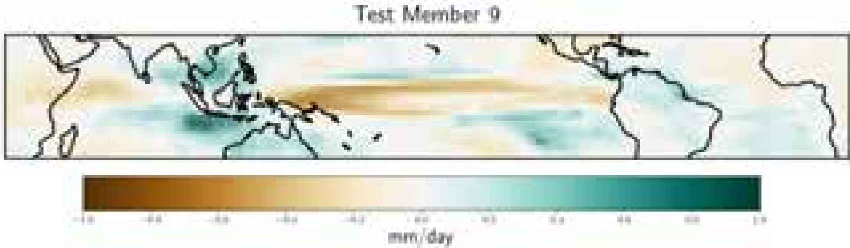
Pacific Northwest

Correct 20% Most Confident Predictions

Negative Anomaly Prediction



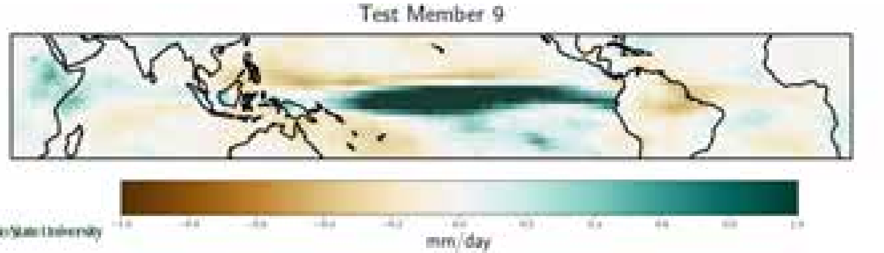
Positive Anomaly Prediction



California

Negative Anomaly Prediction

Positive Anomaly Prediction



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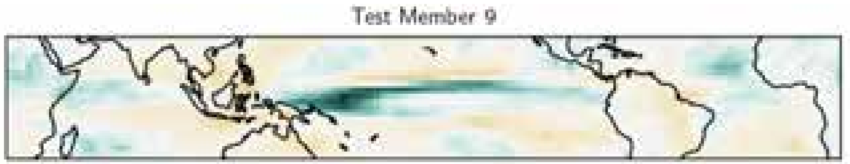
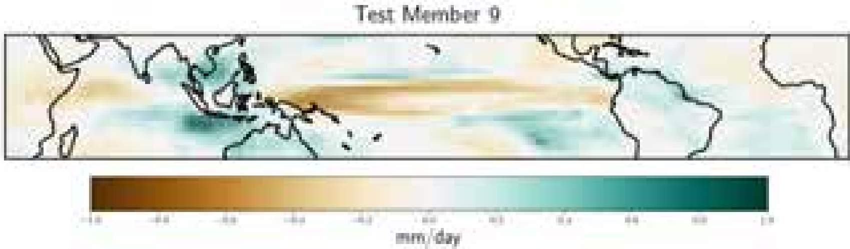
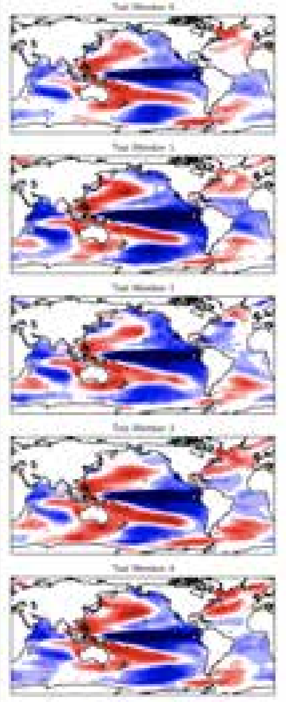


Positive Anomaly Prediction



SST Anomalies during FOOs

20% **Most** Confident
Correct Negative Anomaly Predictions



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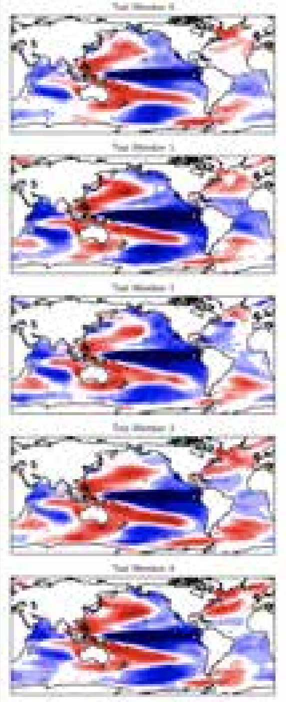
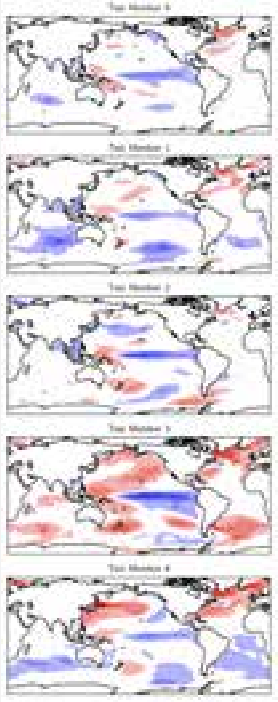
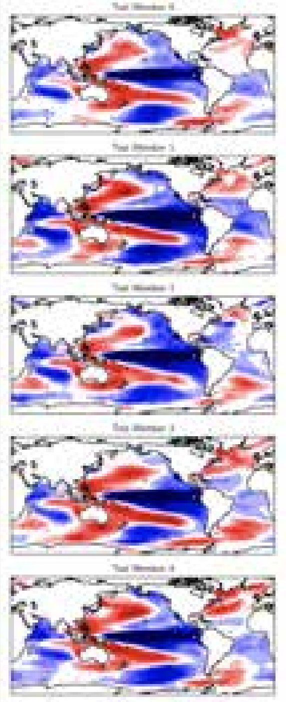


20% **Least** Confident
Correct Negative Anomaly Predictions

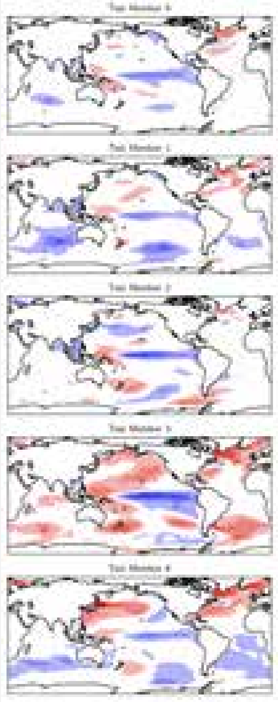


SST Anomalies during FOOs

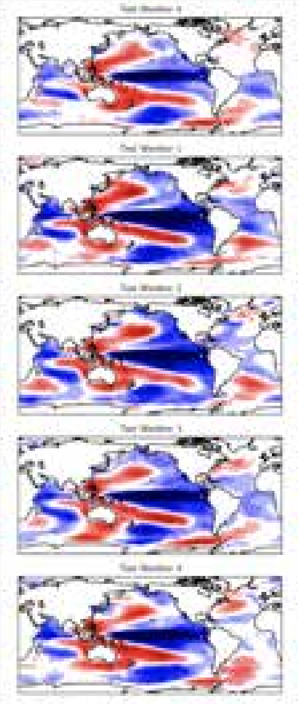
20% **Most** Confident
Correct Negative Anomaly Predictions



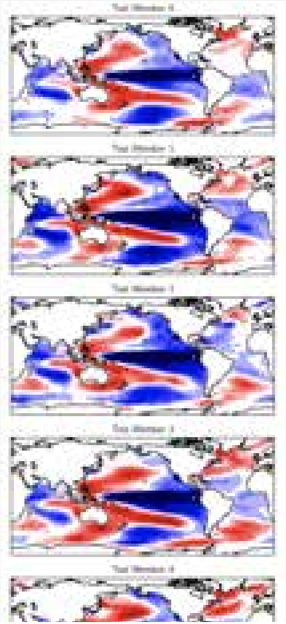
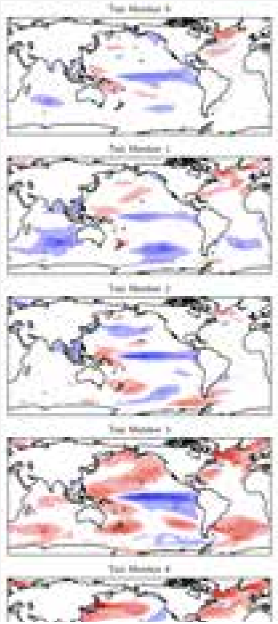
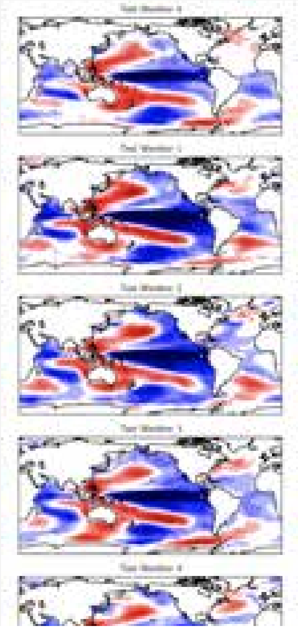
20% **Least** Confident
Correct Negative Anomaly Predictions



Difference



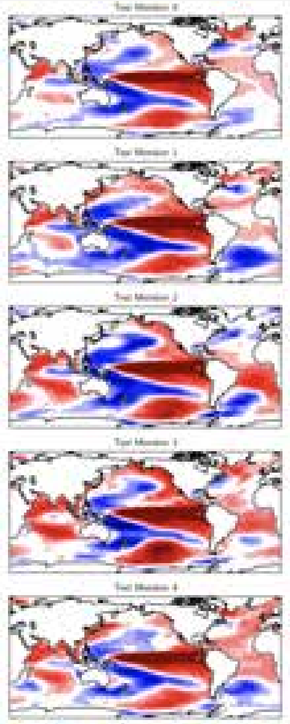
SST Anomalies during FOOs

20% **Most** Confident Correct Negative Anomaly Predictions	20% **Least** Confident Correct Negative Anomaly Predictions	Difference
		

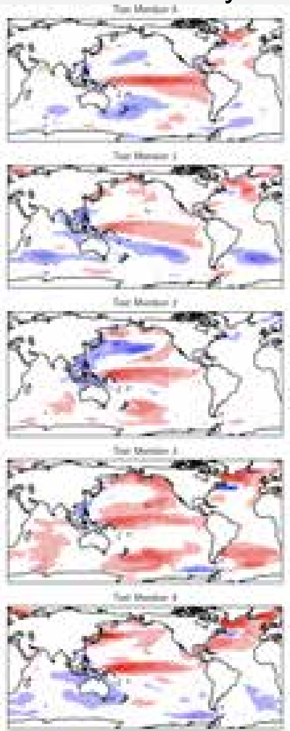
Network uses ENSO-like state to make correct and confident predictions *and* global SST patterns including the Indian Ocean, N Pacific, and N Atlantic

SST Anomalies during FOOs

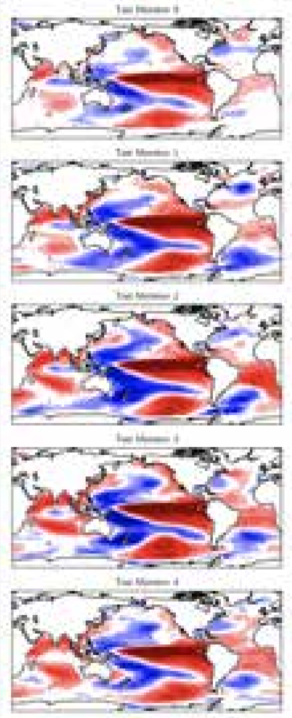
20% **Most** Confident
Correct Positive Anomaly Predictions



20% **Least** Confident
Correct Positive Anomaly Predictions



Difference



This is my project