An Interpretable Neural Network Approach for Identifying Sources of Predictability on Decadal Timescales in the CESM2-LE

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CESM Workshop ESPWG Meeting 2023

Can we predict near-term climate trends?

In the future climate, we consider predictability from 2 sources:

- External forcing
- Internal variability

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- Internal variability

Predictability from external forcing

Anthropogenic climate change means that global mean temperature will continue to rise

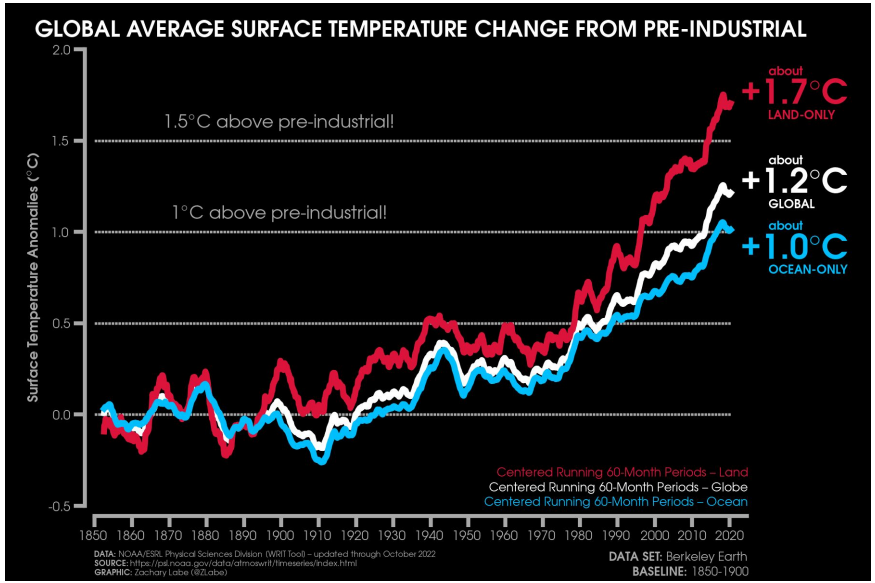


Figure created by Zack Labe, used with permission

Can we predict near-term climate trends?

In the future climate, we consider predictability from 2 sources:

- External forcing
- **Internal variability**

Predictability from internal variability

Large scale ocean patterns like Pacific decadal variability (PDV) and Atlantic multi-decadal variability (AMV) can provide predictability e.g. Meehl et. al 2016, Borchert et. al 2018, Gordon et. al 2021, Gordon and Barnes 2022

Observed PDO/PDV

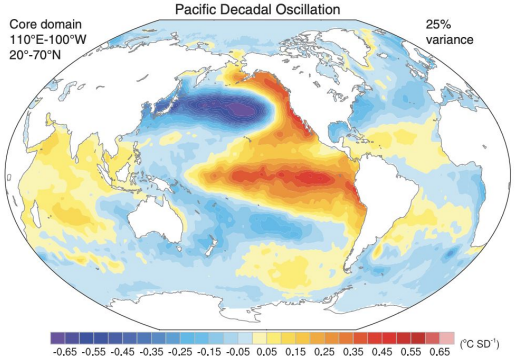


Figure from Trenbert & Fasullo 2013, *Earth's Future*

Observed AMO/AMV

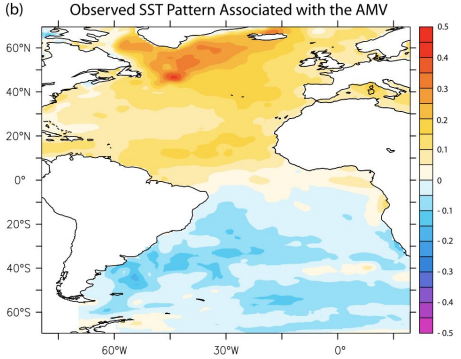
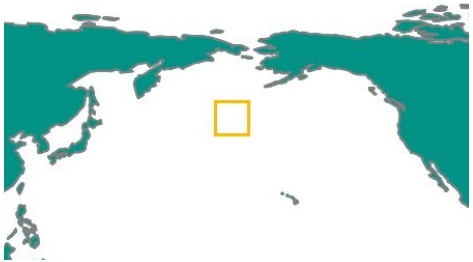
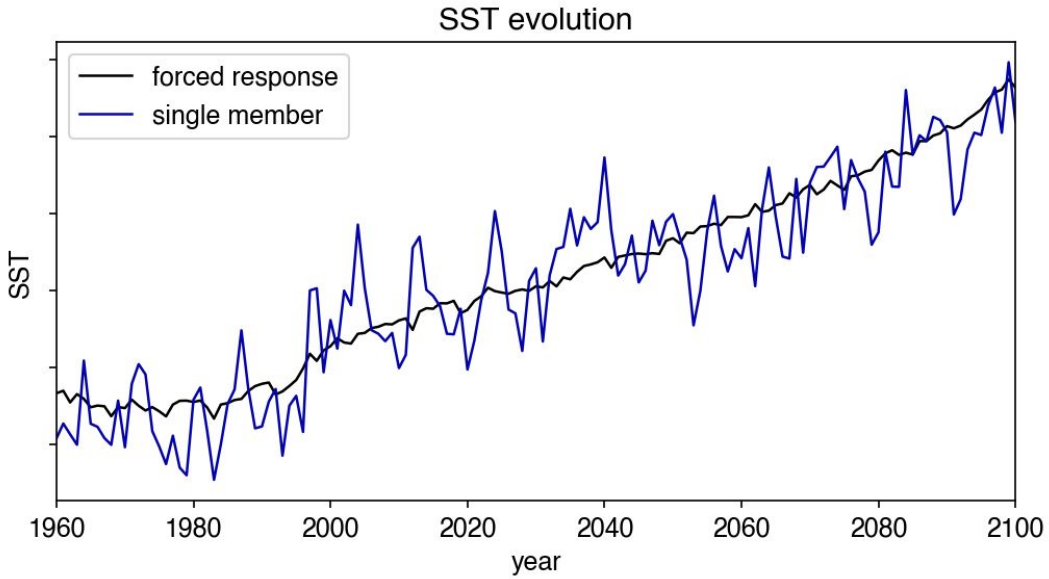


Figure from Zhang et. al 2019, *Reviews of Geophysics*

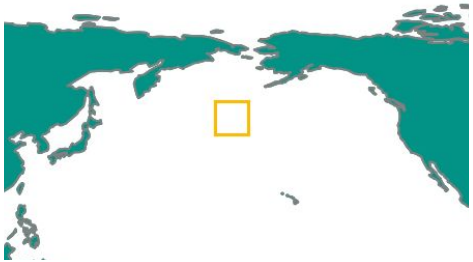
Predicting regional decadal climate trends



- 10 x 10 degree box
- Annual mean SST
- CESM2 LENS from 1960 to 2100



Predicting regional decadal climate trends



- 10 x 10 degree box
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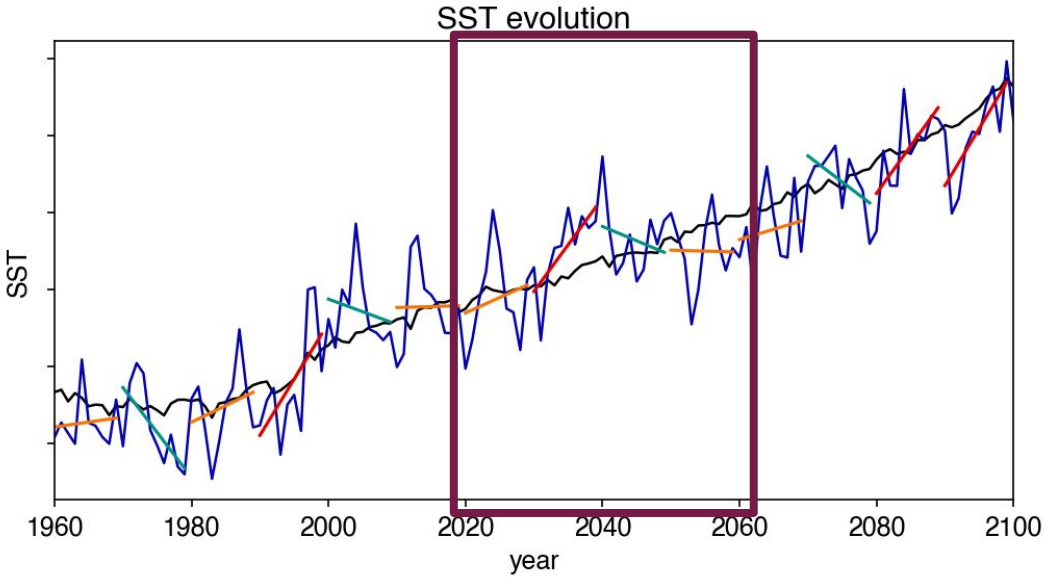
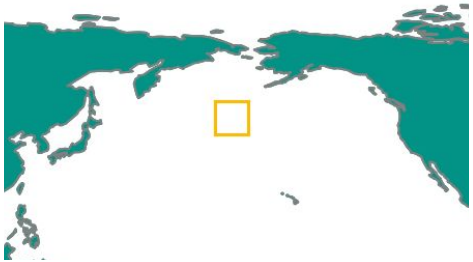
Regional evolution shows periods of **increased warming** and even **cooling** with high anthropogenic forcing



Predicting regional decadal climate trends



- 10 x 10 degree box
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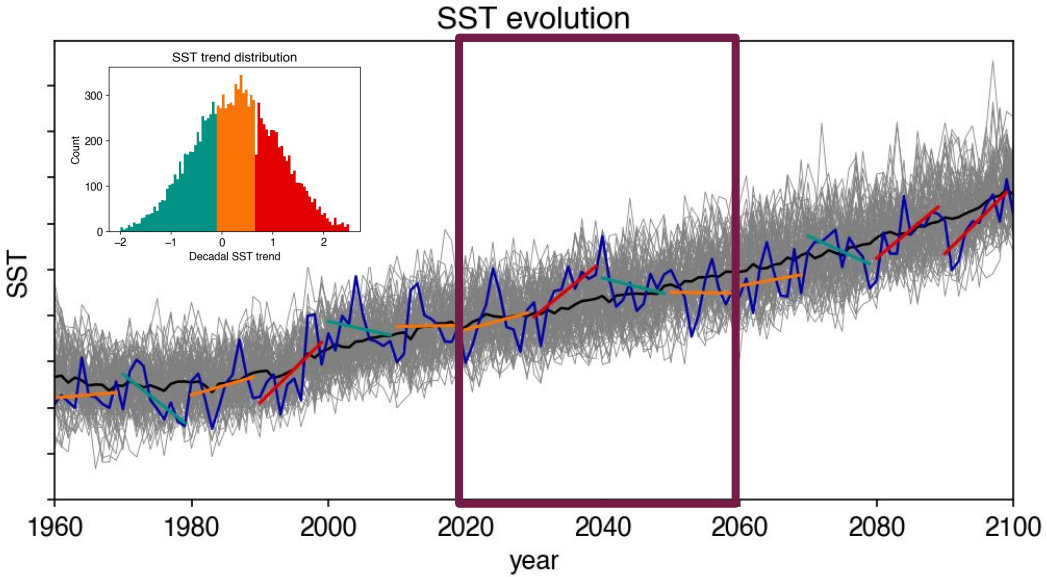
- Calculate decadal (10 year) SST trends
- Build a distribution of these trends from 2020-2050, rank in terciles (thirds)

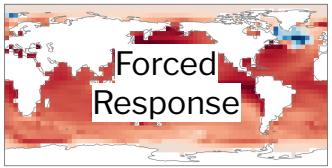


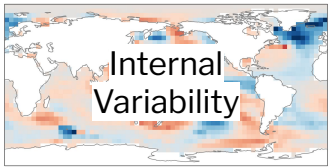
Predicting regional decadal climate trends

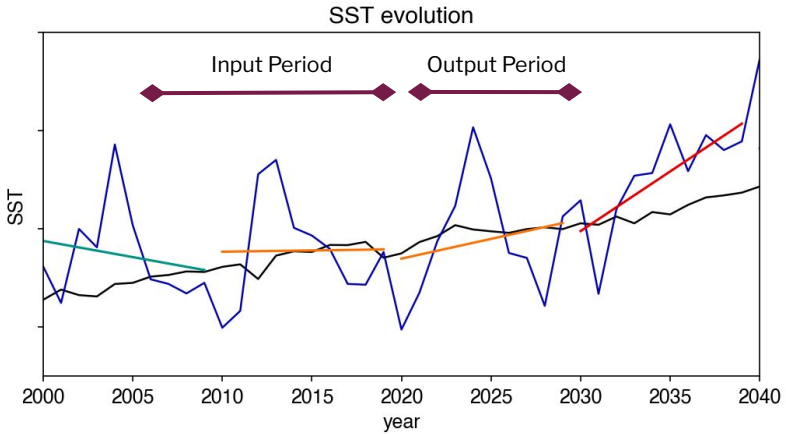
A machine learning approach …

Input full maps of the model **forced response** and **internal variability** averaged over the input period

e.g. in this example, input maps averaged over 2010-2020

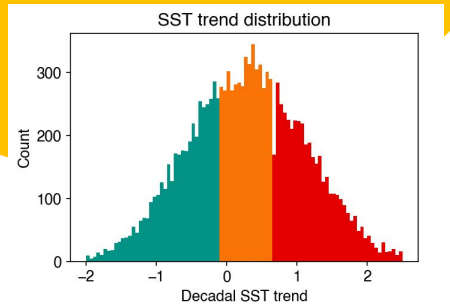






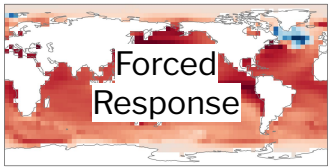
Predicting regional decadal climate trends

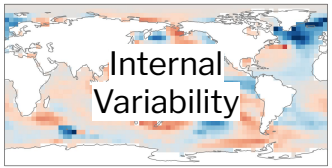
A machine learning approach …

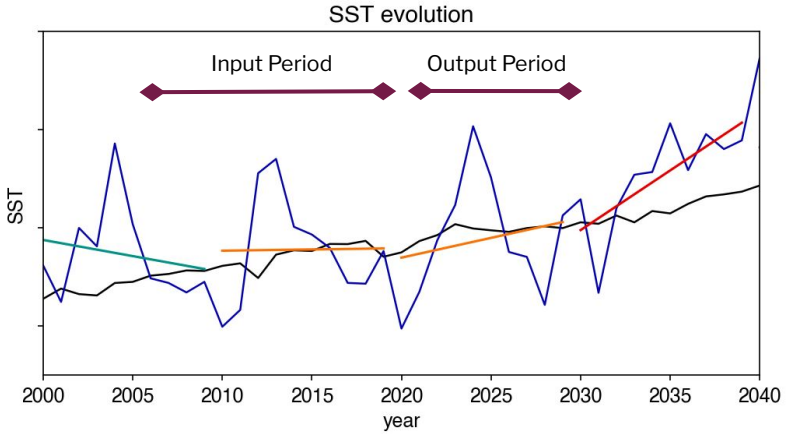


Output a prediction of the future 10 year trend

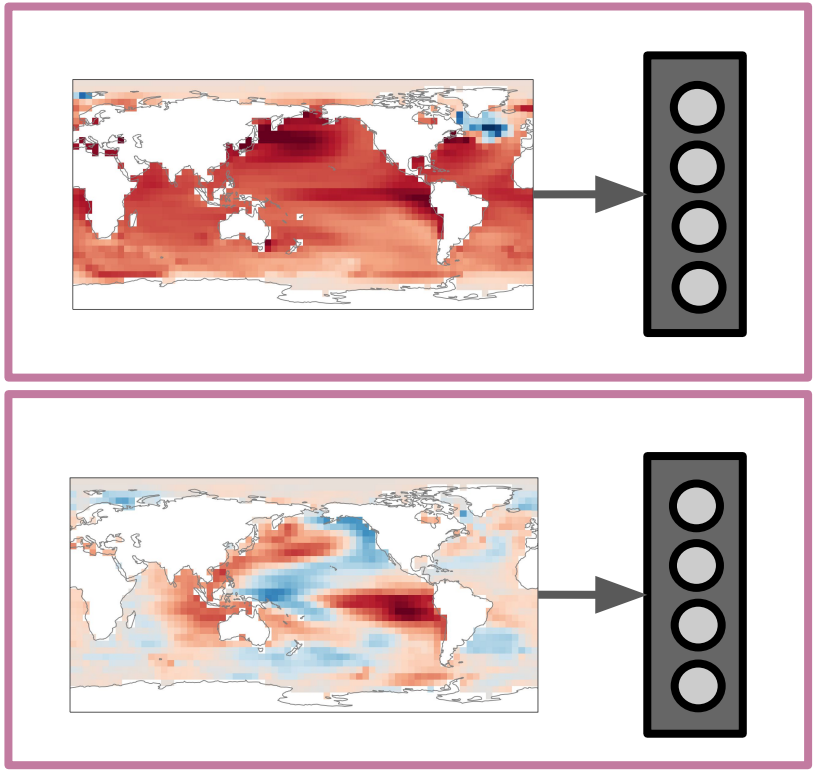
e.g. predict whether the 2020-2030 trend will be in the lower, middle, or upper third





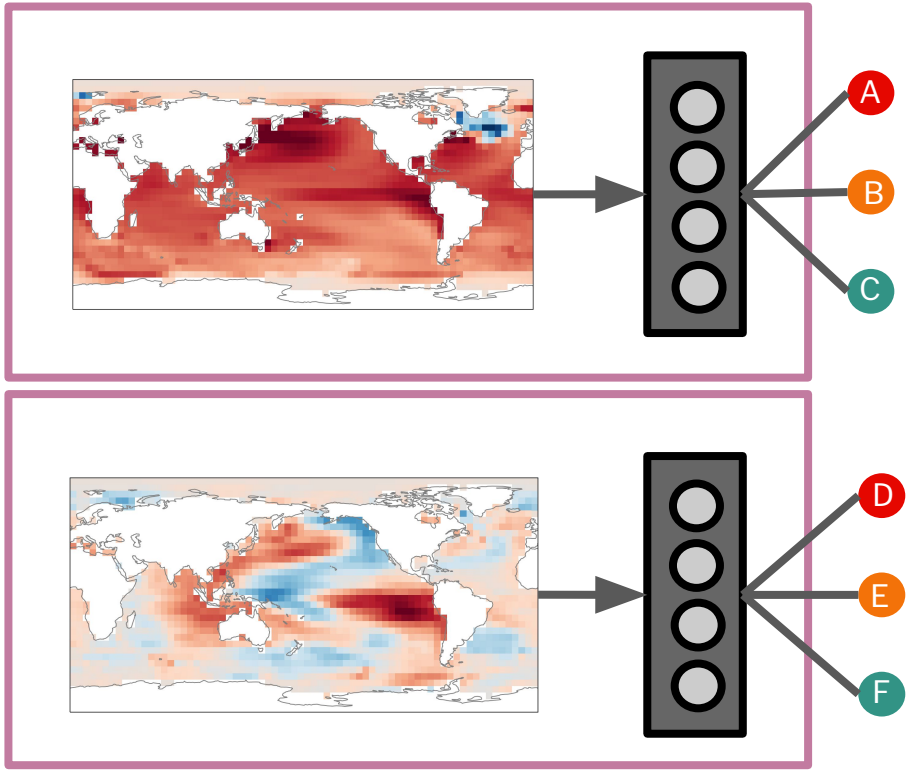


Designing an interpretable neural network



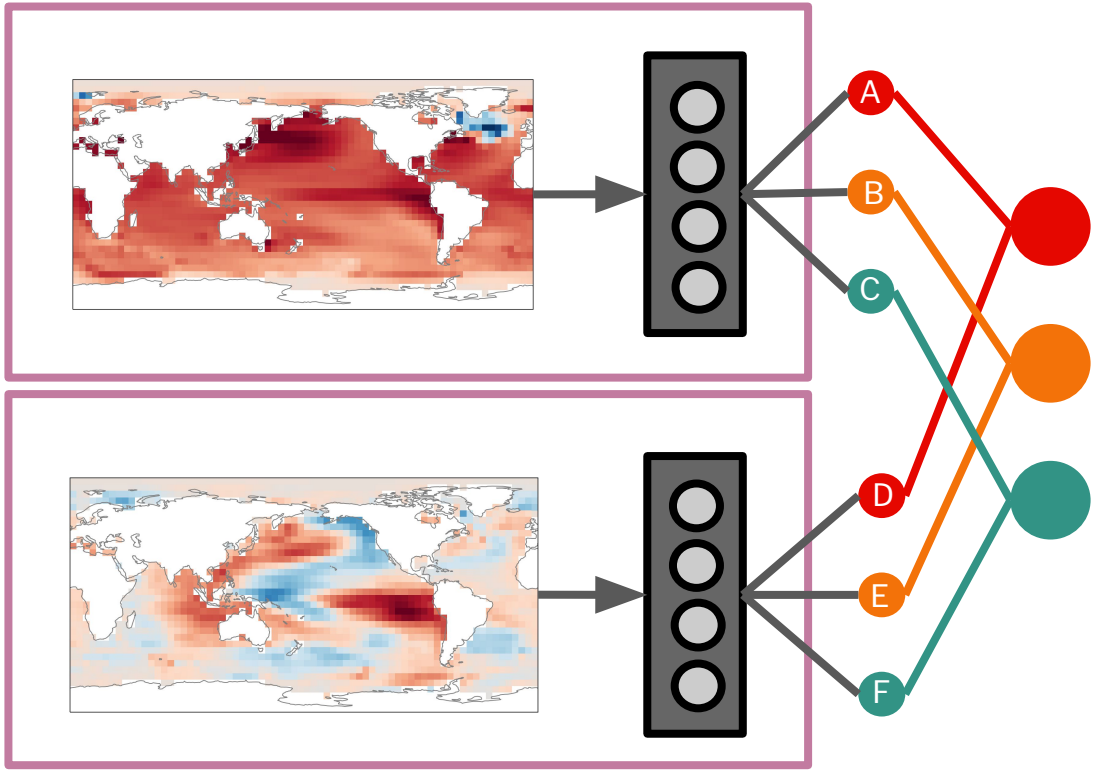
Each map is connected to a separate neural network

Designing an interpretable neural network



Each network outputs its own tercile predictions

Designing an interpretable neural network



Upper Third = A + D

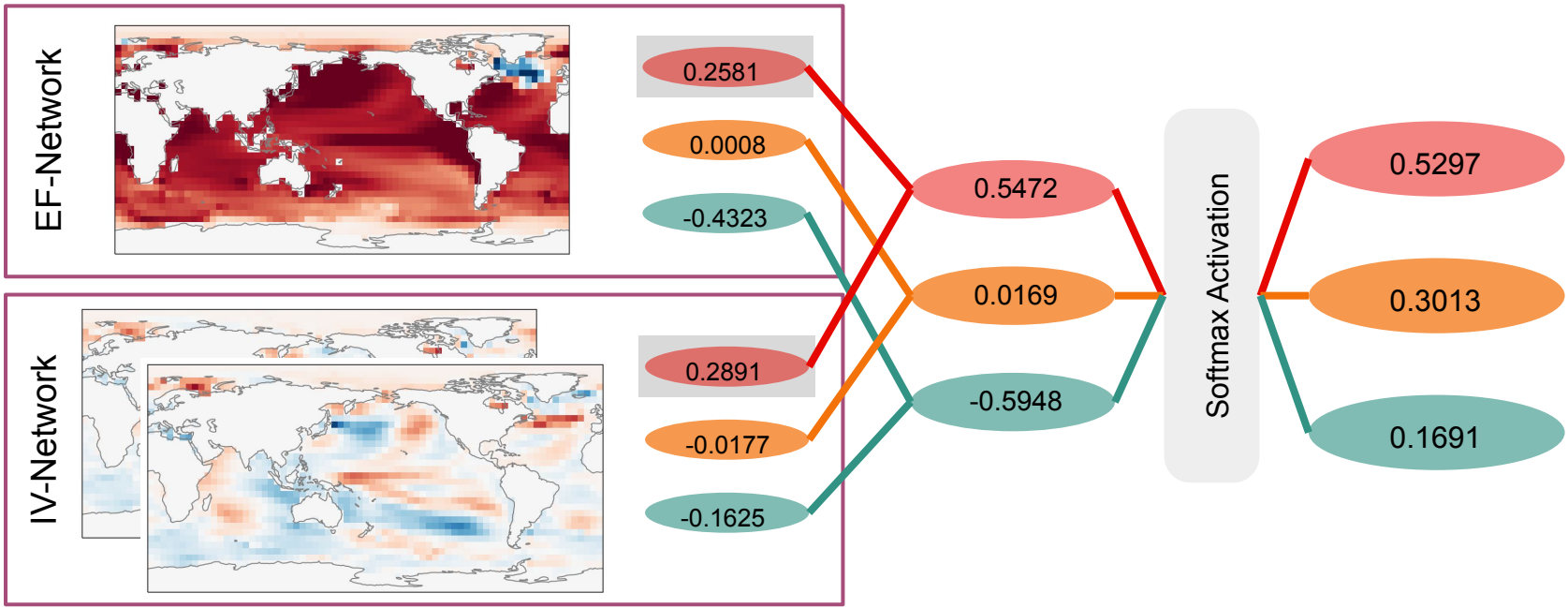
Middle Third = B + E

Lower Third = C + F

Outputs are summed to make the final predictions, highest sum is the ‘winning’ prediction

Example Predictions

Predicting 20S-30S, 60W-70W, model year 2045-2054, mem #9



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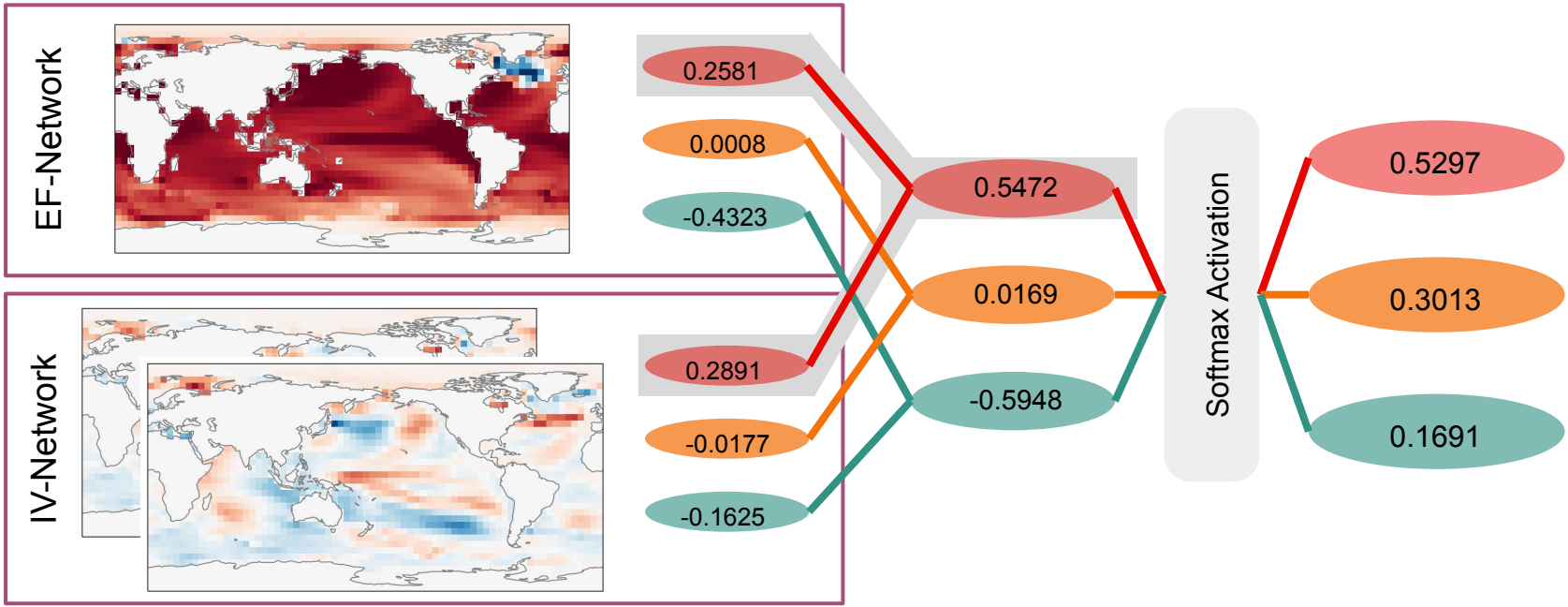

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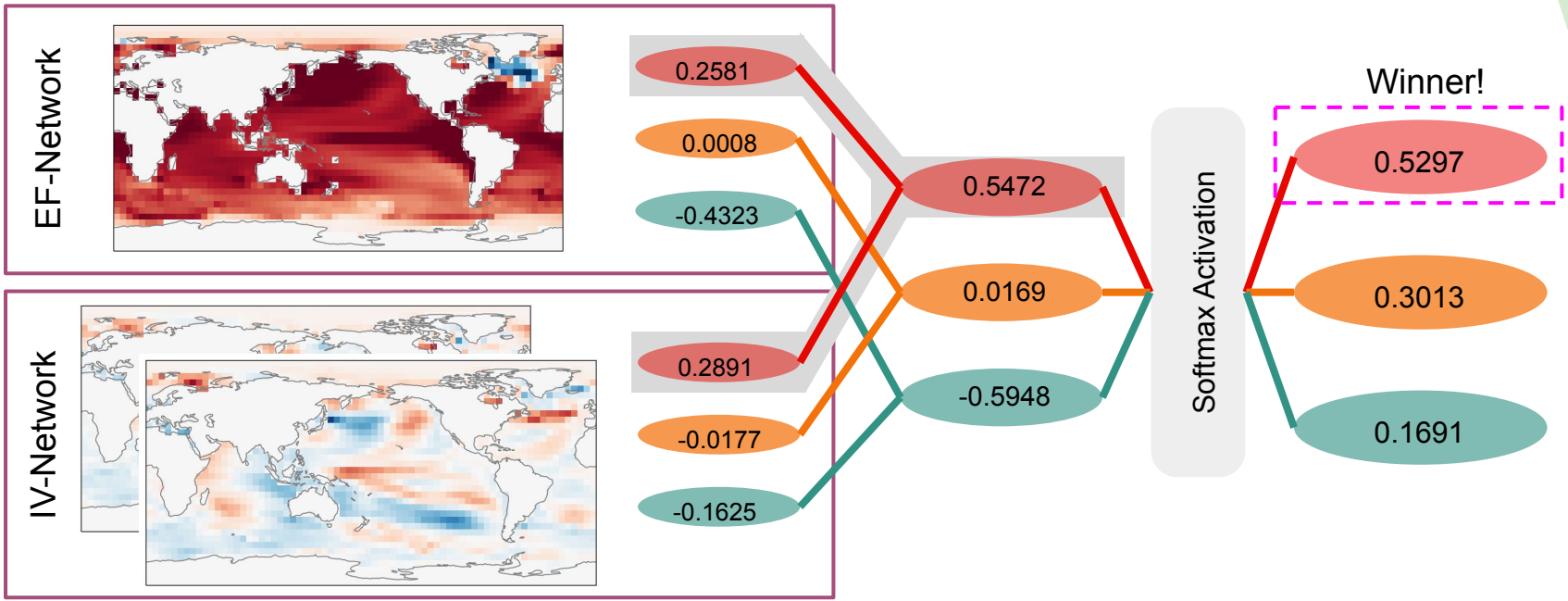
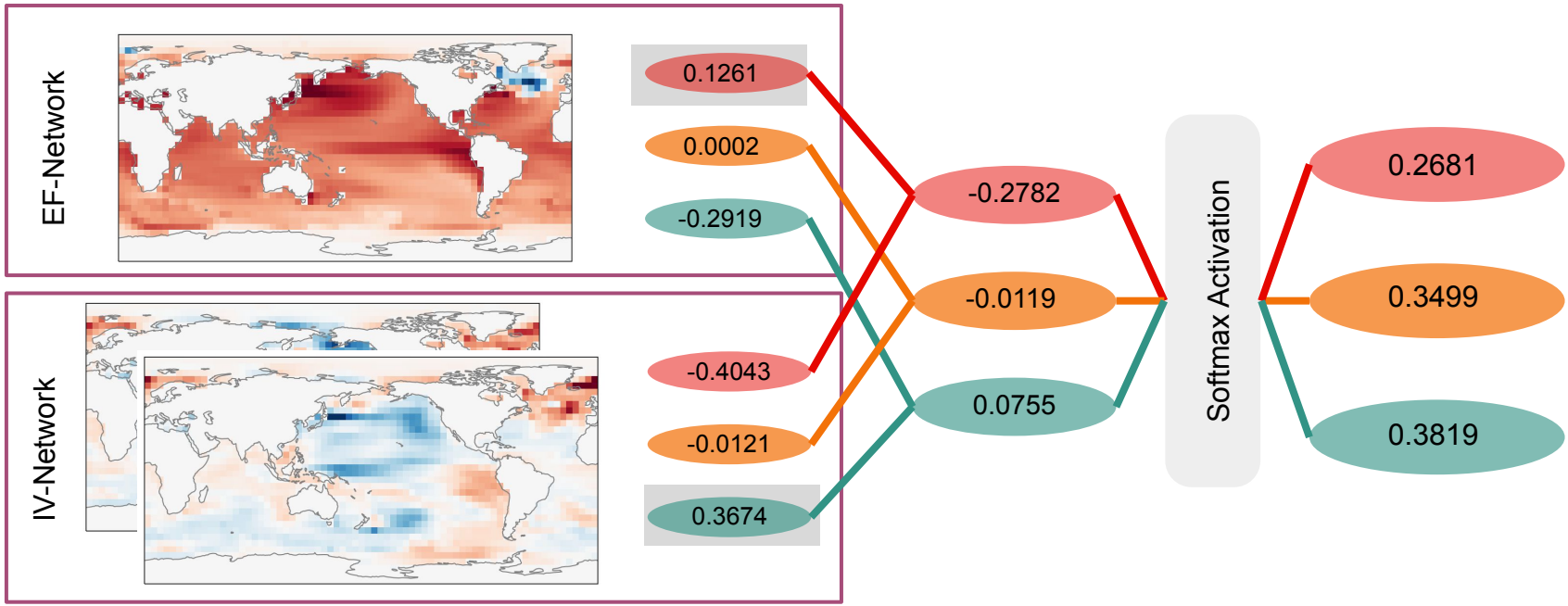


Example Predictions

Predicting 20S-30S, 60W-70W, model year 2033-2042, mem #9



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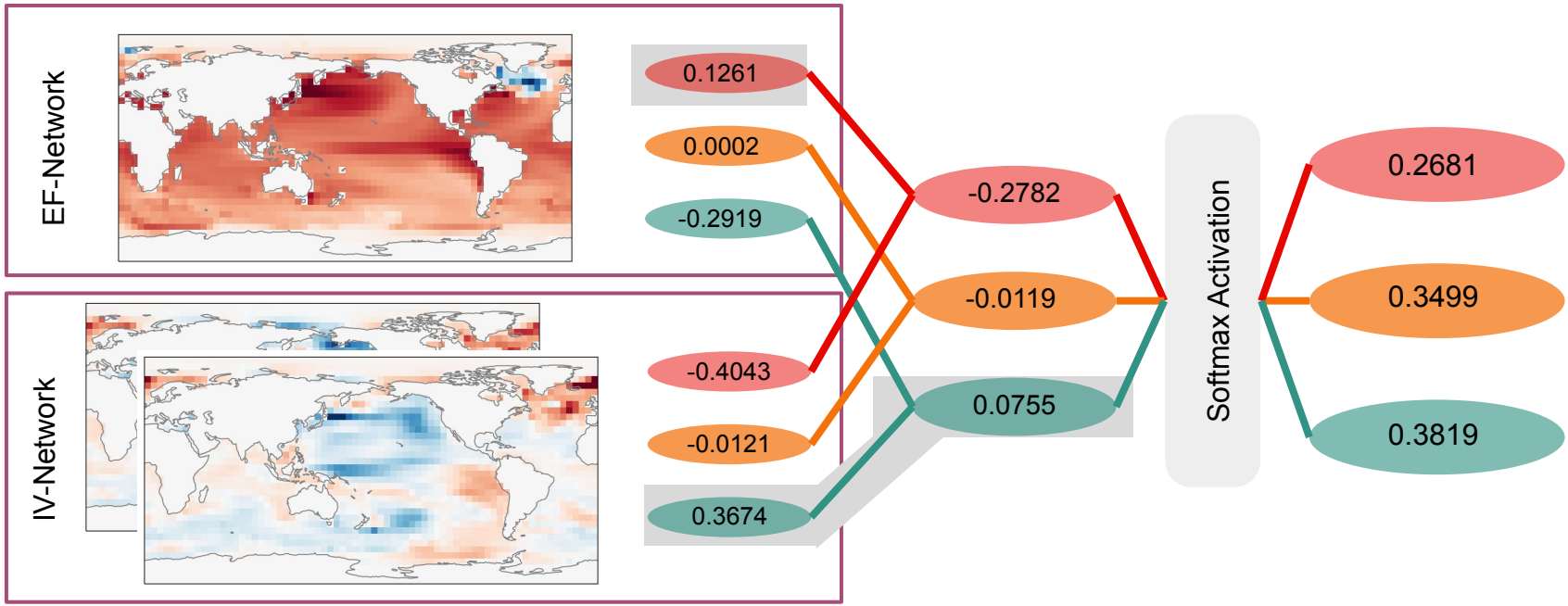

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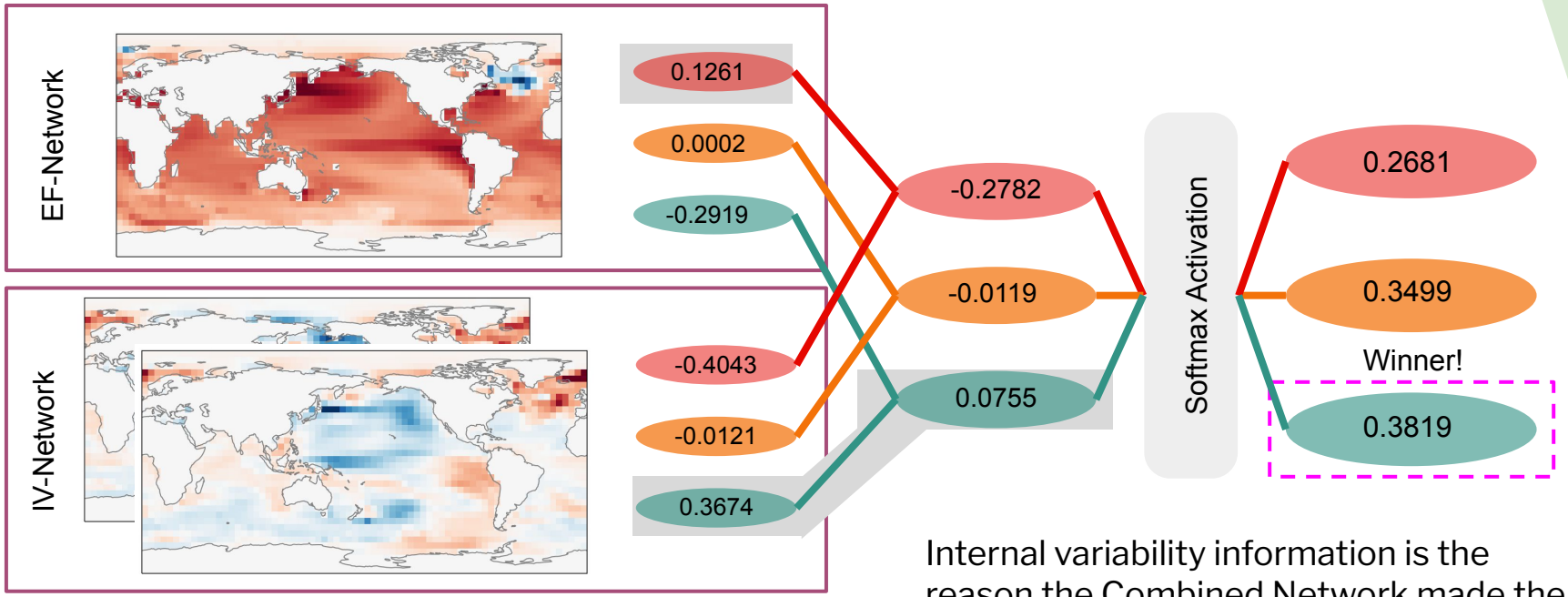
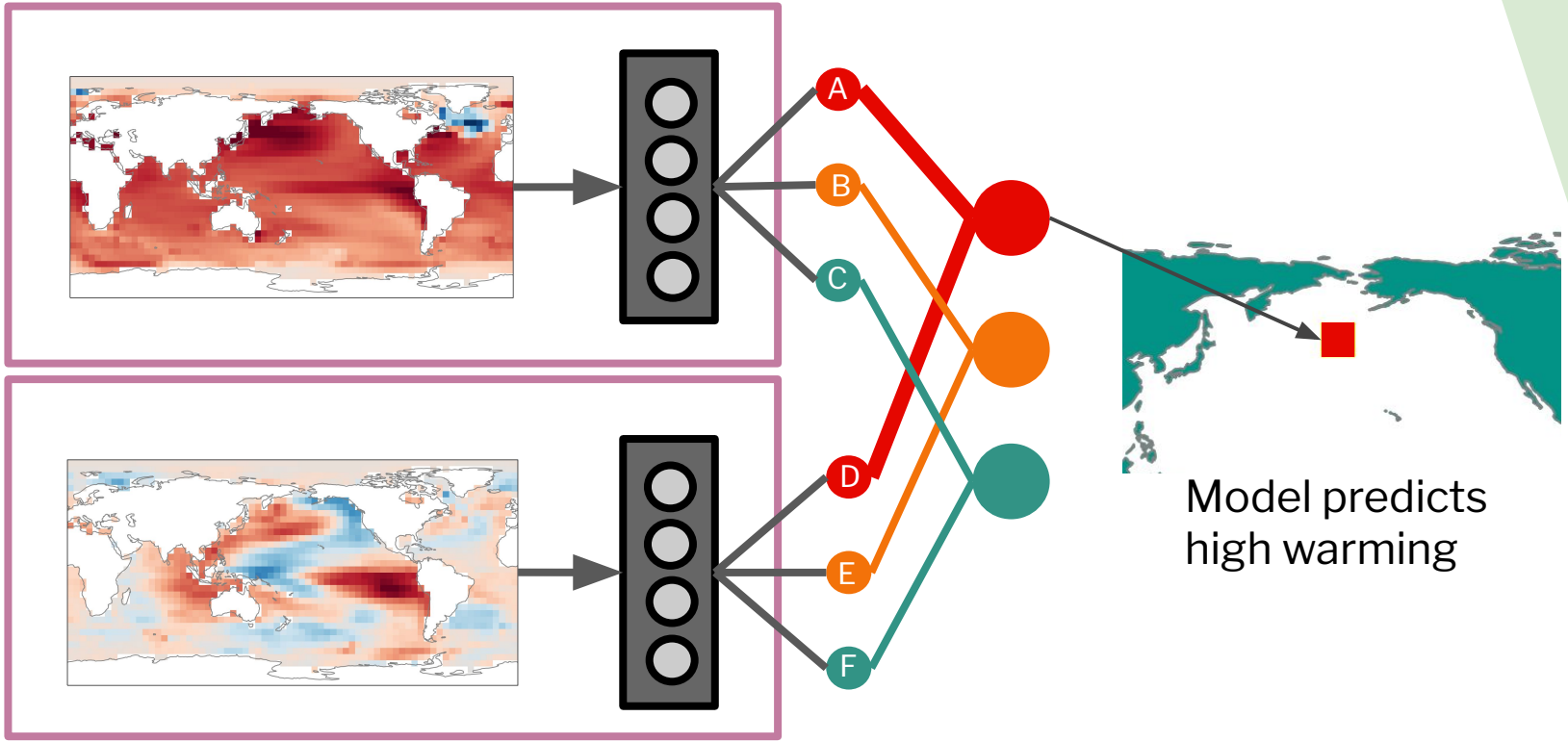


Internal variability information is the reason the Combined Network made the correct prediction!

Designing an interpretable neural network



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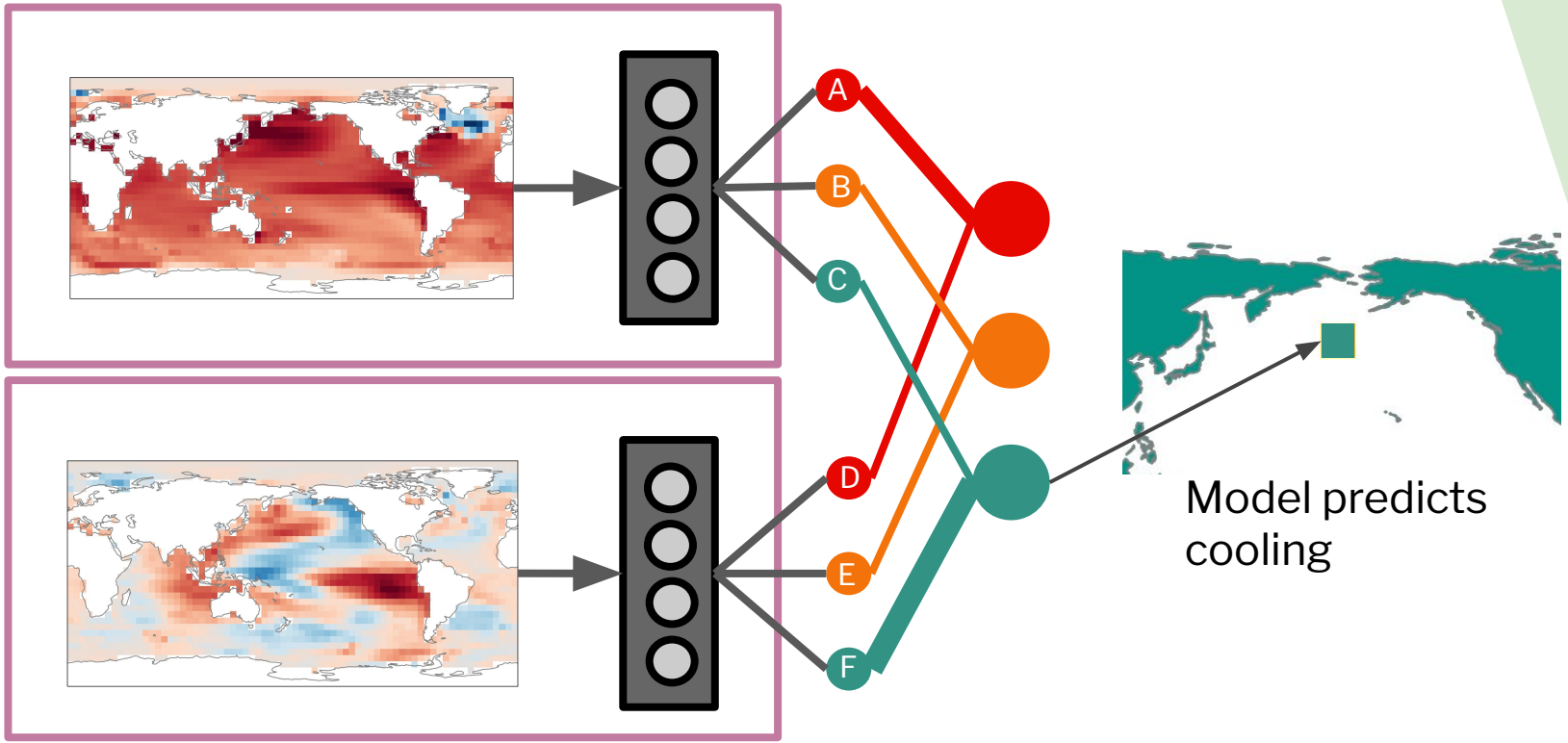

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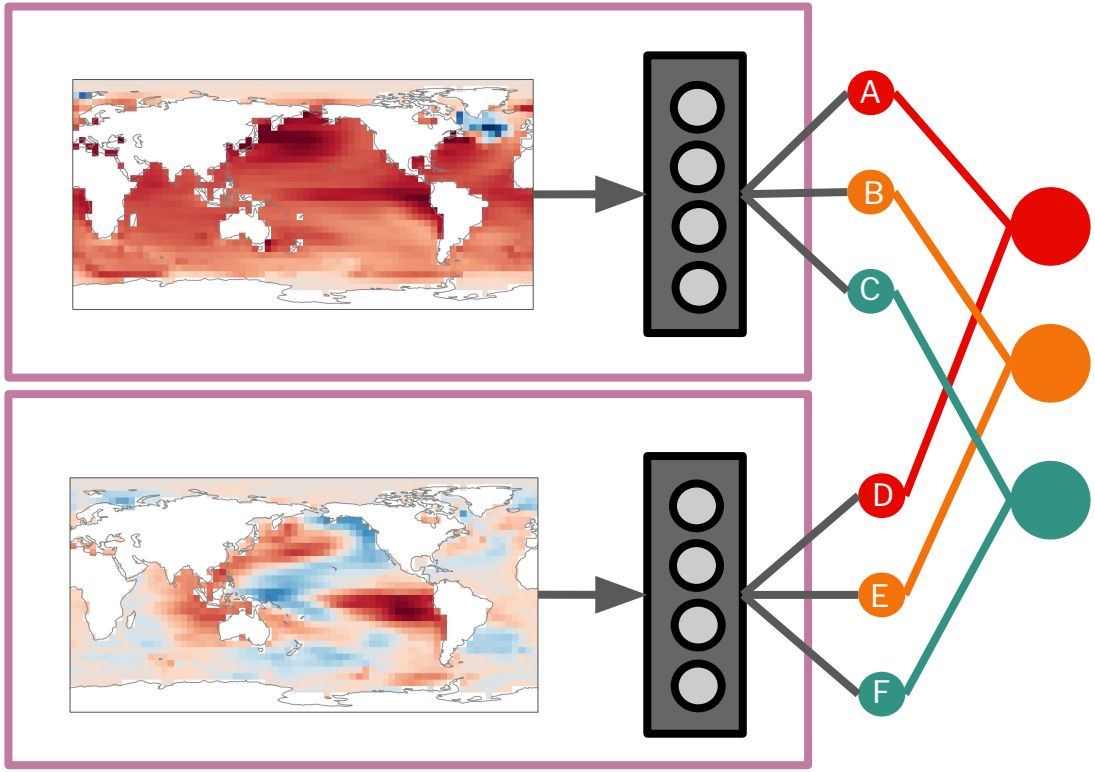
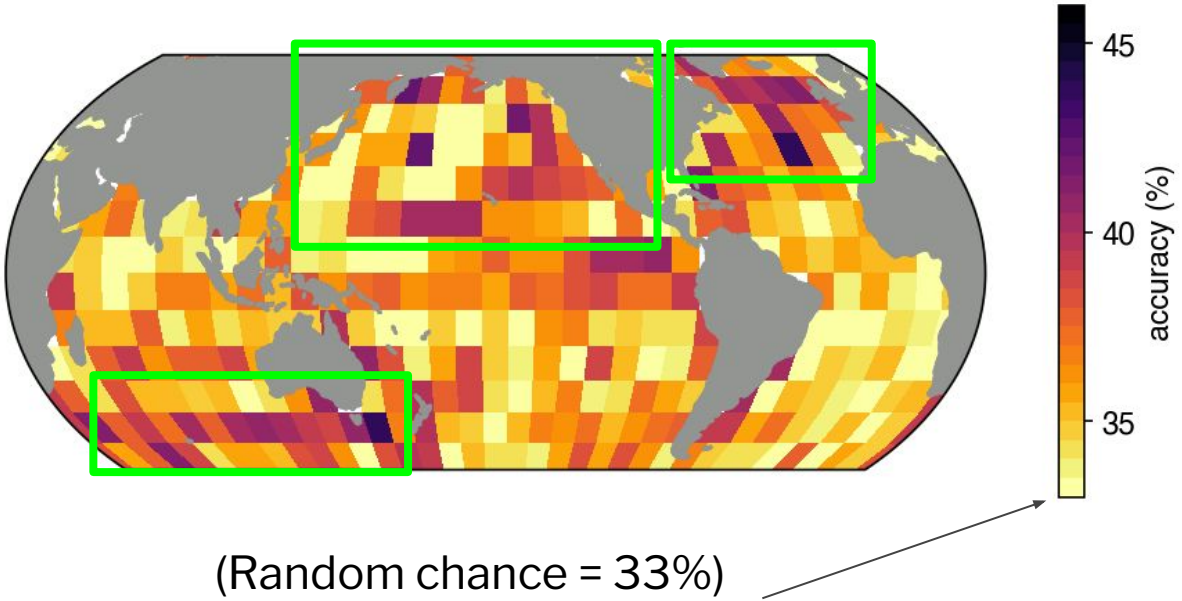


We can calculate the **contribution** of **internal variability** and **external forcing** to a particular prediction

Calculate accuracy over 2020-2050



(Random chance = 33%)

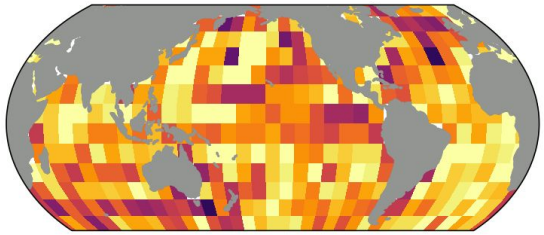
More accurate in North Atlantic, North Pacific and Southern Indian oceans (, Meehl et. al 2017)

✓ Neural network is making sensible predictions

Gordon et. al *in prep.*

Predictability from internal variability vs external forcing over 2020-2050

Calculate accuracy at each 10 x 10 location



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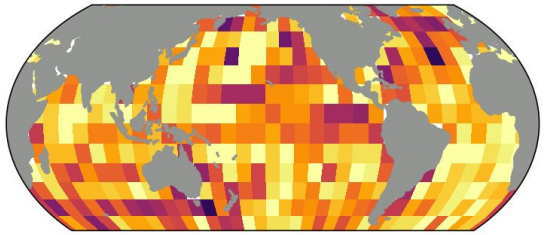
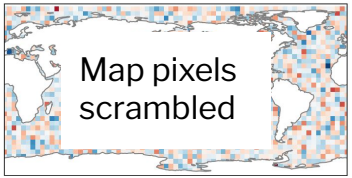
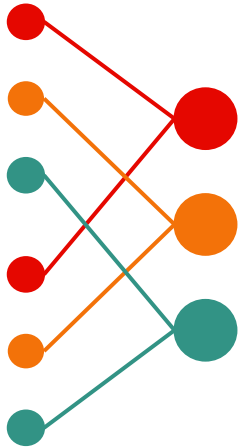


Scramble the pixels of the internal variability (IV) input and input "new" testing into networks





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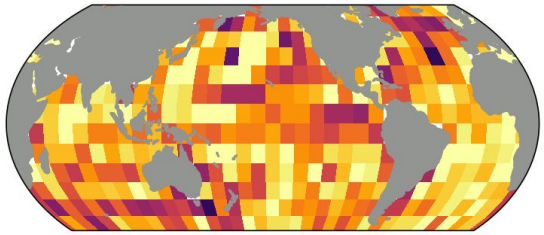

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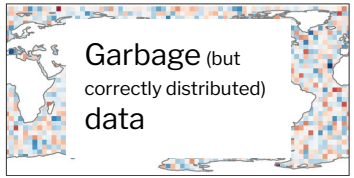

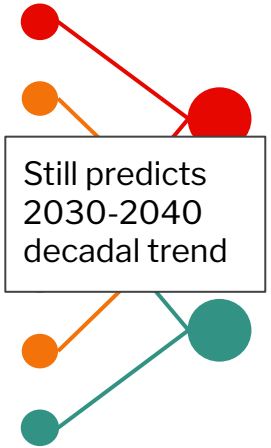

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Predictability from internal variability vs external forcing over 2020-2050

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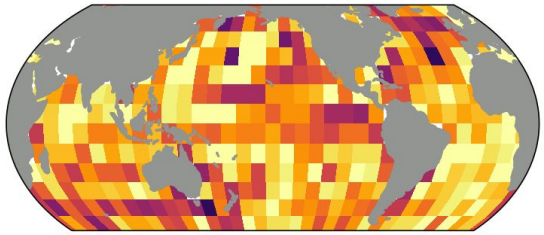

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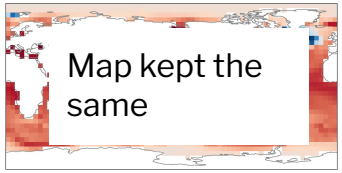
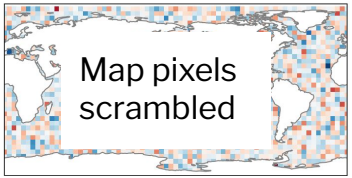
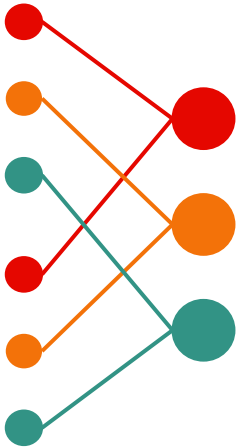
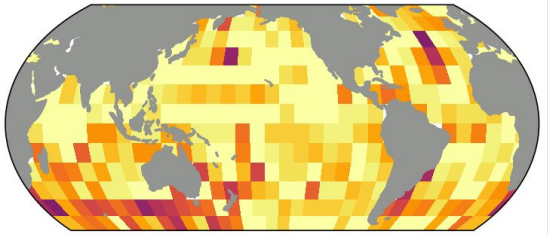






Re-calculate accuracy with scrambled IV data



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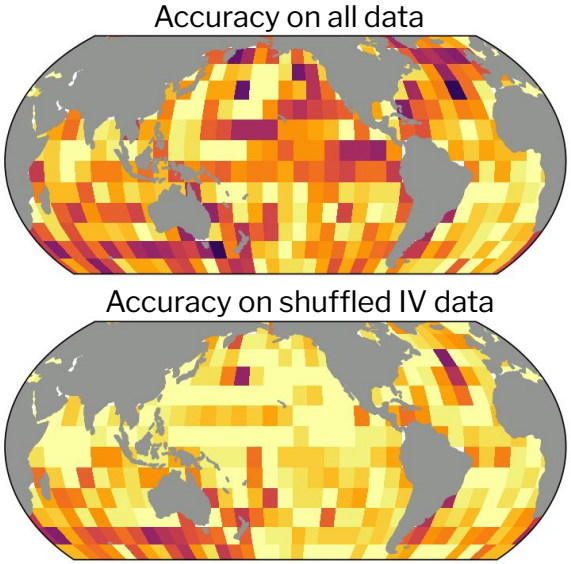
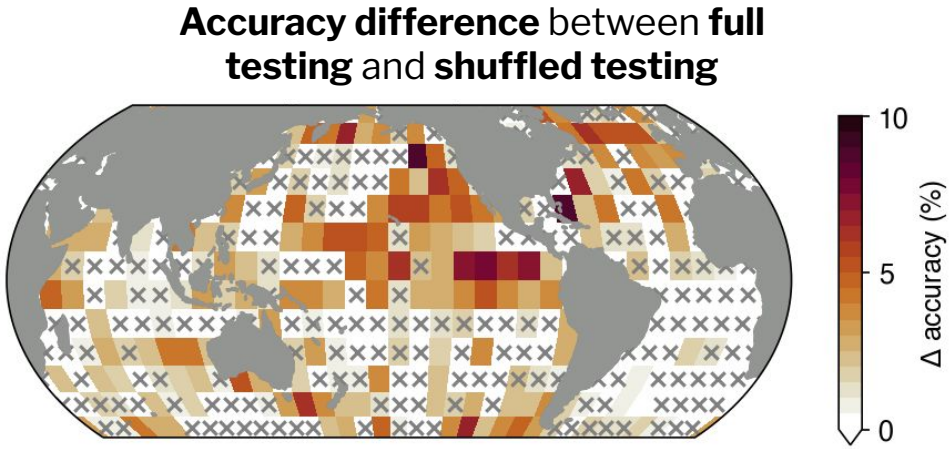
Predictability from internal variability vs external forcing over 2020-2050





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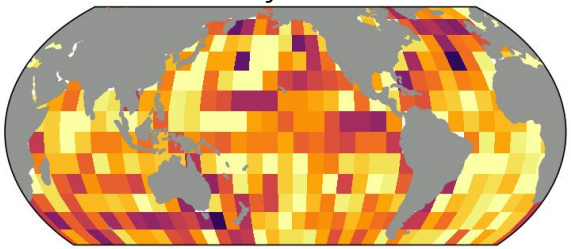
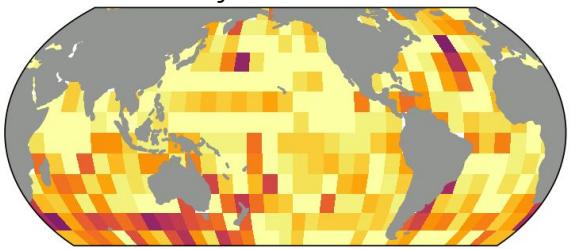
Predictability from internal variability vs external forcing over 2020-2050

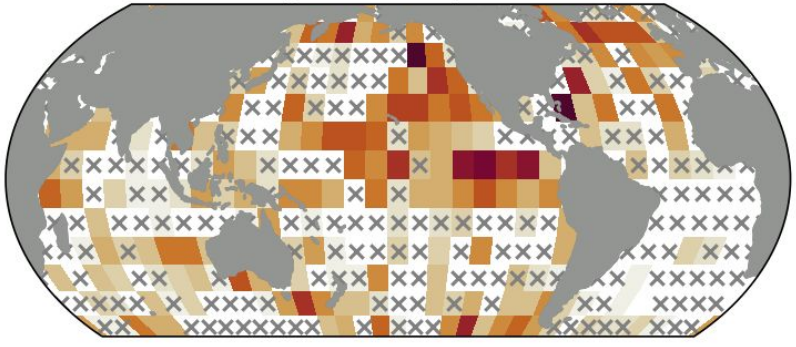
Accuracy on all data



Accuracy on shuffled IV data



Accuracy difference between **full testing** and **shuffled testing**



Interpretation: If networks only used the forced response for its predictions, this figure would be zeros everywhere

Key Takeaway: In many regions, **internal variability significantly increase network's accuracy** above external forcing

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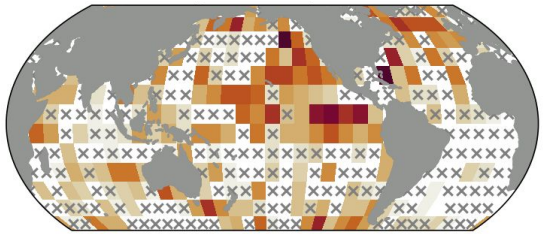
Are some grid points predictable for the same initial state?



Take grid points with increased skill from internal variability (i.e. unstippled)

Gordon et. al *in prep.*

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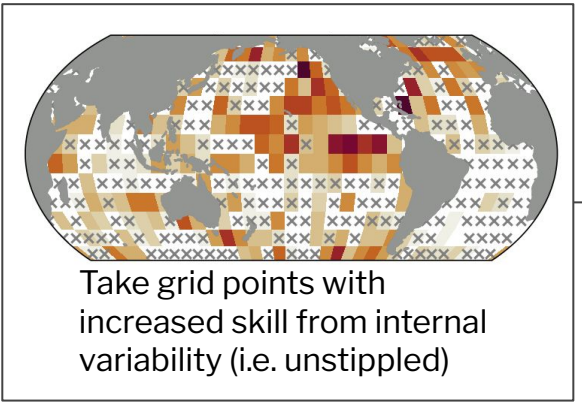

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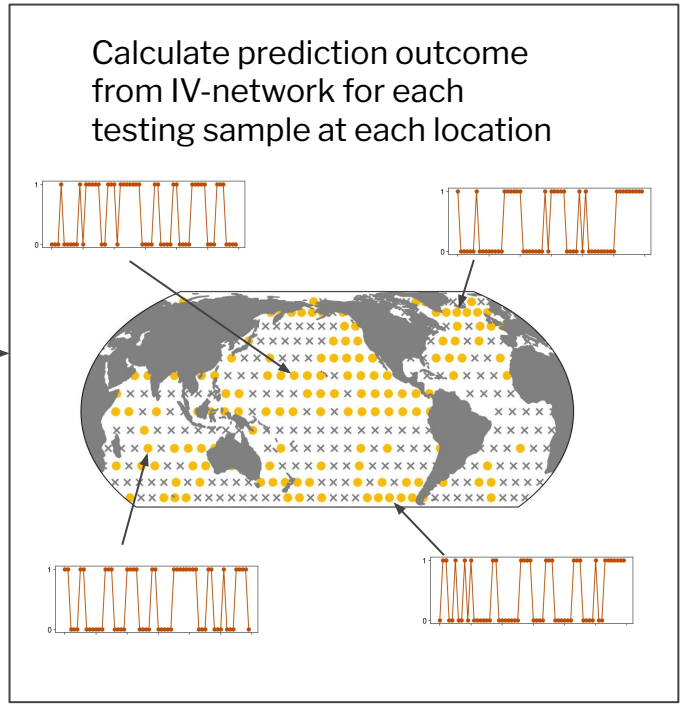

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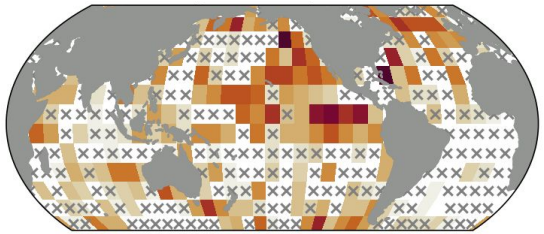
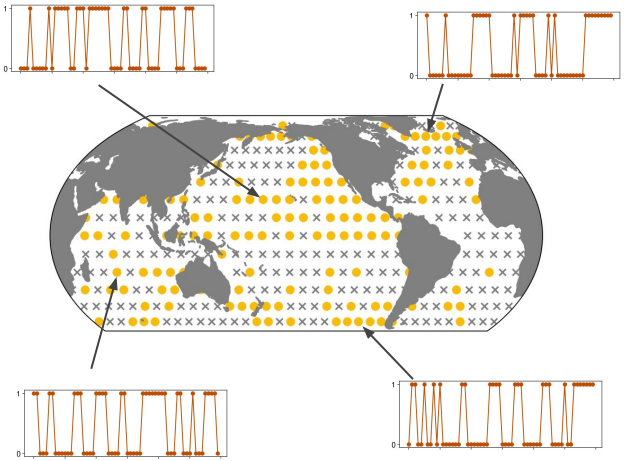


Take grid points with increased skill from internal variability (i.e. unstippled)

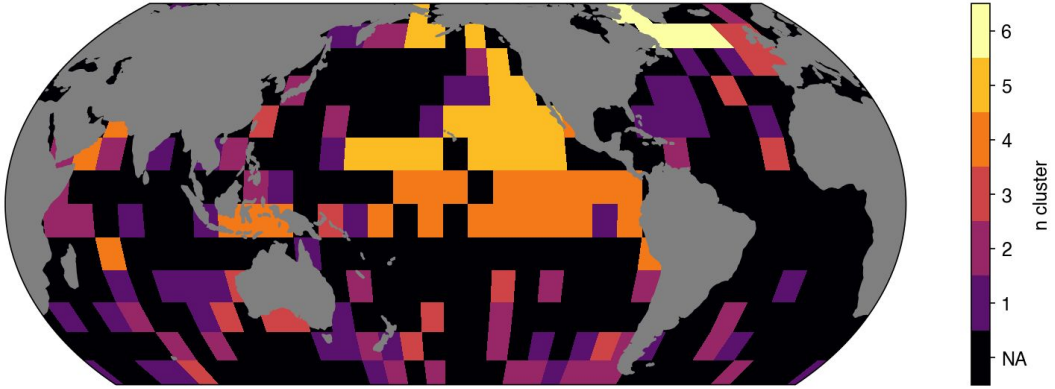
Calculate prediction outcome from IV-network for each testing sample at each location



Kmeans cluster prediction outcome to group grid points where prediction skill covaries with input state

Gordon et. al *in prep.*

Are some grid points predictable for the same initial state?



3 obvious spatial regions, 3 maybe not so obvious

Gordon et. al *in prep.*

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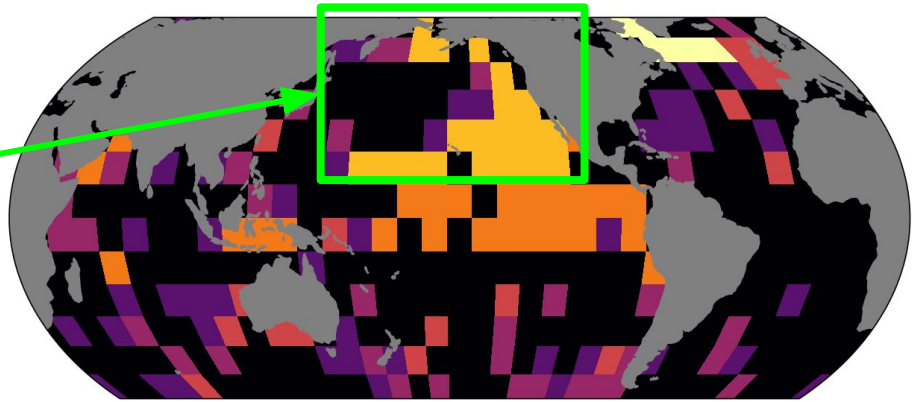
Grid cells resemble PDO horseshoe

Predictability is derived timescale of the PDO



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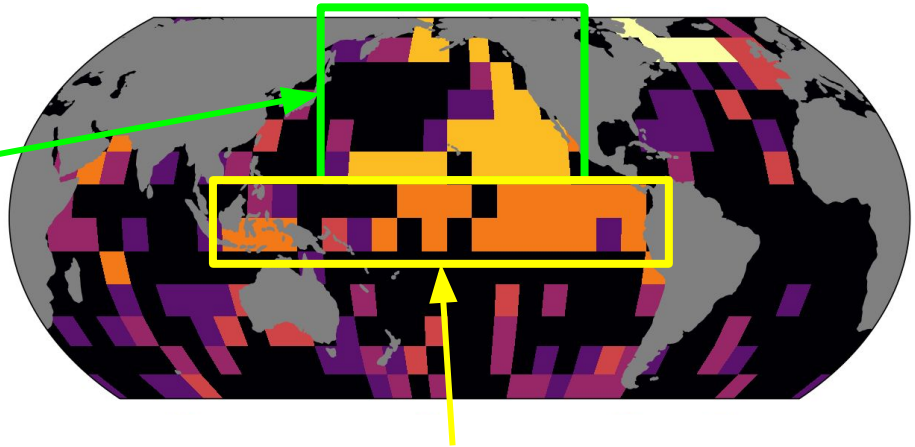

Tropical Pacific/ENSO region

Predictability on decadal timescale likely aliasing of interannual ENSO

Gordon et. al *in prep.*

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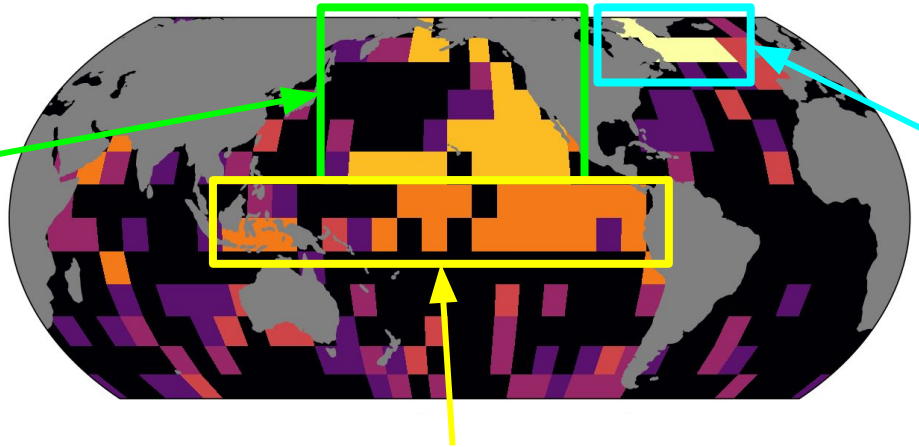

North Atlantic Subpolar Gyre

Predictability is associate with timescale of heat transport into gyre

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Gordon et. al *in prep.*

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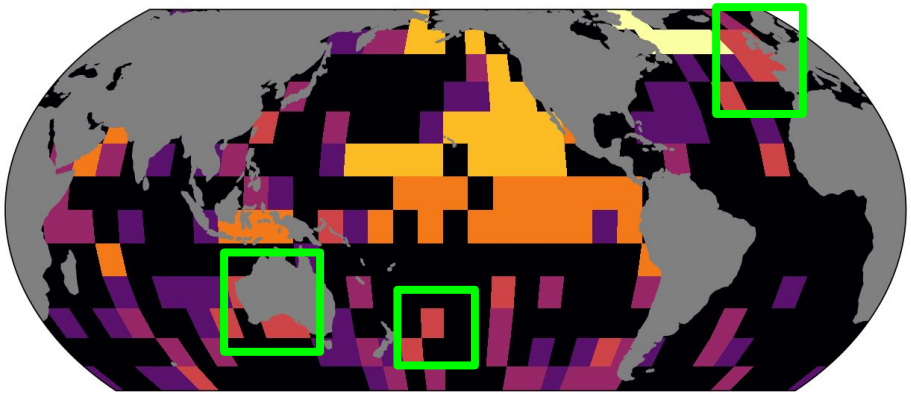
Northeast Atlantic + Australia/New Zealand?



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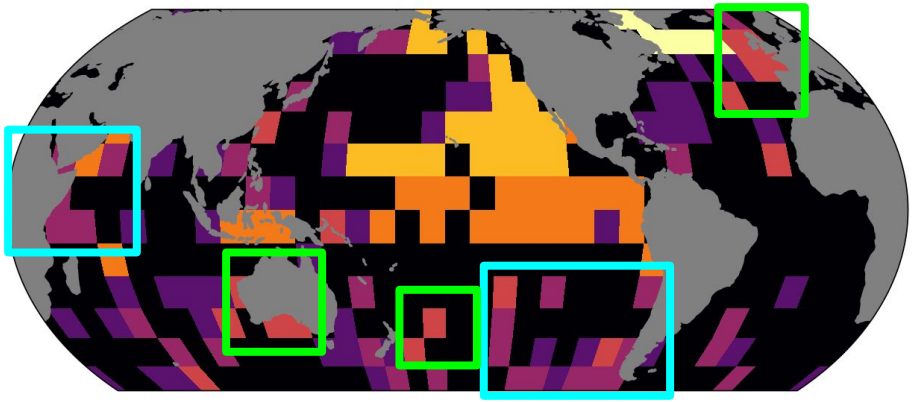

South Pacific + Coastal Indian Ocean?

Gordon et. al *in prep.*

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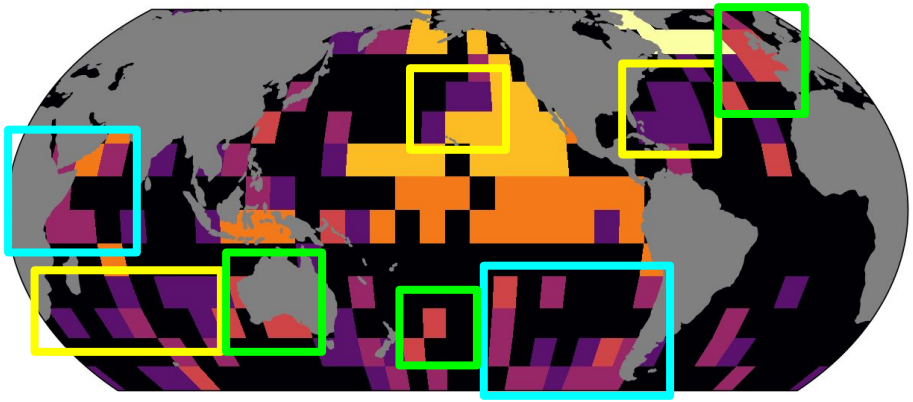


Subtropical Atlantic + Subtropical North Pacific + Subtropical Southern Indian?

South Pacific + Coastal Indian Ocean?

Gordon et. al *in prep.*

Takeaways

- Decadal SST trends can be predictable in the CESM2-LE in the near term (2020-2050)
- Internal variability contributes to predictability of SST trends
- Predictability is associated with decadal scale processes in the North Atlantic and North Pacific Oceans

Contact me!

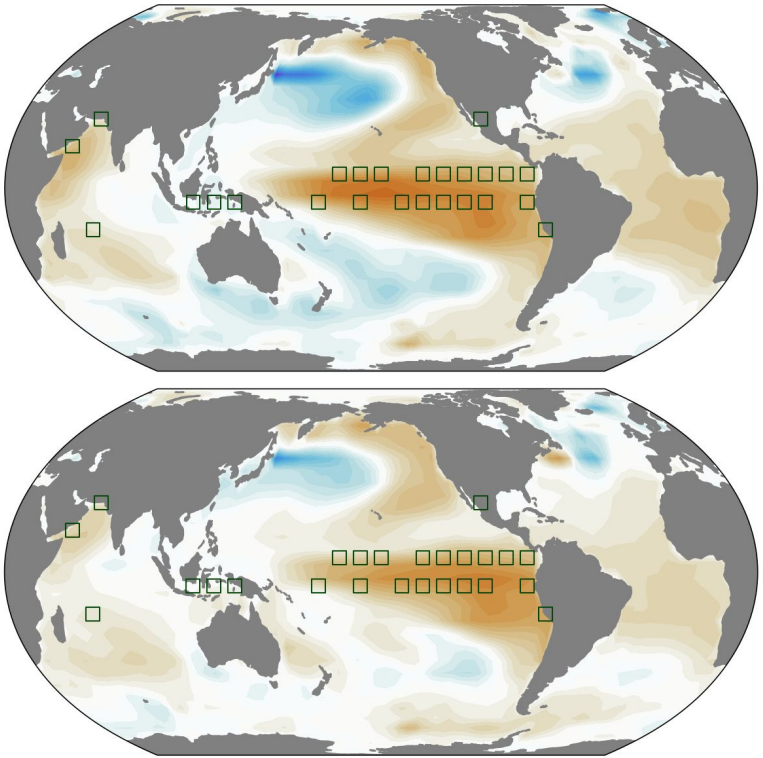
emily.gordon@colostate.edu

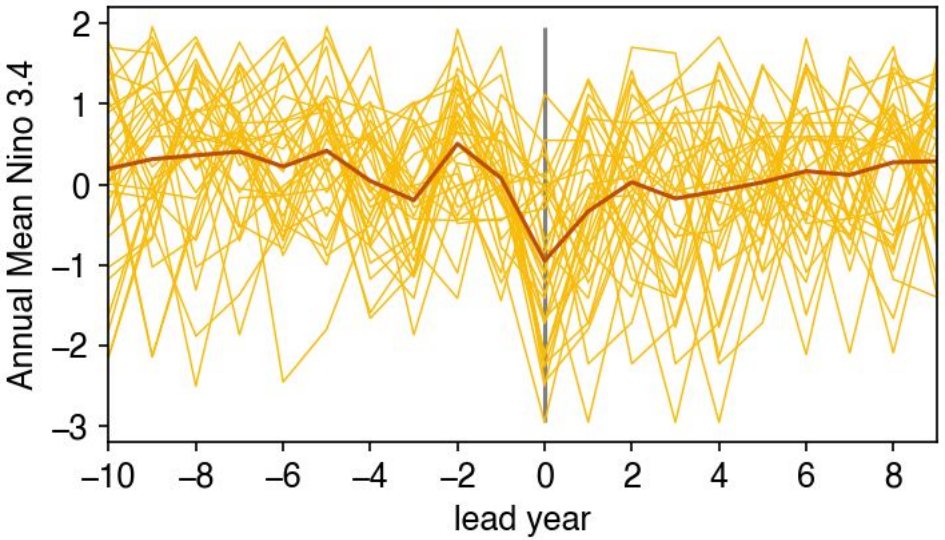
emily-gordy

FULBRIGHT New Zealand
TE TŪĀPAPA MĀTAURANGA O AOTEAROA ME AMERIKA

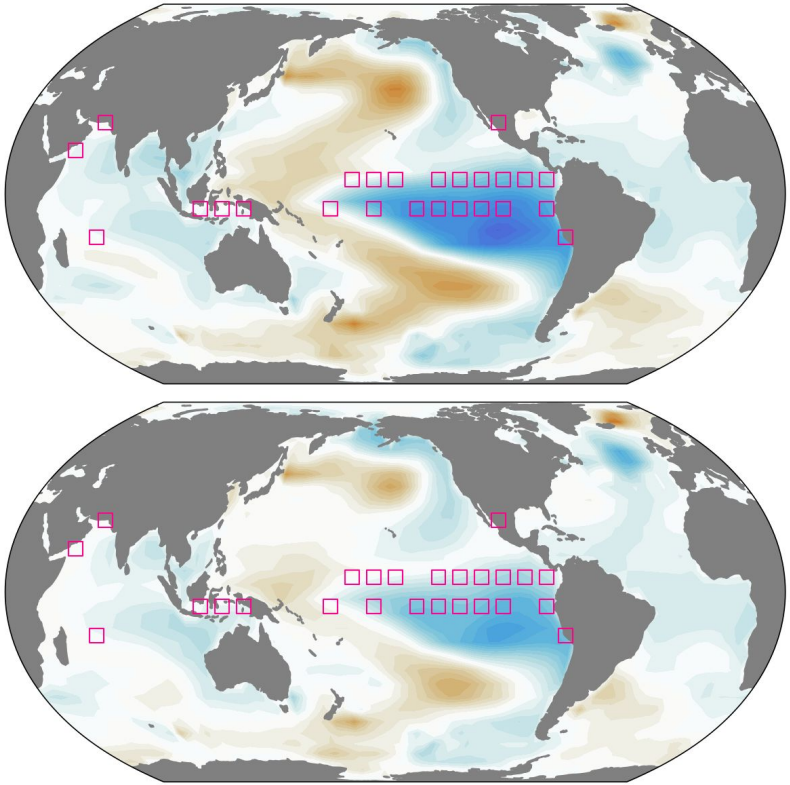
Fin

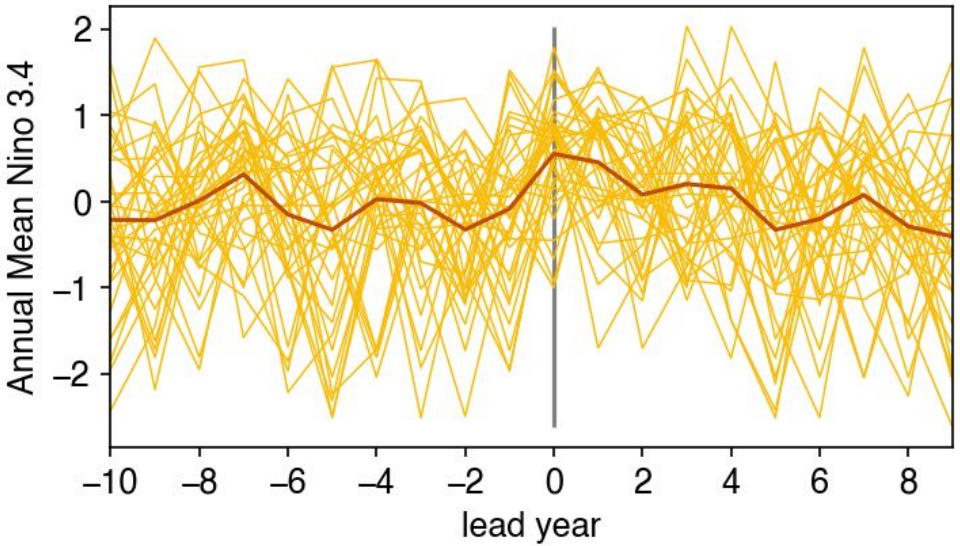
Tropical Pacific, predict positive SST trend





Tropical Pacific, predict negative SST trend





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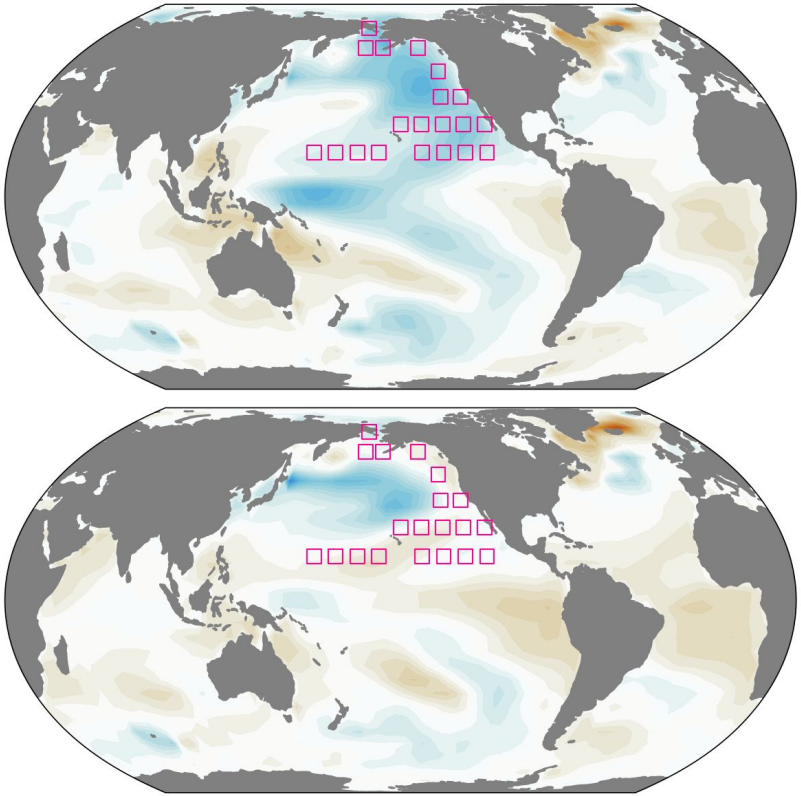

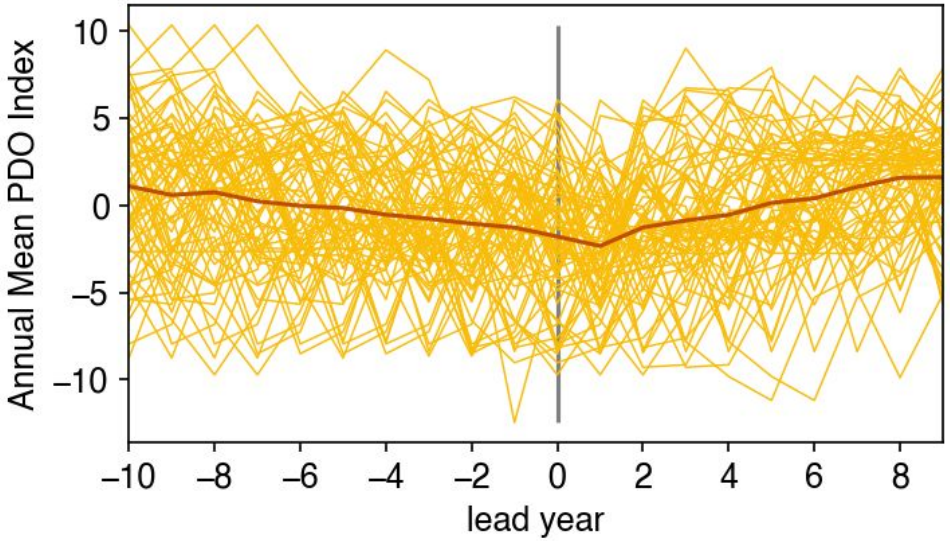

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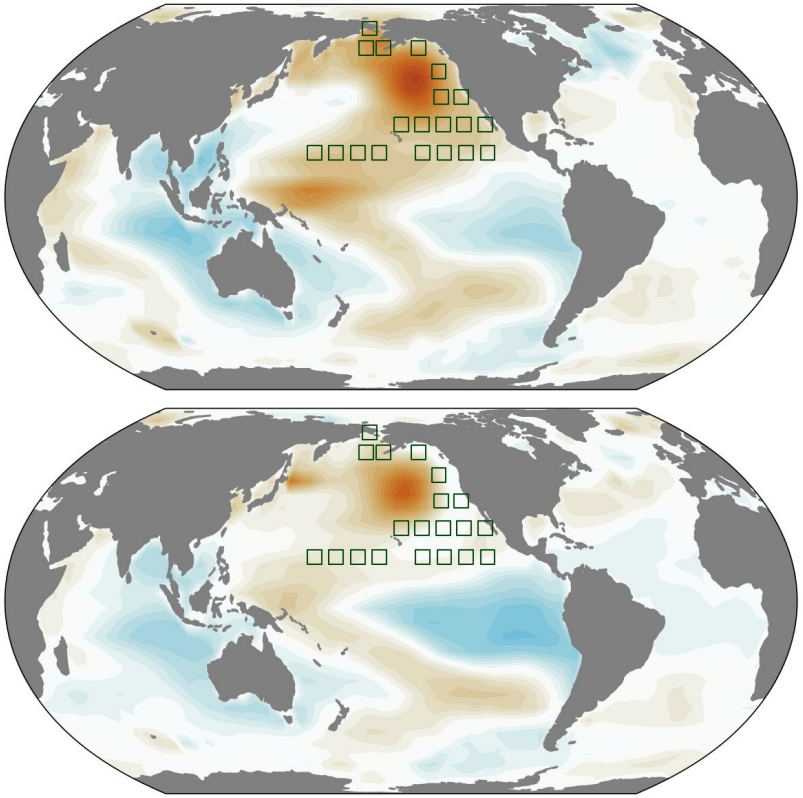
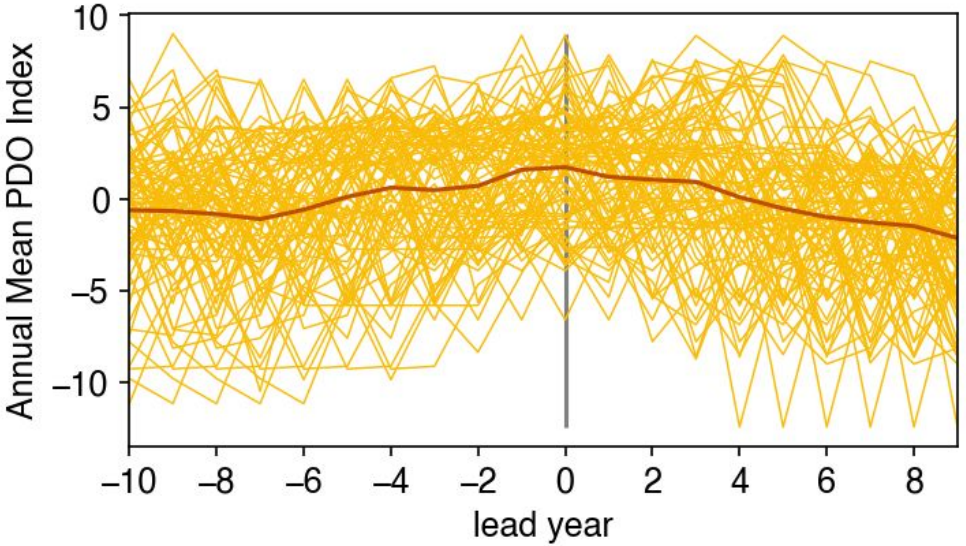
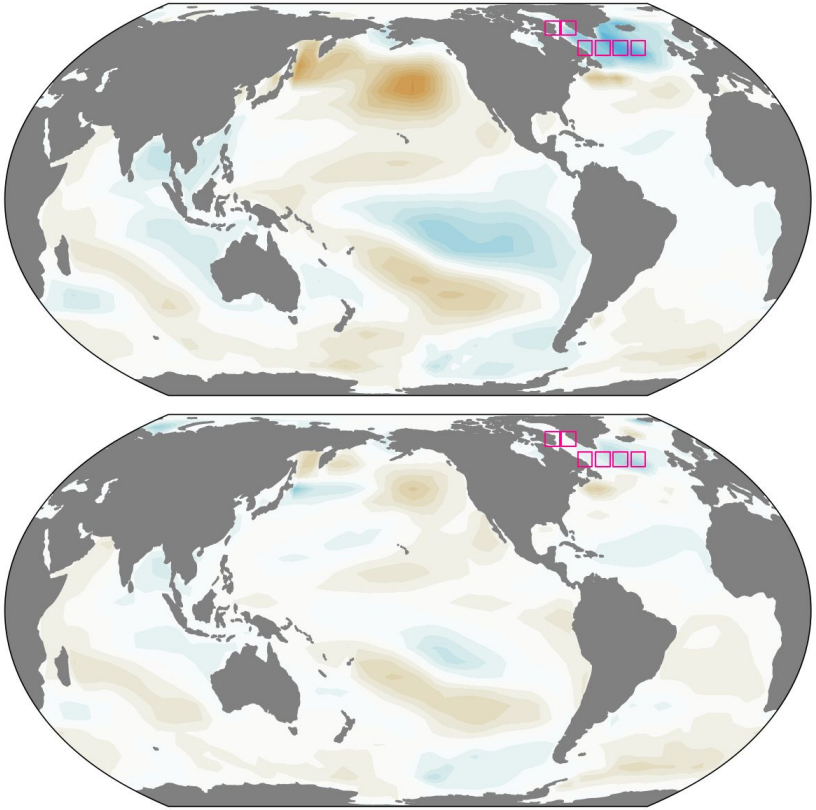
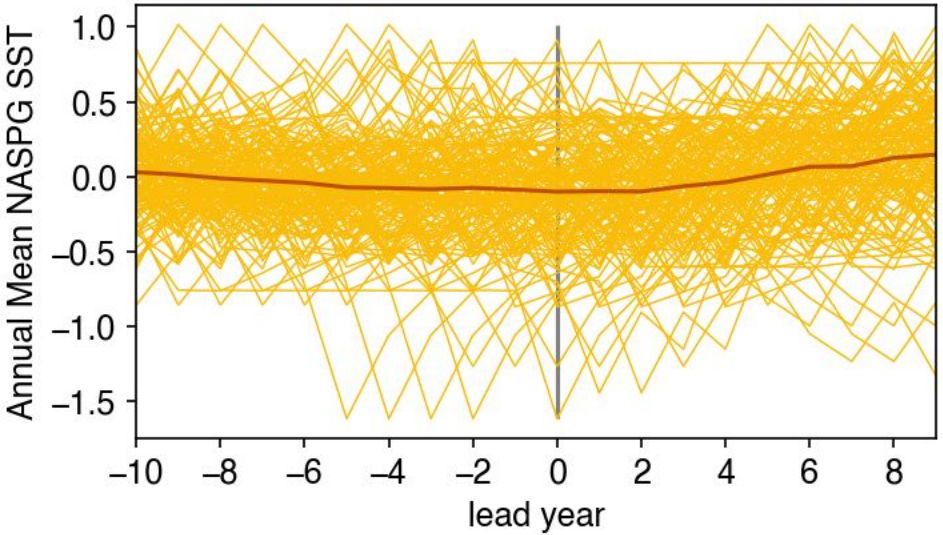




North Atlantic, predict negative SST trend





North Atlantic, predict positive SST trend