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# Skillful Wintertime Temperature Forecasts out to 6 Weeks with Machine Learning Methods

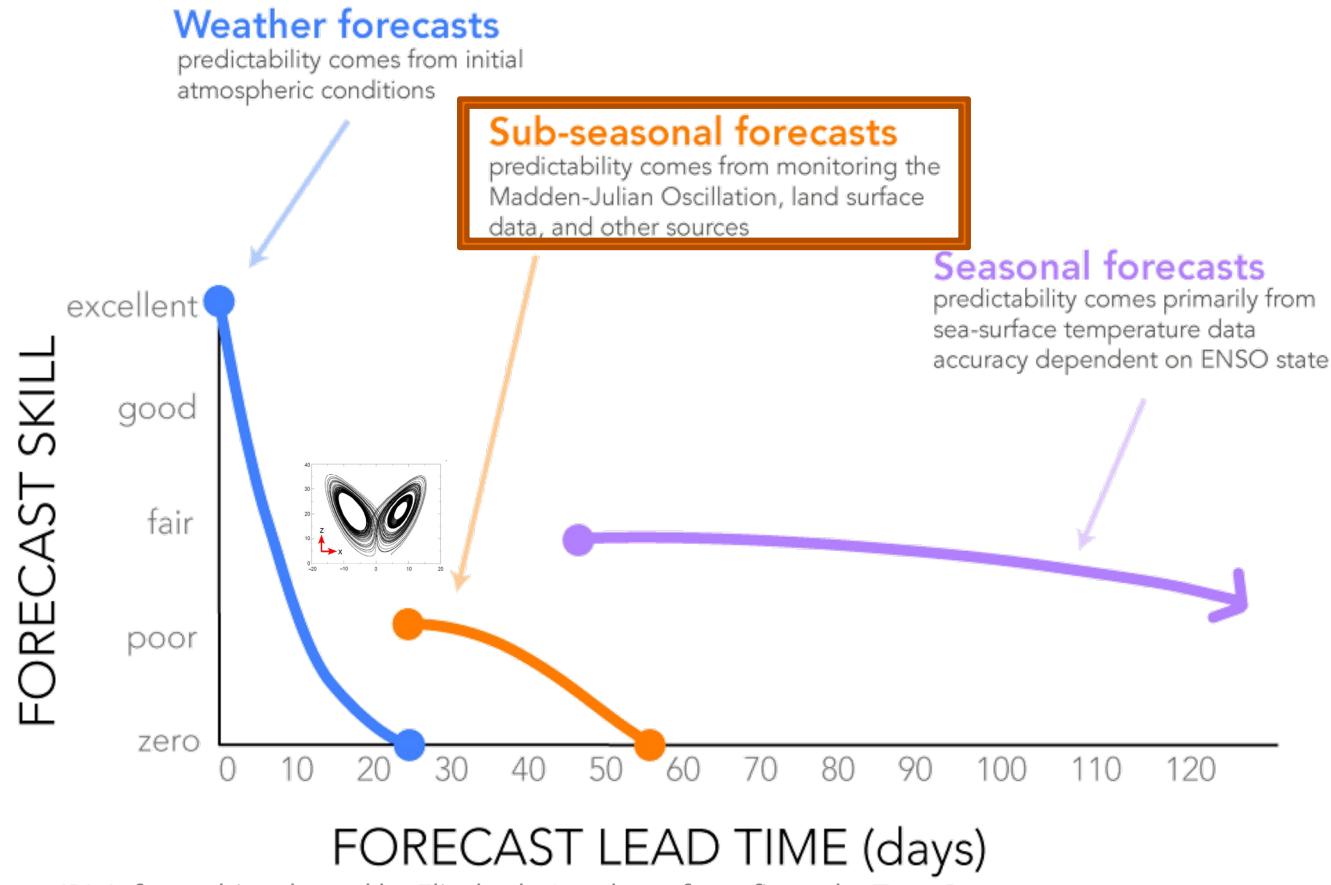
**Presented By:** Will Chapman

**With Collaborators:** Fernando Arizmendi, David Benson, Tim Higgins, Yakelyn R. Jauregui, Wenwen Kong, Aneesh Subramanian, Judith Berner

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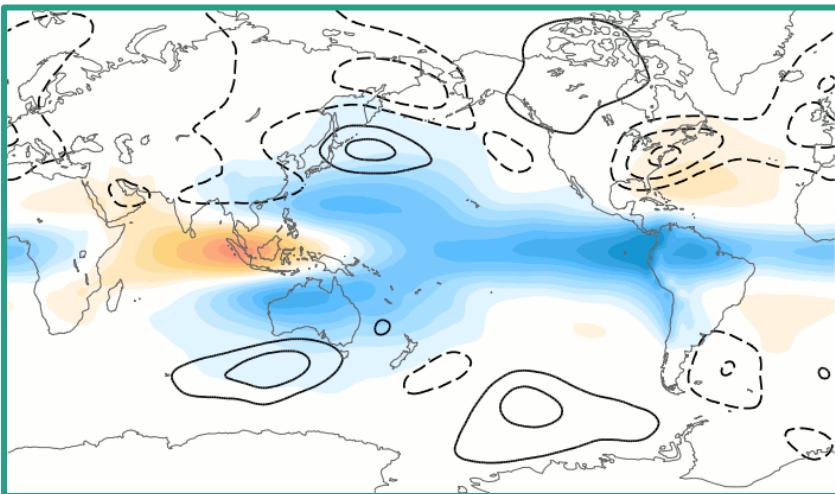


# Subseasonal Skill



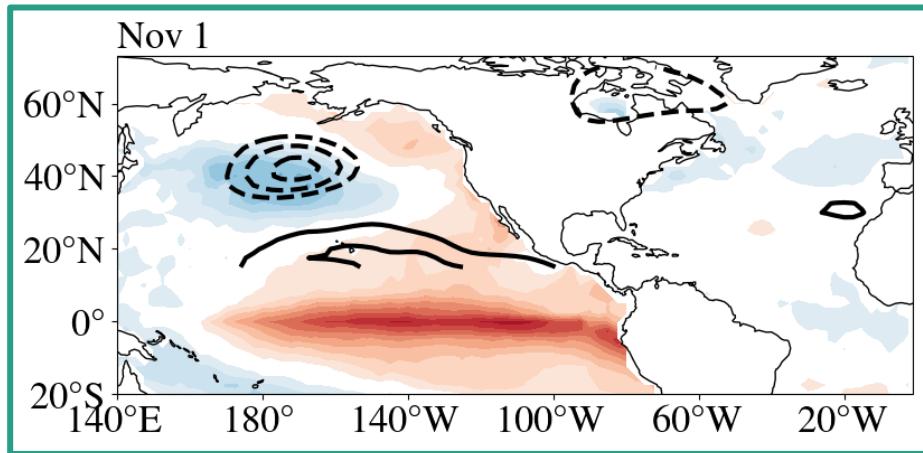
# Teleconnections

-MJO-



Credit: Adames MJO Dynamics Group

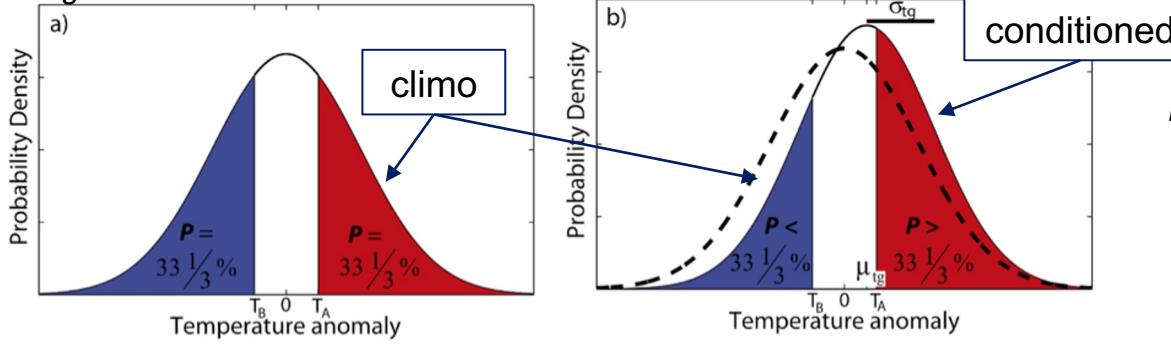
-ENSO-



# Motivation

Johnson et al. 2014: Skillful Wintertime North American Temperature Forecasts out to 4 Weeks  
**Based on the State of ENSO and the MJO**

Fig. 2 Johnson et al. 2014



"we assume that the ENSO and MJO impacts are independent"

$$\mu_{tg} = \mu_{tig} + \mu_{tjg}$$

$$\sigma_{tg}^2 = \sigma_{tig}^2 + \sigma_{tjg}^2$$

*g*: grid point

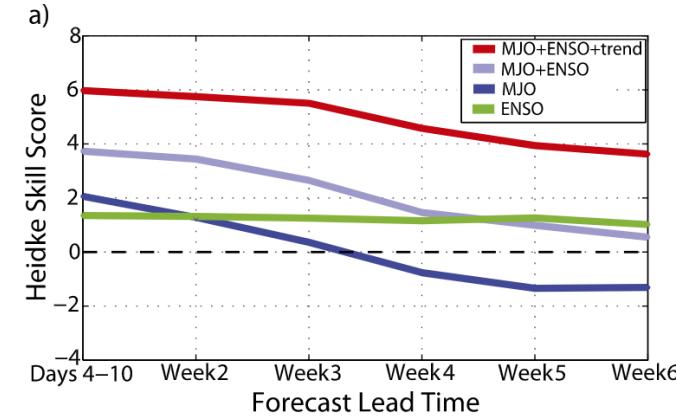
*t*: lead time

*i*: MJO phase (9)

*j*: ENSO phase (3)

Heidke skill score:

Fig. 3 Johnson et al. 2014

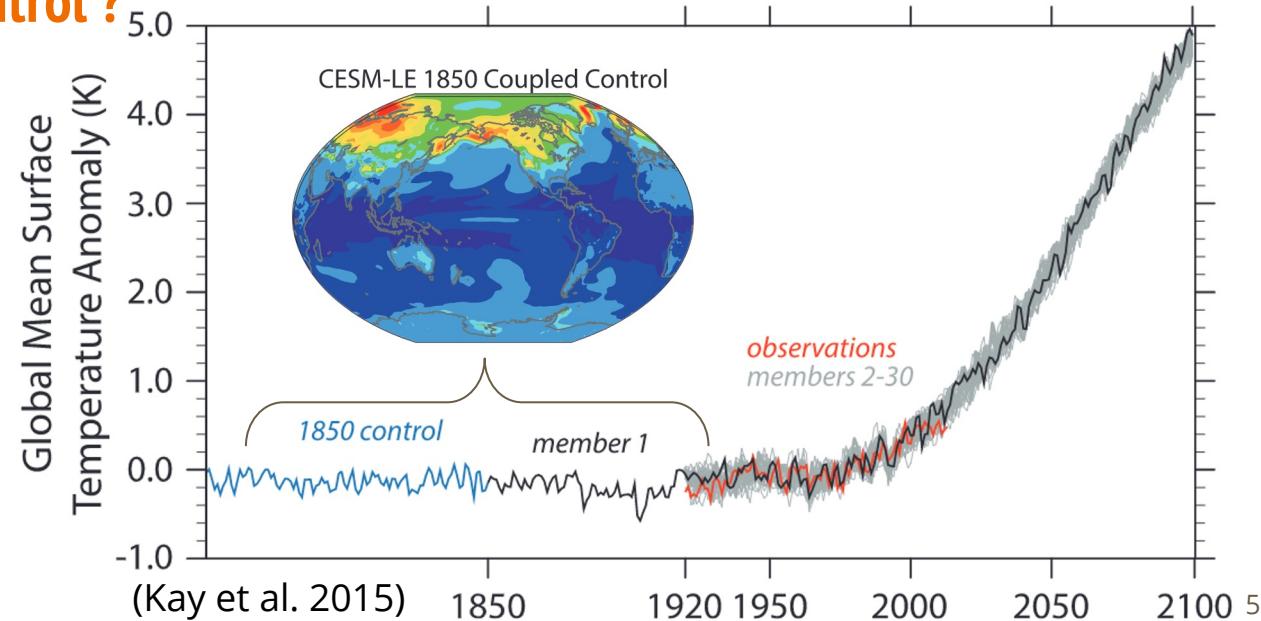


## What / Motivation for using CESM

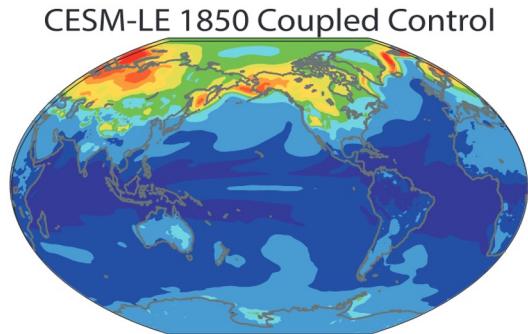
What:

- 1) Test various statistical models for T2m prediction skill at S2S lead times
- 2) See if the statistical models can identify forecast windows of opportunity

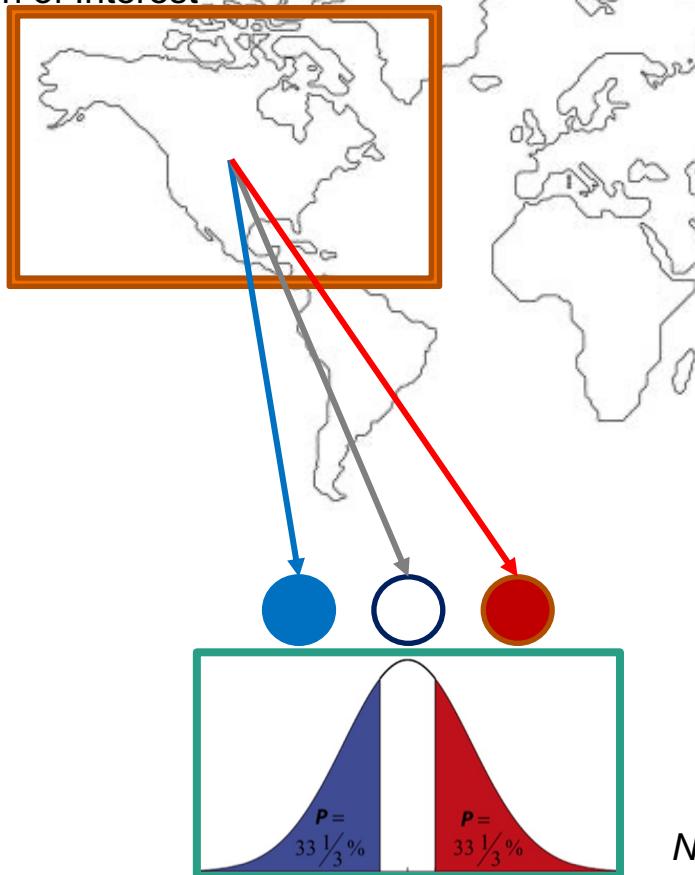
Why CESM LENS pi - control ?



# Target Variable



## Region of Interest

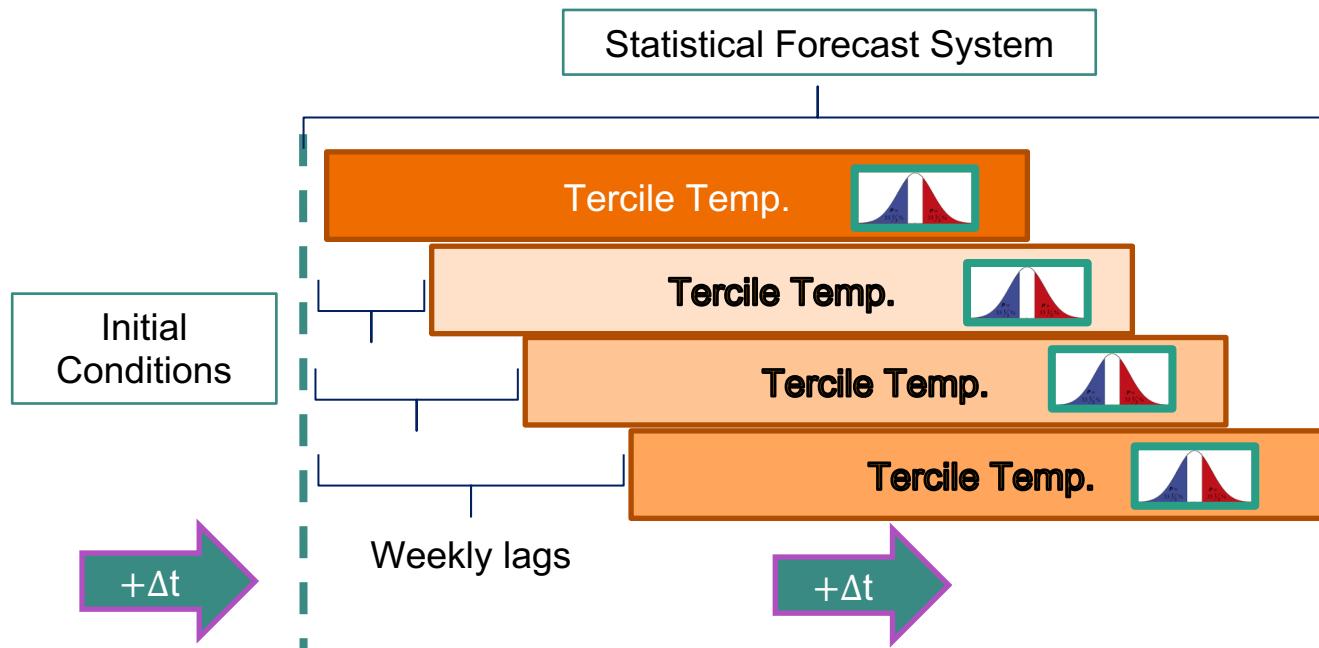


## CESM LENS Pi – Control

- Rolling **Weekly Averaged** Surface Temp.
- Train on Model Years 400-600
- Test on Model Years 700-800

*NDJFM Climatology*

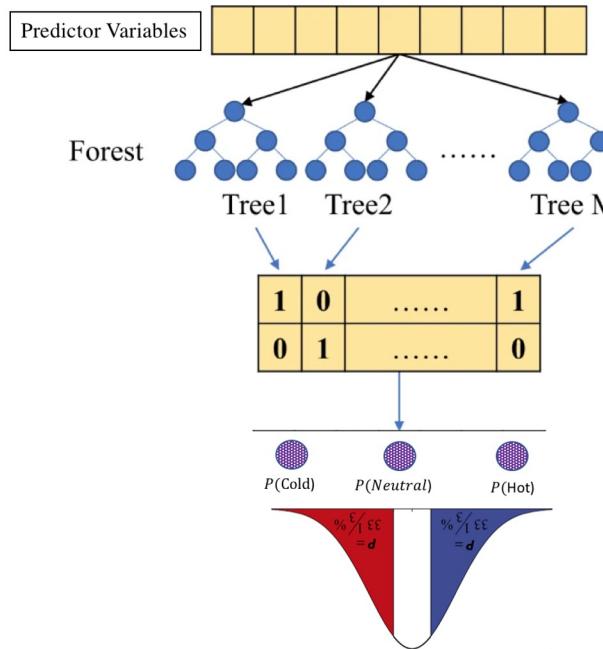
# Forecast Framework



# Statistical Models (Random Forest):

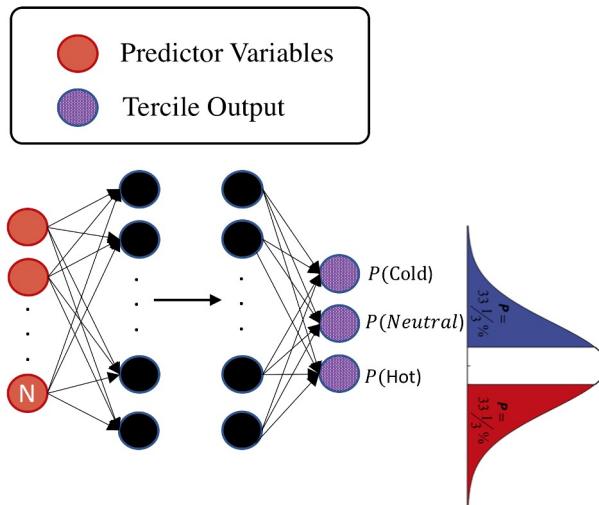
Models: (a) Independent Gradient Boosted Classifier

- **Predictors** : CESM LENS CNTRL: ENSO and RMM indices, 1hot encode MJO phase (DJF)
- **Predictand** : CESM LENS CNTRL: 7-day avg. T2m at every land lat/lon



# Statistical Models (Neural Network):

- **Predictors** : CESM LENS CNTRL: ENSO and RMM indices, 1hot encode MJO phase (DJF)
- **Predictand** : CESM LENS CNTRL: 7-day avg. T2m at every land lat/lon



Configuration:

2 layers = [128, 8]

Batch\_size = 256

L2 Regularization:  $a(1e-2)$

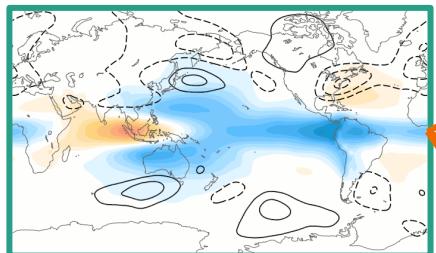
# Framework

Input:

Model:

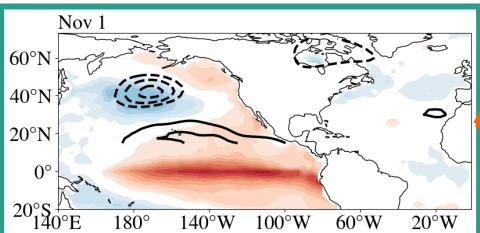
Target:

-MJO-



Credit: Adames MJO Dynamics Group

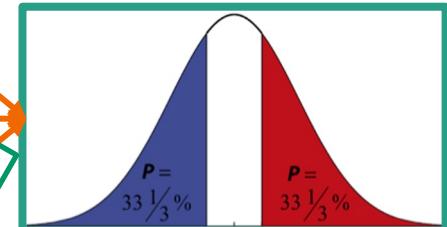
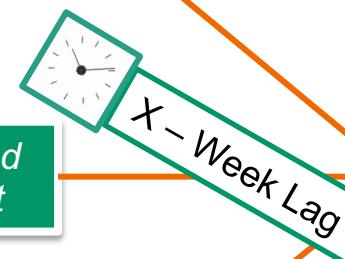
-ENSO-



*Johnson et al. 2014*

*Gradient Boosted Random Forest*

*Neural Network*

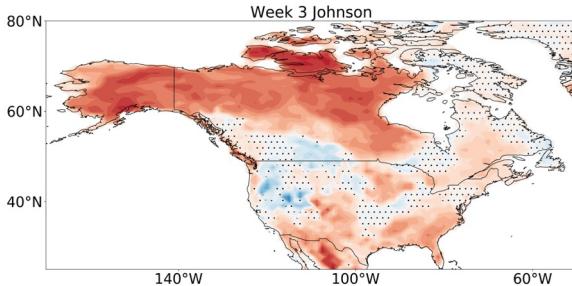


$P(\text{Cold})$        $P(\text{Hot})$   
 $P(\text{Neutral})$

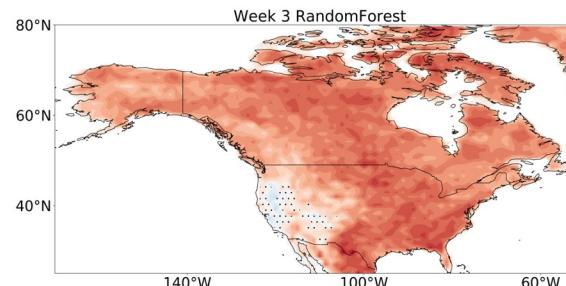
# Results

## HSS score - Lead time 3 week

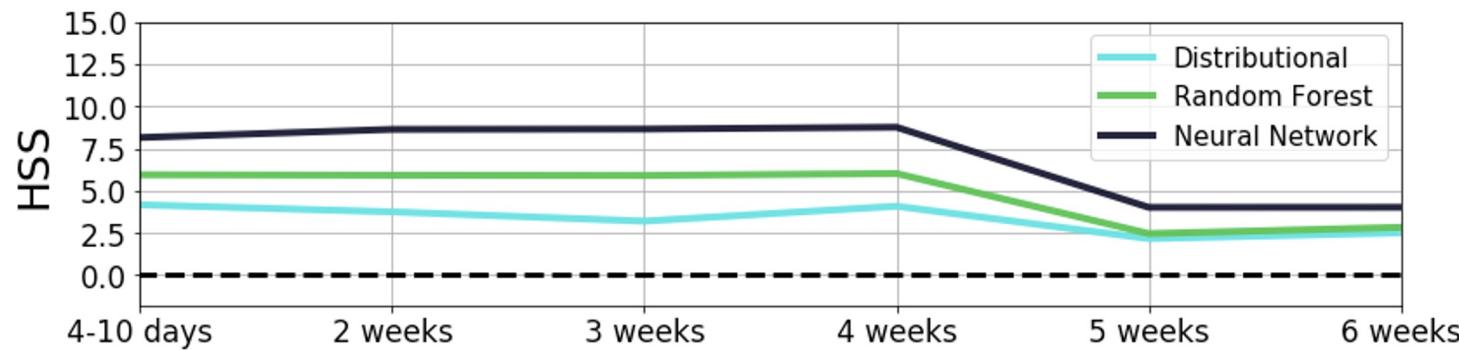
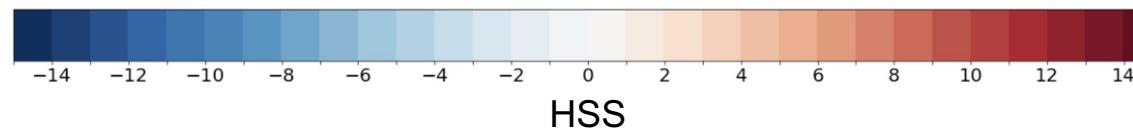
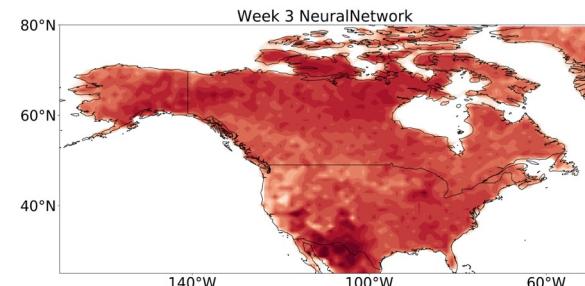
Johnson



Random Forest

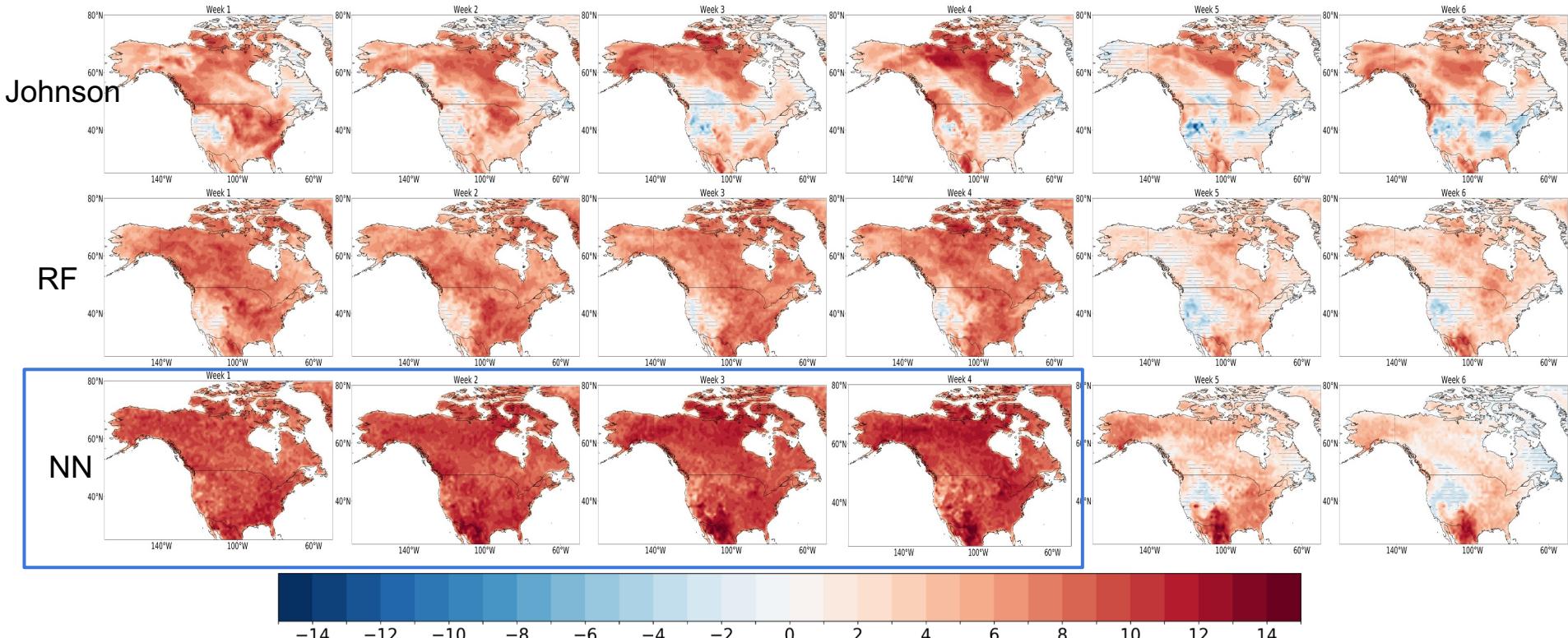


Neural Net



# Results

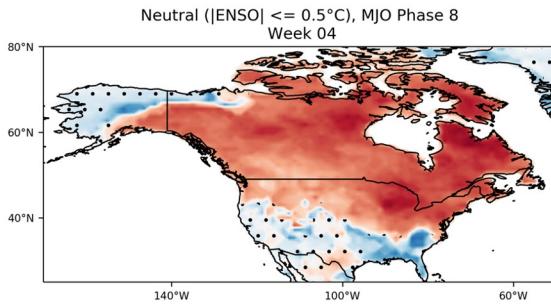
## US: NN's performance overshadow Johnson and RF (lead time week 1-4)



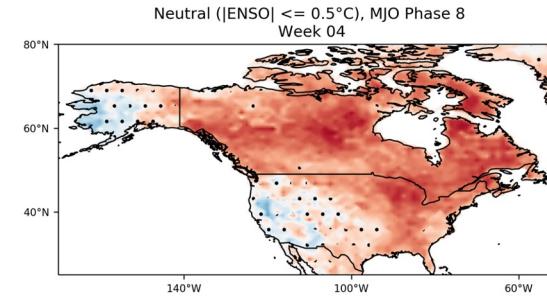
# Results

## HSS score observed for Neutral ENSO, MJO phase 8 - Lead time 4 week

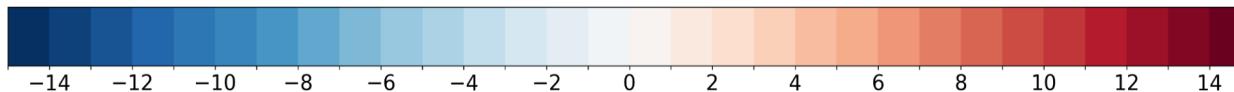
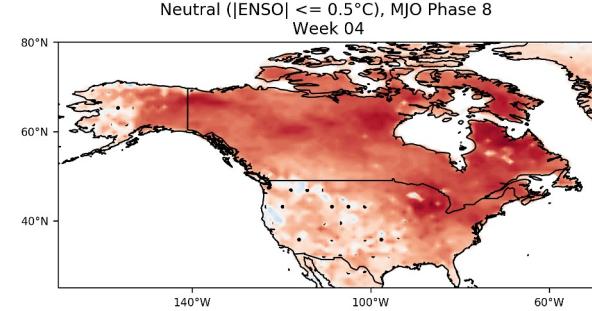
Johnson



Random Forest



Neural Net

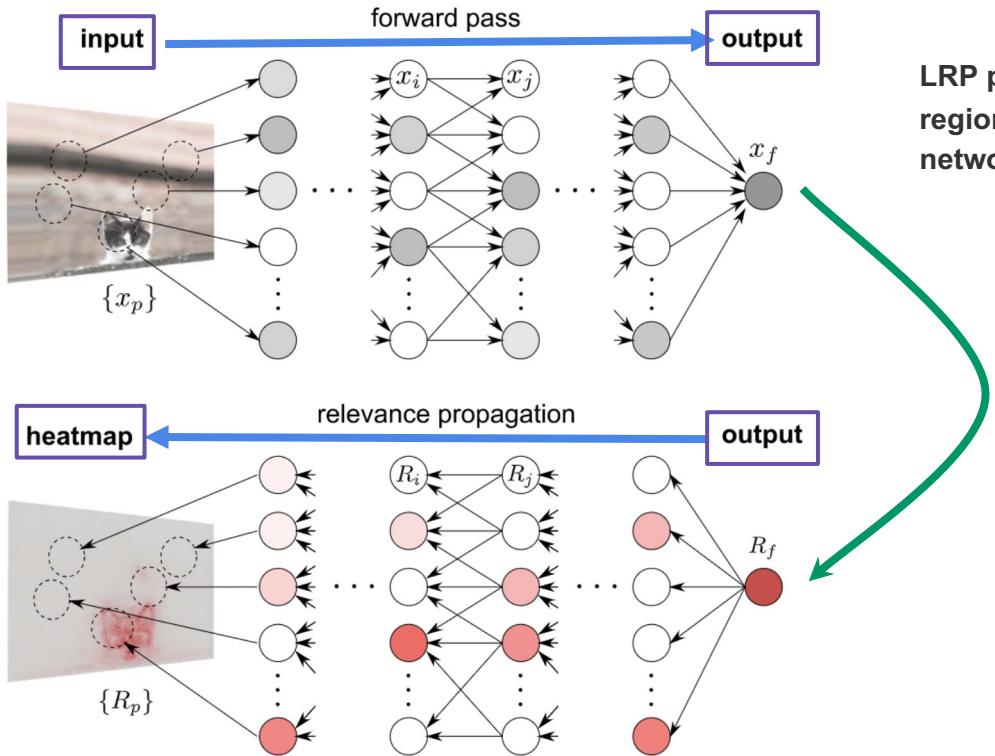


HSS

Lack of significance= hatched regions

NN does better mostly everywhere contrary to RF and the baseline method

# Layer-wise Relevance Propagation (LRP)



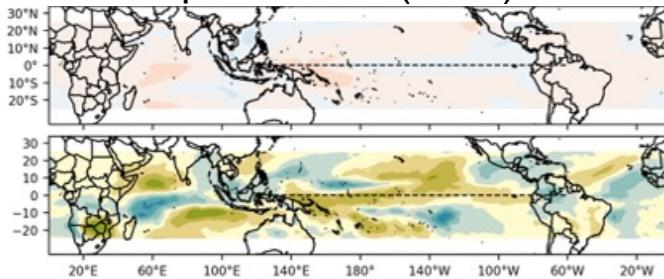
LRP produces a heatmap of the most relevant regions of the input for each prediction by the network

# Results

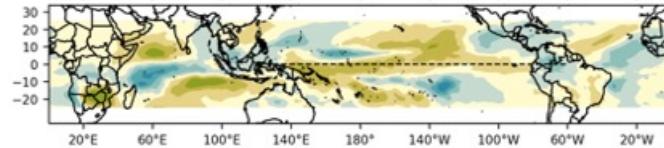
## Layer-wise Relevance Propagation (LRP) in Northern Mexico – 3 week forecast



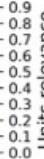
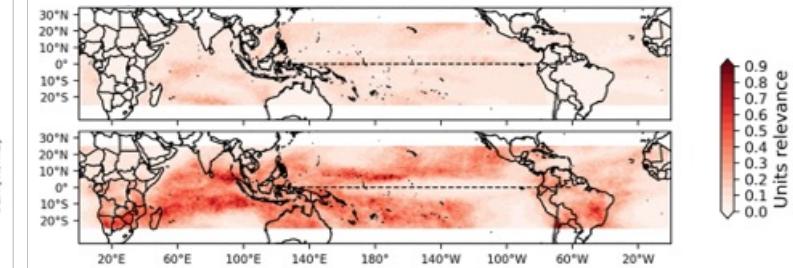
SST:



OLR:



LRP for  $P(\text{HOT}) > 0.75$



Predictors: tropical 2m temperature  
and OLR

Predictand: 2 meter air temperature

## How Do We Calibrate this Probabilistic Forecast?

1. Non-parametric quantile-based probabilities transformed to a full predictive distribution (Scheuerer et al., 2020)

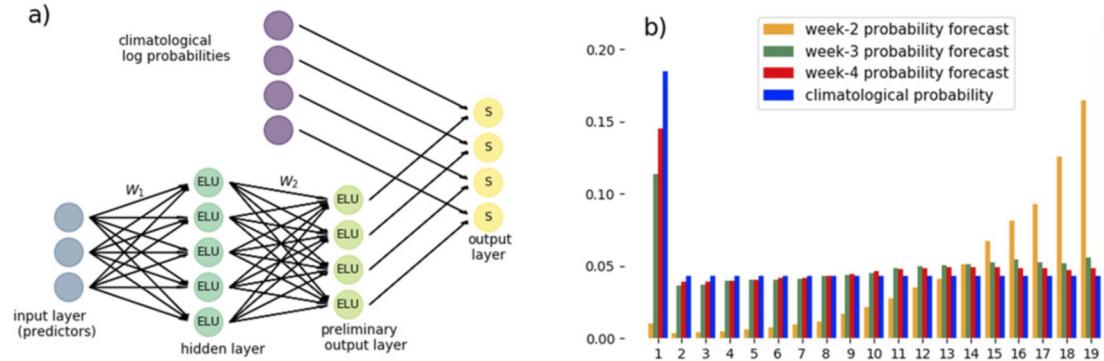


FIG. 2. (a) A schematic of the ANN architecture used in this study. For improved readability the ANN is depicted with 5 (instead of 10) nodes in the hidden layer, and 4 (instead of 20) categories for which forecast probabilities are calculated. (b) The categorical forecast probabilities for 8–14 Jan 2017 precipitation accumulations at a grid point in the Tahoe National Forest.

Transfer Learning → Observations.

# Conclusions

- We use the Heidke skill score (HSS) to assess the forecast skill. Both Random Forest (RF) and Neural Network (NN) models produce skillful forecasts.
- Forecast lead times from 1-4 weeks using NN models show higher HSS over the whole domain of interest. After week 4, the NN skill degrades over Midwest and Northeast United States; however, stays skillful in central America to the southern United States.
- The interpretable NN identify coherent spatial patterns of the most known modes of S2S variability (ENSO, MJO) and highlights convective regions with well-known downstream effect over US.
- These results highlight the **NN model's ability to improve the S2S 2m temperature forecast over the US.**