

NOAA Weeks 3-4 & S2S Webinar

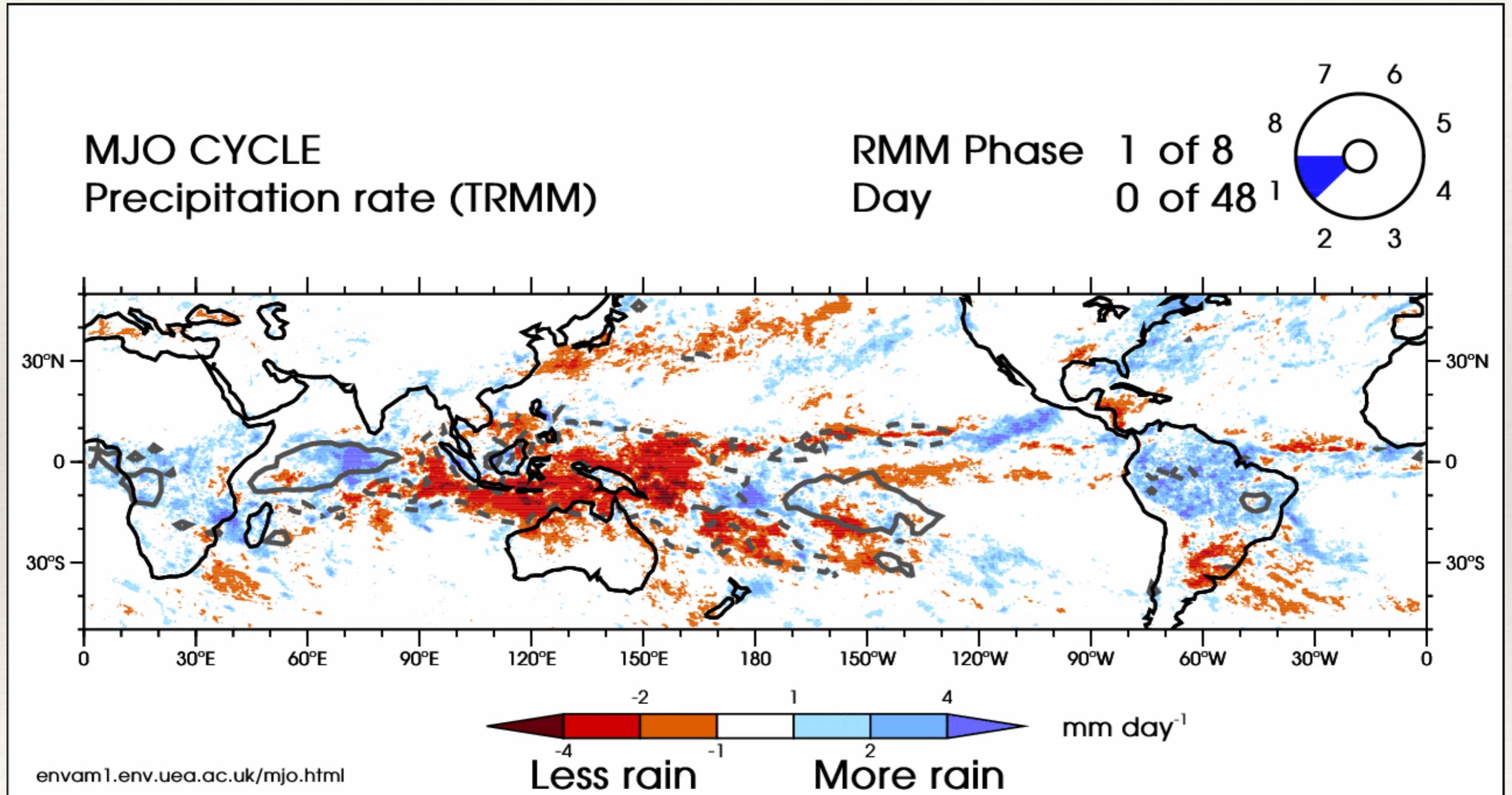
October 4, 2021

# Using simple, explainable neural networks to predict the Madden-Julian oscillation

Zane Martin  
Elizabeth Barnes  
Eric Maloney



# The Madden-Julian Oscillation





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# Summary of MJO Prediction

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## From 2010 up to ~now ...

### Statistical Models

Empirical models which use statistical techniques to predict future MJO behavior given past relationship

- ~2 weeks of skill
- Wide range of approaches, but nearly all methods linear

### Dynamical Models

(Global) models which solve fluid dynamic & related equations, initialized from observations

- 3-5 weeks of skill
- Since 2000s, model processes improved, ensembles grew, intercomparisons developed



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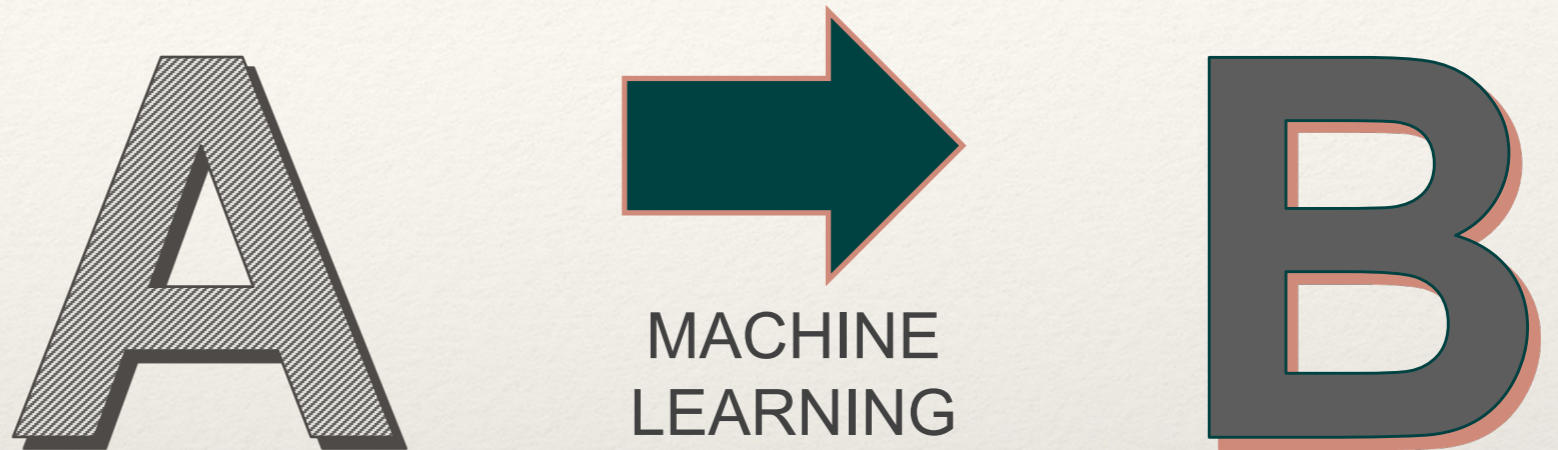
# Summary of MJO Prediction

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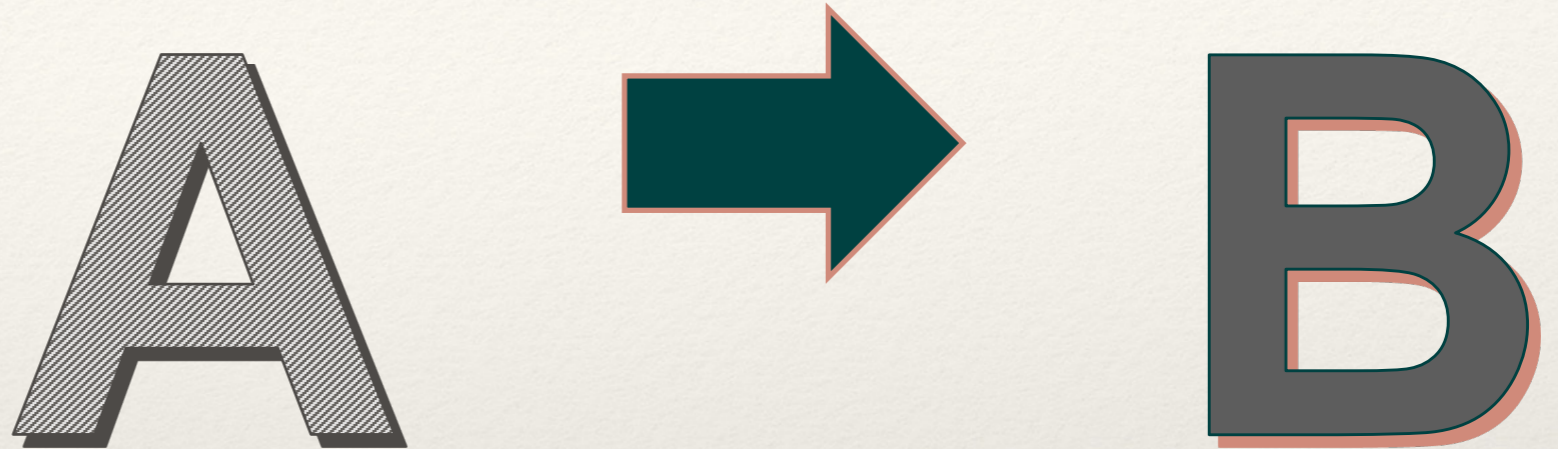
**The future of statistical MJO prediction...**

Non-linear methods and machine learning!

# Machine Learning



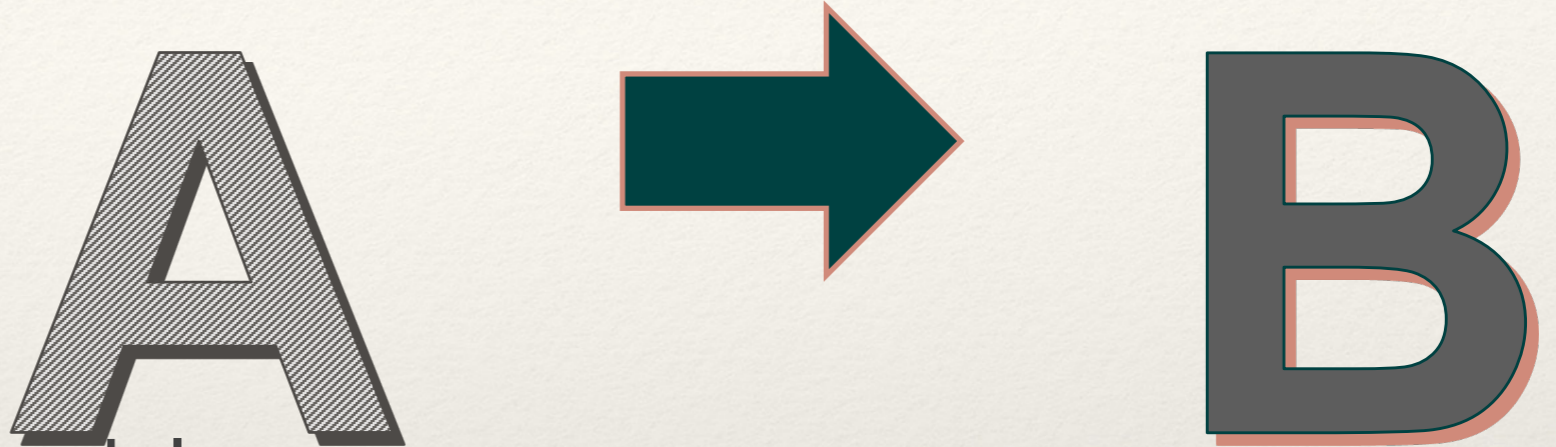
# Machine Learning



*A linear* data transformation might take the form:

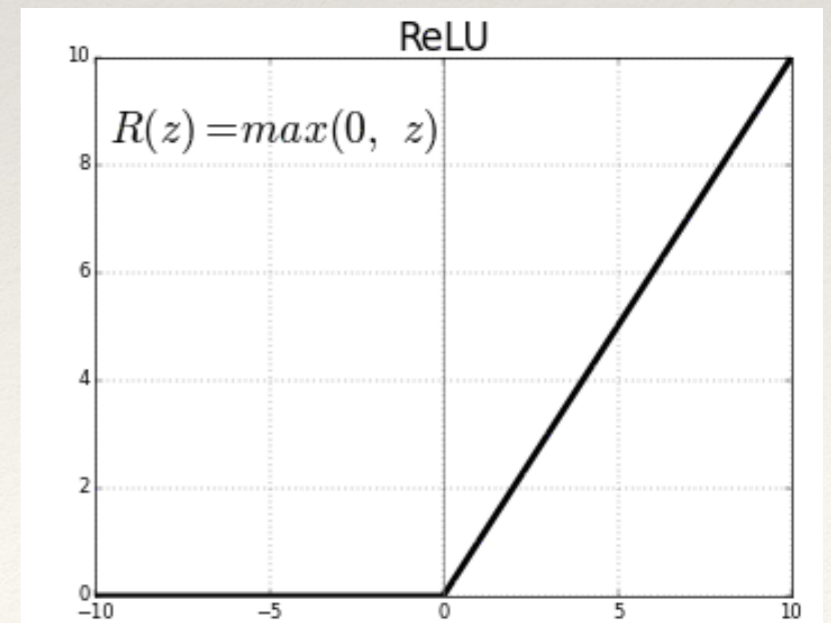
$$X \cdot A + y$$

# Machine Learning



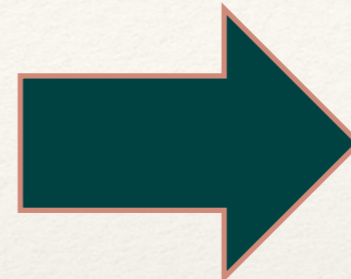
Artificial neural network models:

- Incorporate non-linearity into the data transformations
- Iterate over data during “training” data to minimize a *loss function* that describes how skillful the model prediction are



# Machine Learning & the MJO

Maps of the key daily  
tropical variables  
(pre-processed)



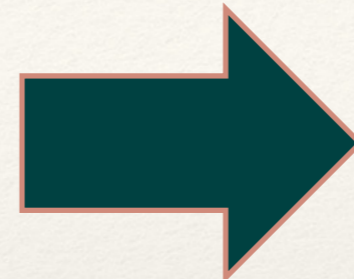
MACHINE  
LEARNING

Information  
about an  
**MJO index** at  
various leads



# Machine Learning & the MJO

Maps of the key daily  
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MACHINE  
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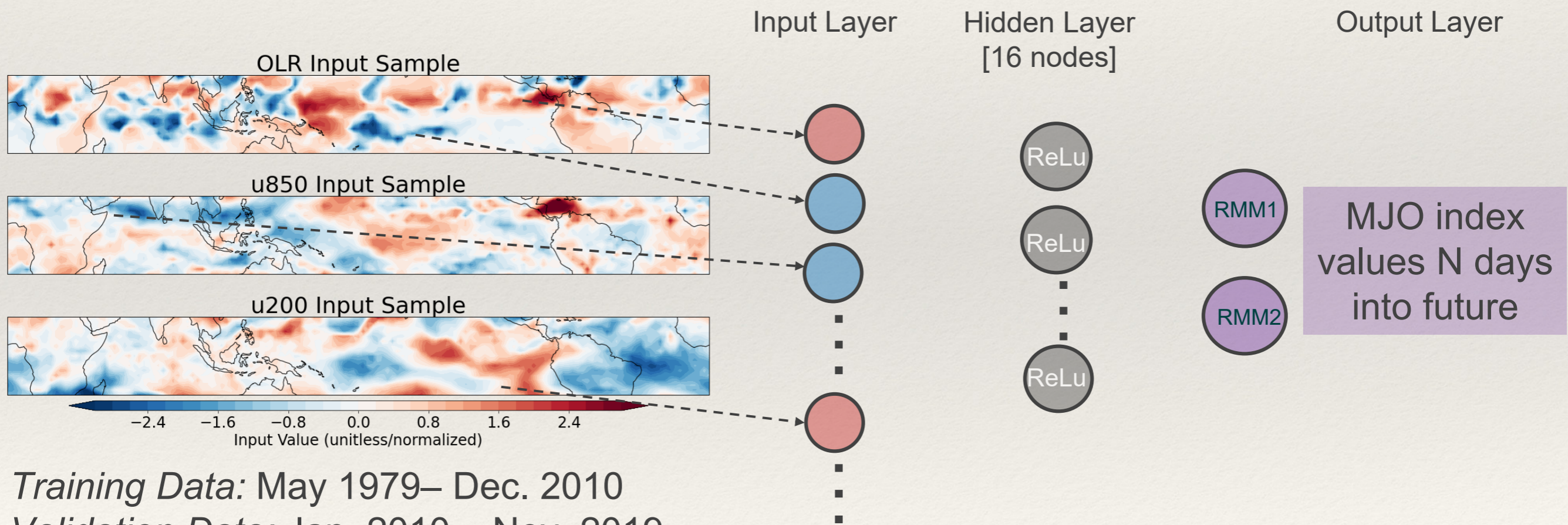
Information  
about an  
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various leads

We explore **2 machine learning frameworks** for MJO prediction:  
one deterministic and one probabilistic

# Machine Learning & the MJO

## Regression Model

- ❖ Deterministic model which outputs *numerical values*

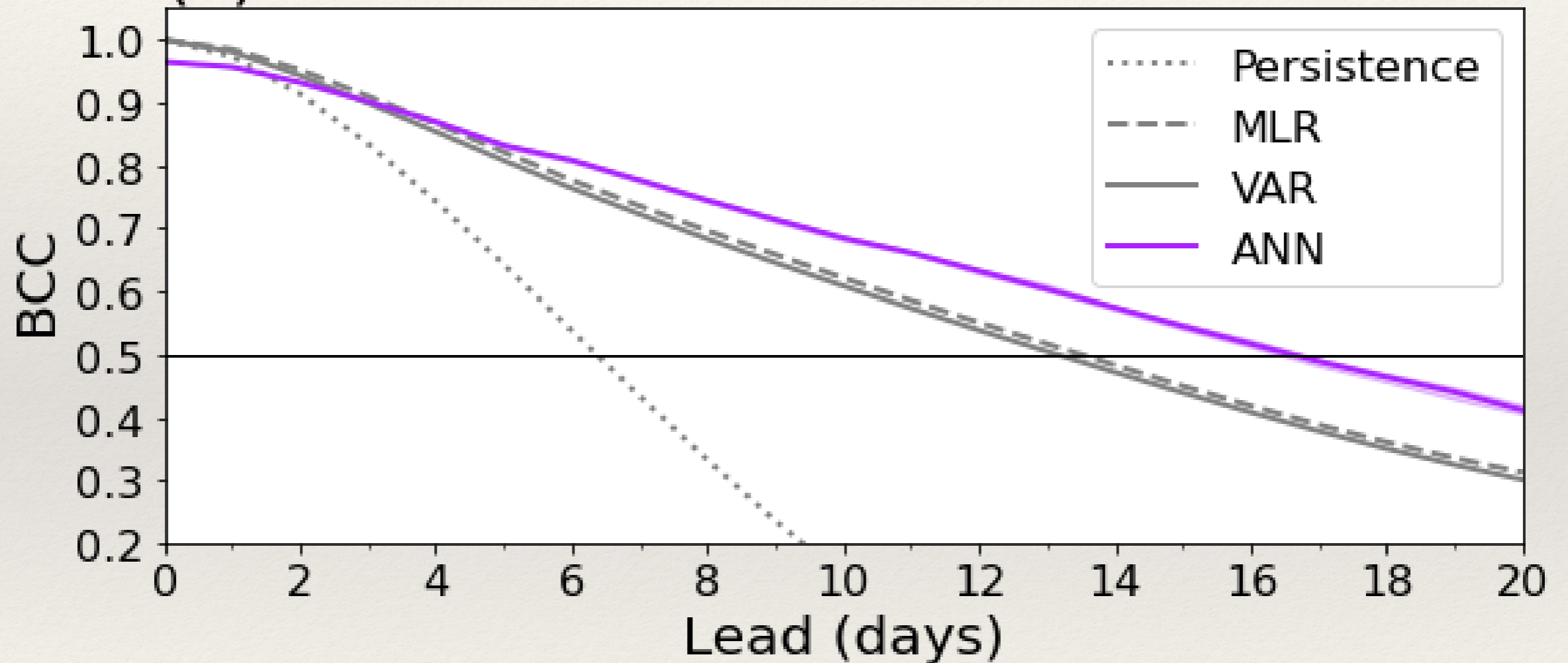


*Training Data:* May 1979– Dec. 2010

*Validation Data:* Jan. 2010 – Nov. 2019

# Regression ANN Model

(a) Winter Model Forecast Skill



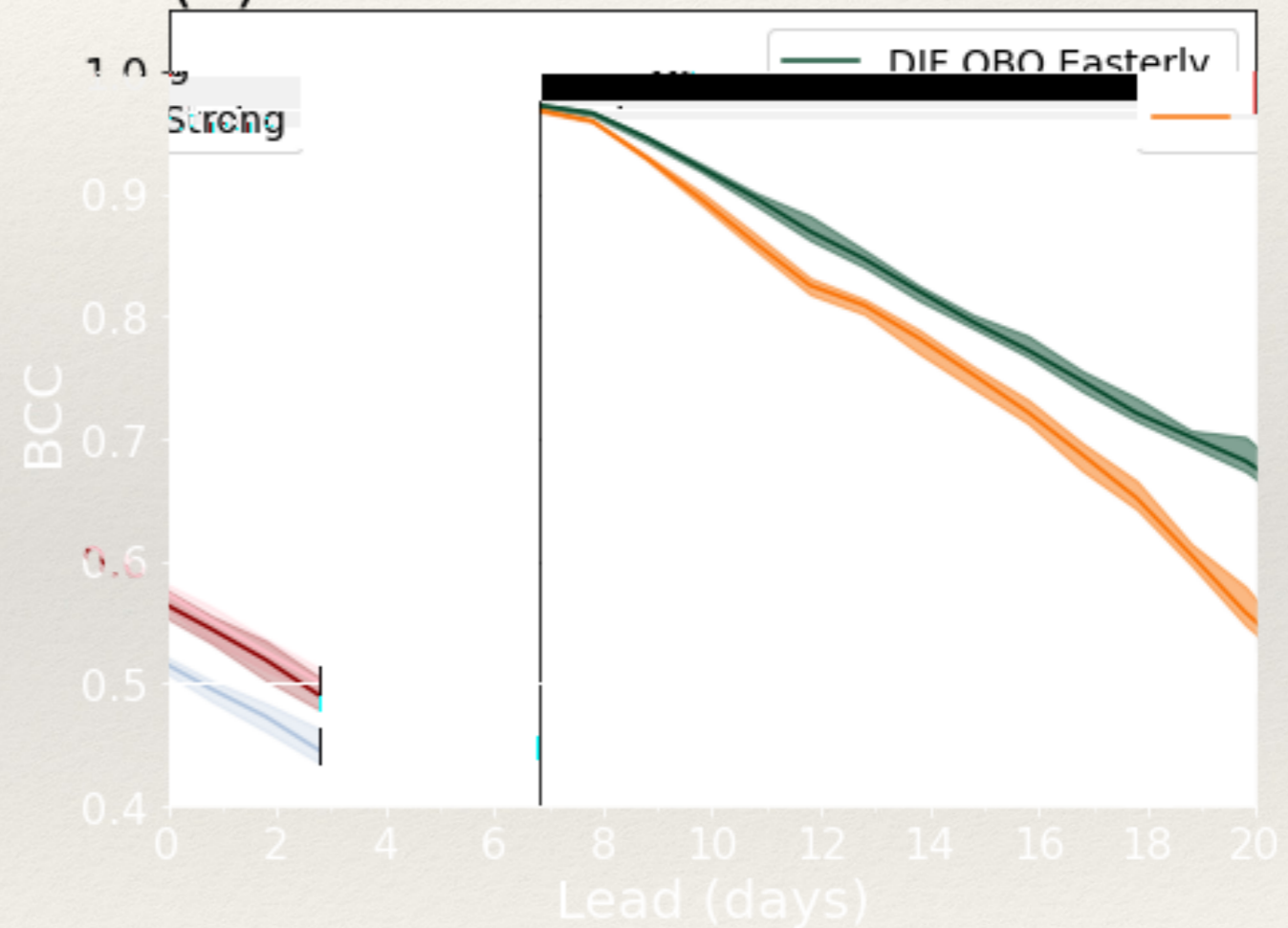
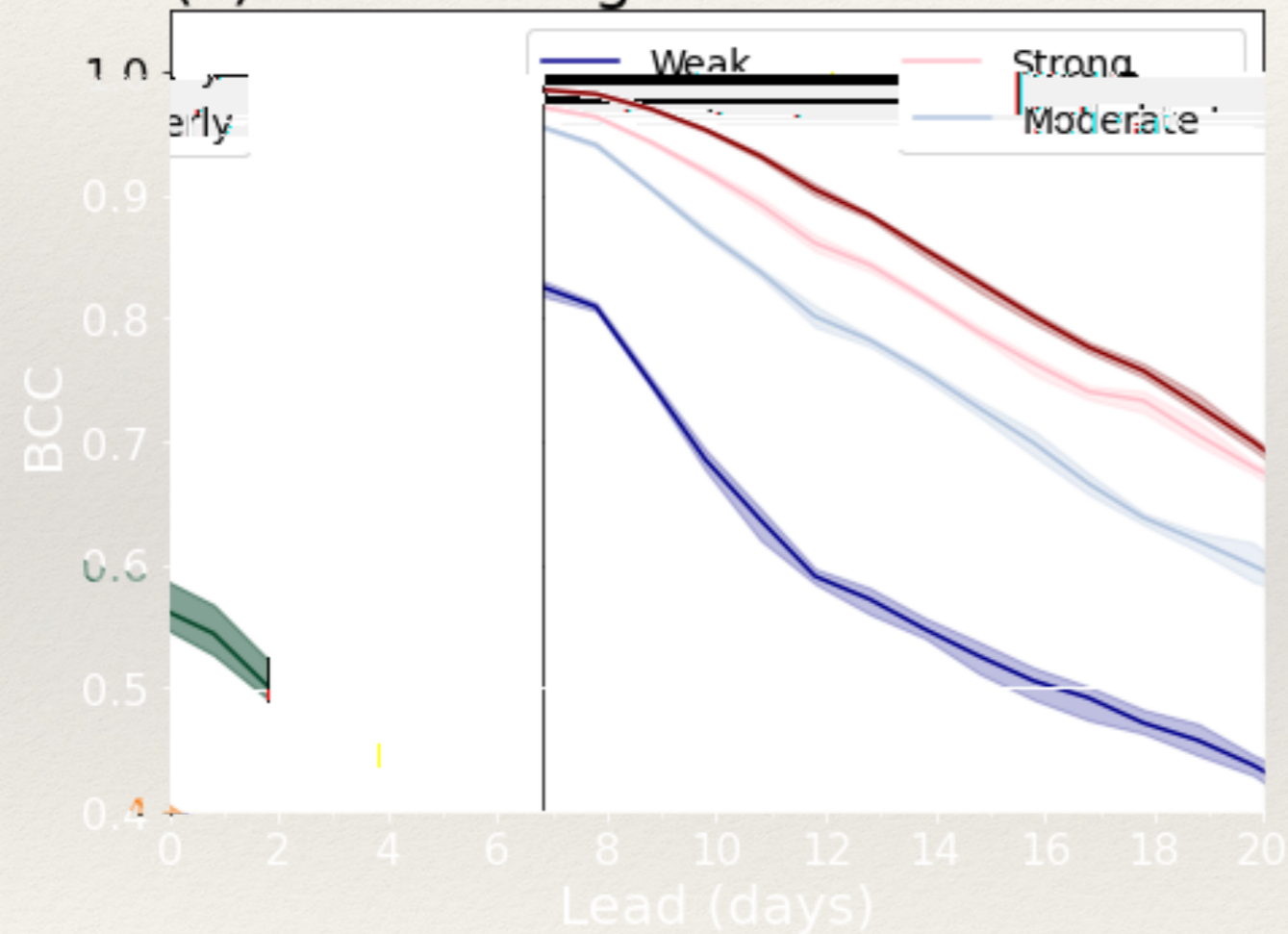
# Regression ANN Model

Skill vs. Initial MJO Amplitude

MJO Skill vs. Stratospheric State

(c) Winter Reg. ANN Skill

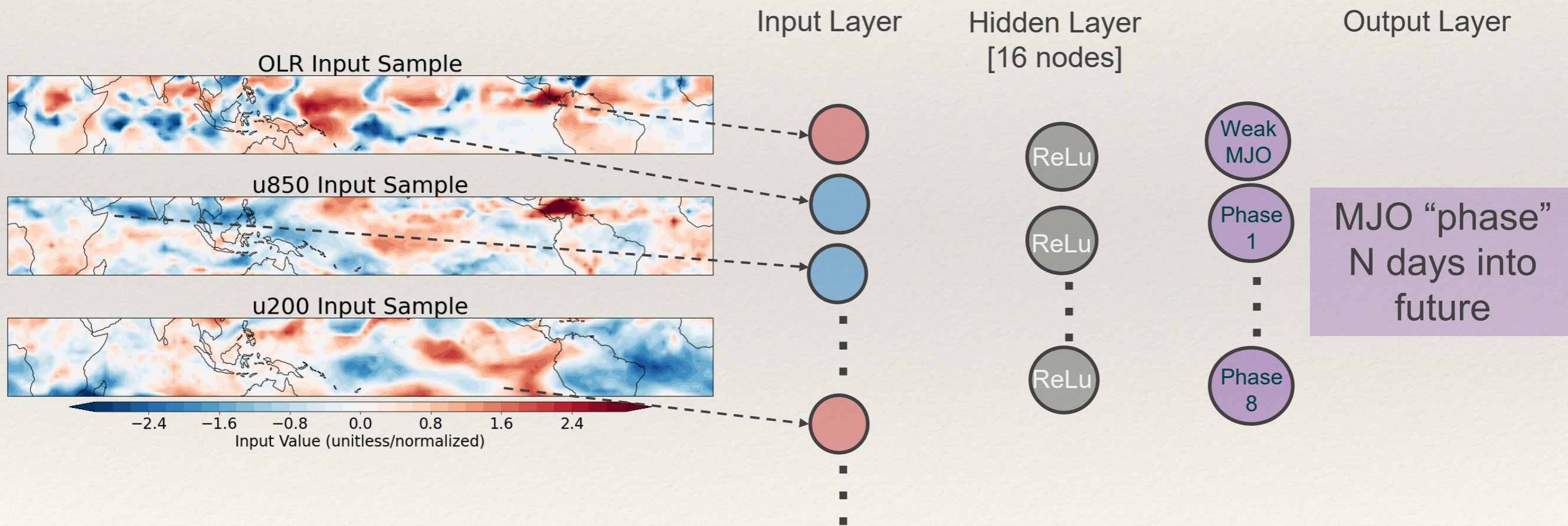
(d) Dec.-Feb. ANN Skill



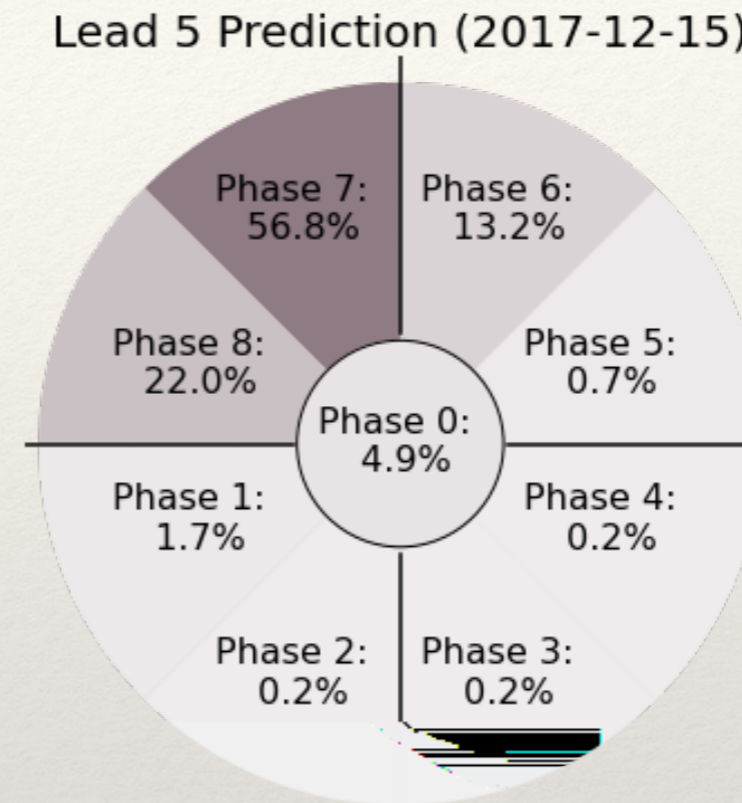
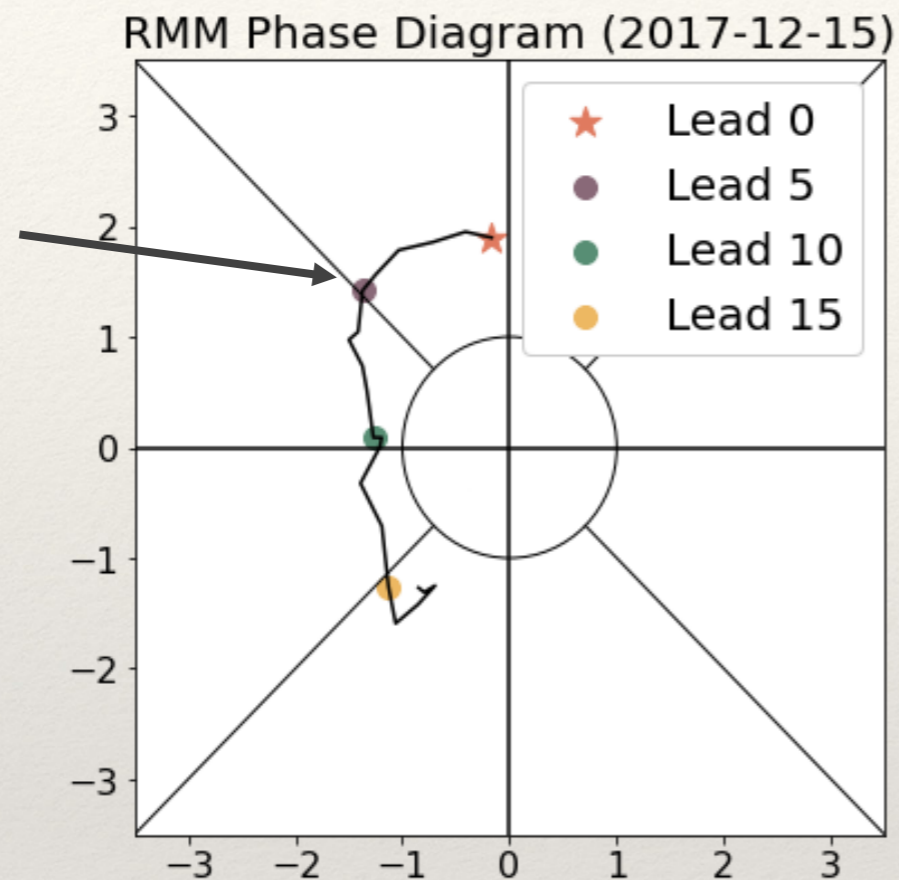
# Classification ANN Model

## Classification Model

- ❖ Model which outputs the *probability* across various categories



# Classification ANN Model

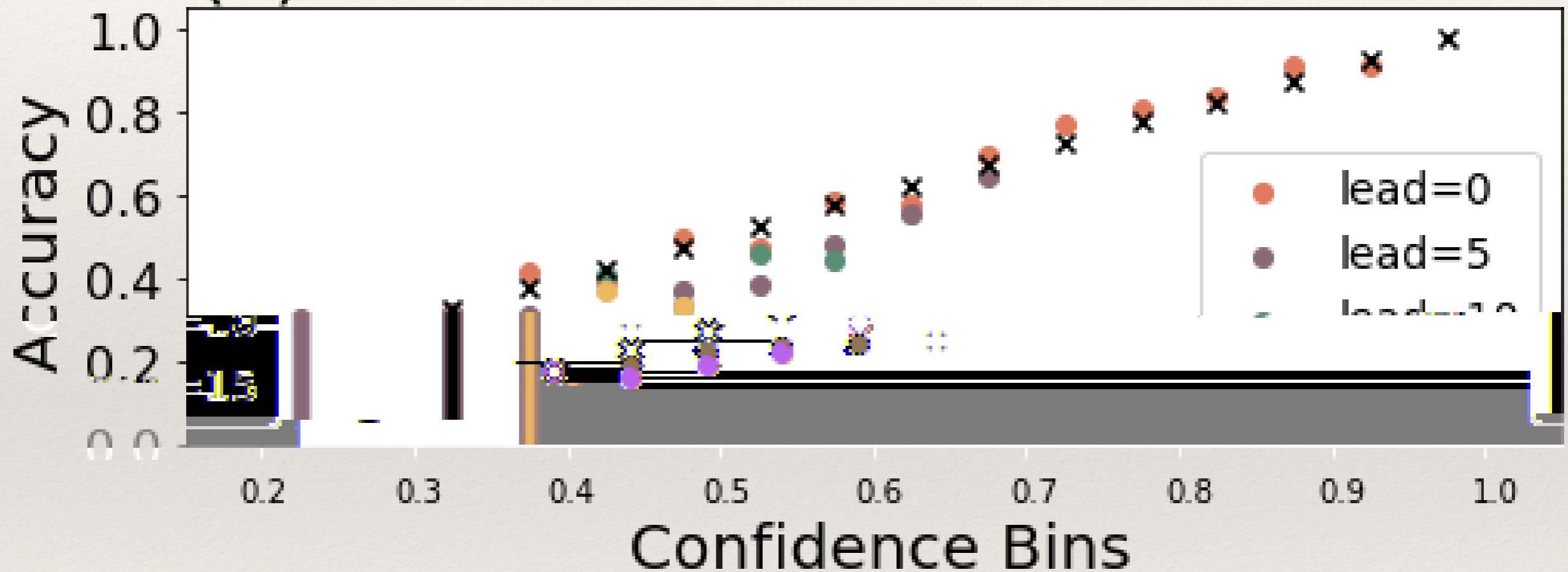


## Classification Model

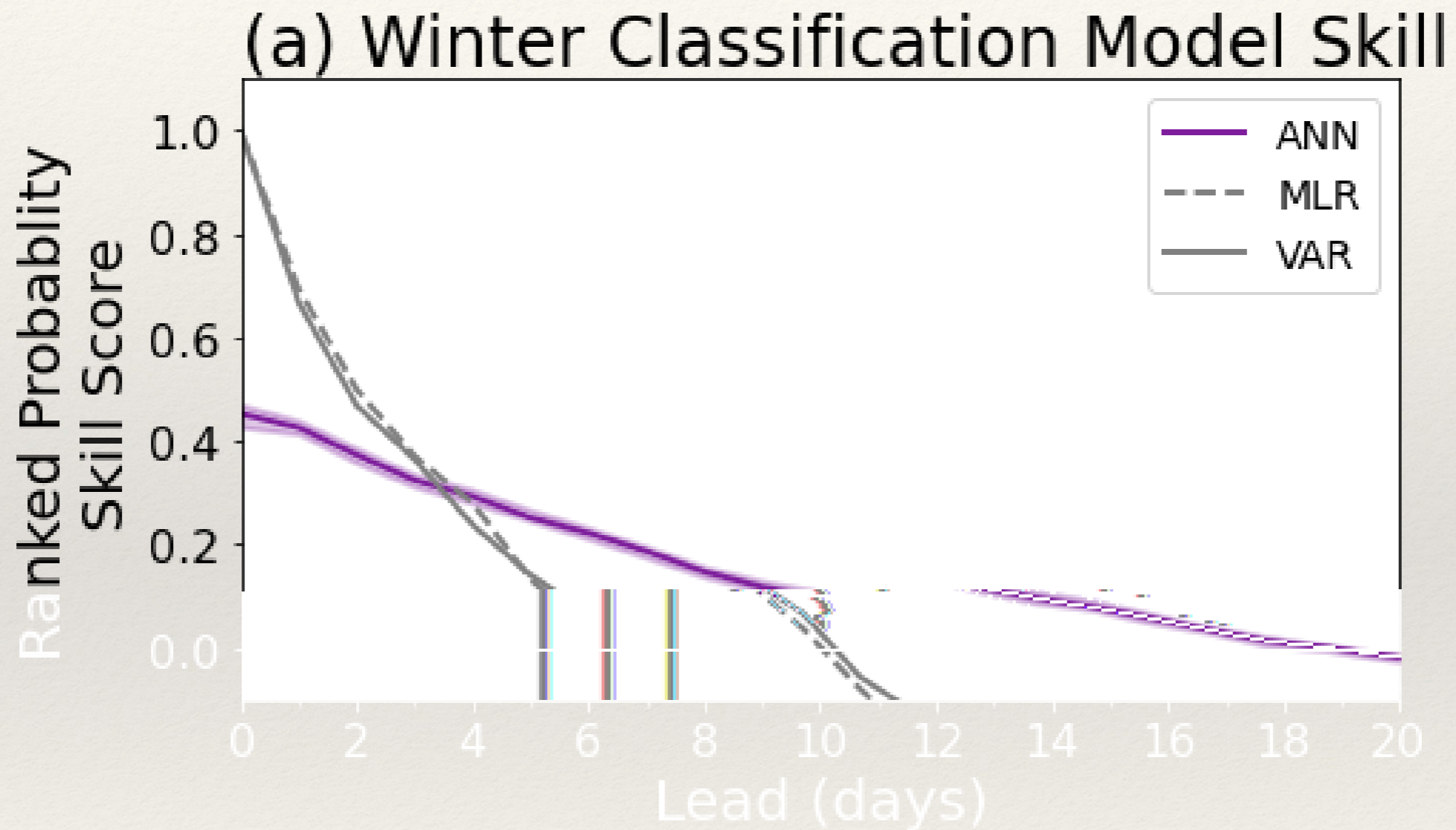
- ❖ A model which outputs the *probability* across various categories

# Classification ANN Model

(b) ANN Performance vs. Confidence



# Classification ANN Model







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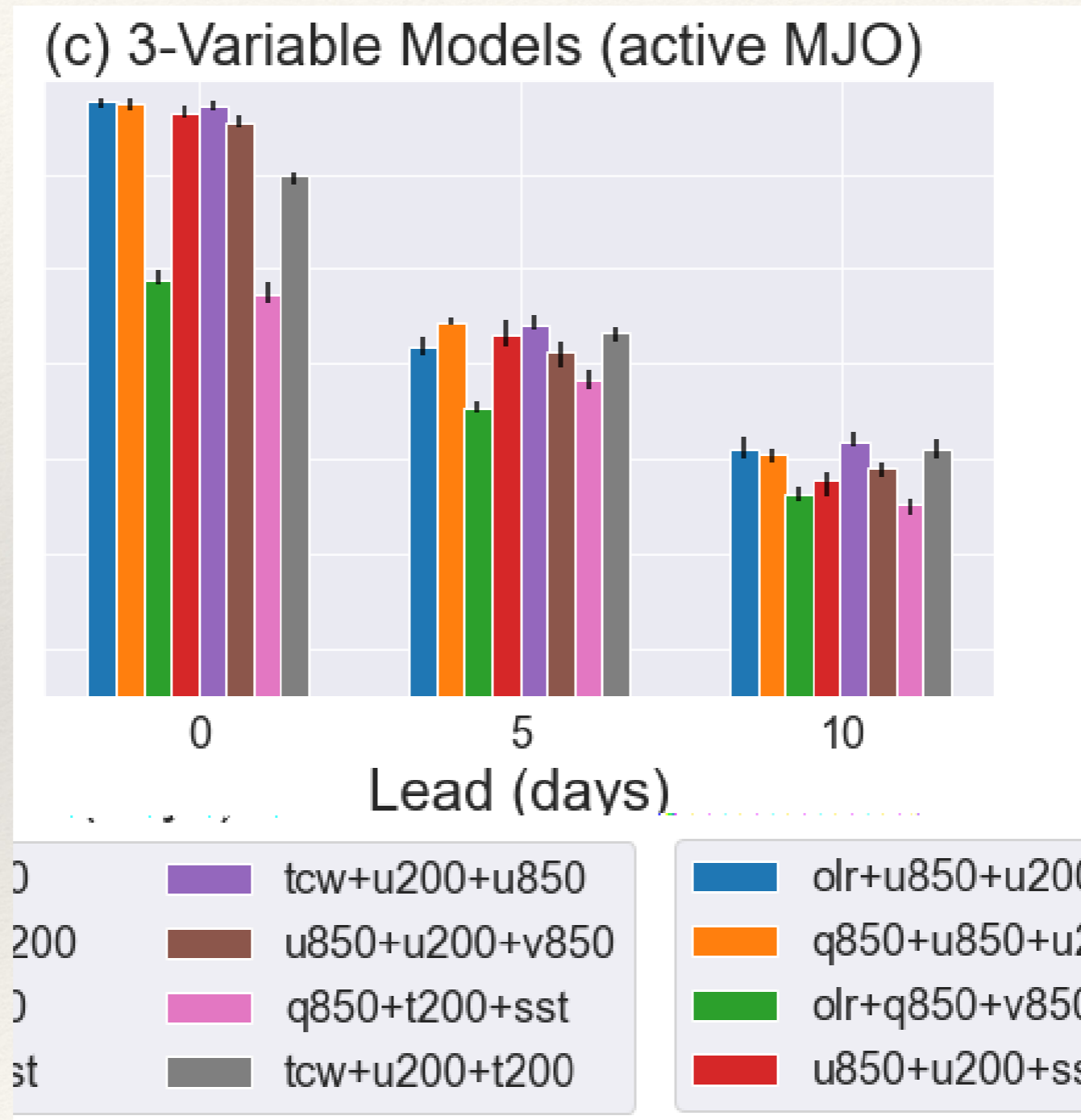
# Machine Learning & the MJO

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- ❖ **How skillful are ML models at predicting the MJO?**
  - ❖ ANN approaches can provide skillful MJO prediction out to past 2 weeks, better than traditional statistical models
- ❖ **How might ML be useful to study and understand the MJO, in addition to predict it?**

Thanks!

# A Machine-Learning Framework for the MJO



# A Machine-Learning Framework for the MJO

“Layerwise-relevance propagation” & other tools can help understand how the models work



The image was classified as **ram**  
with a classification score of 21.37

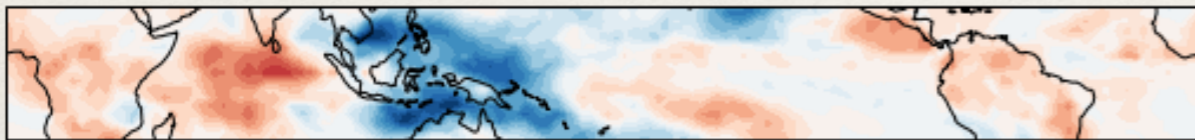
<https://lrpserver.hhi.fraunhofer.de/image-classification>



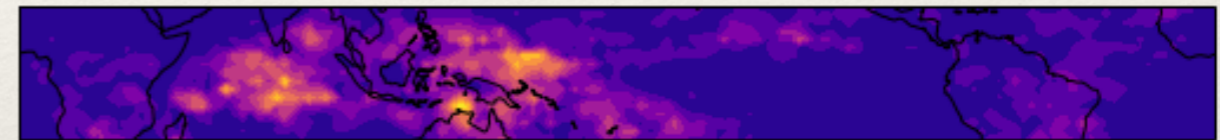
# A Machine-Learning Framework for the MJO

“Layerwise-relevance propagation” & other tools can help understand how the models work

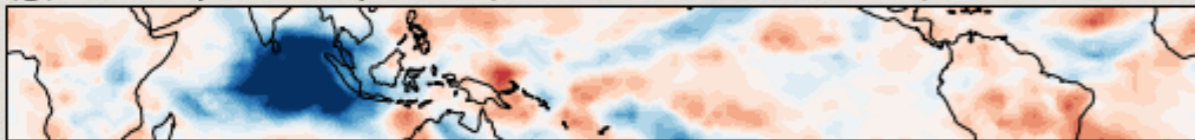
(a) Lead 0 OLR Composite (Phase 5)



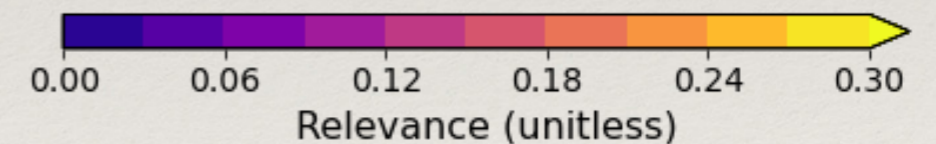
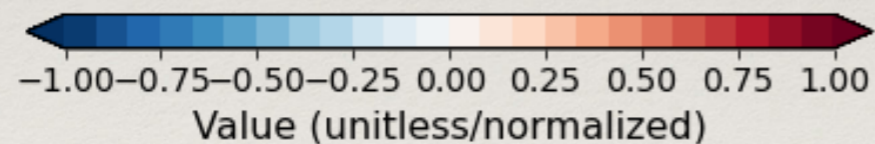
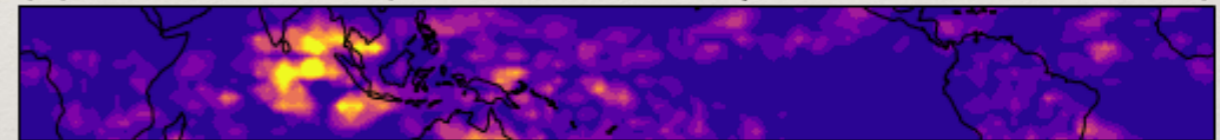
(b) Lead 0 OLR Relevance (Confidence  $\geq$  60 percentile)



(g) OLR Input Composite (Phase 5; Lead-10 ANN)



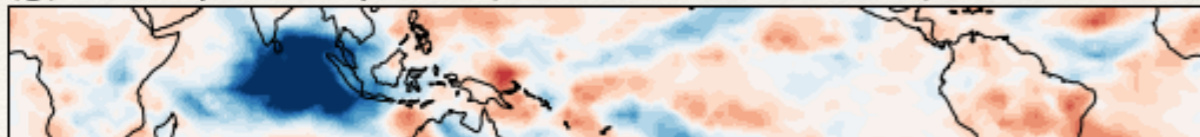
(h) OLR Relevance (Confidence  $\geq$  60 percentile; Lead-10 ANN)



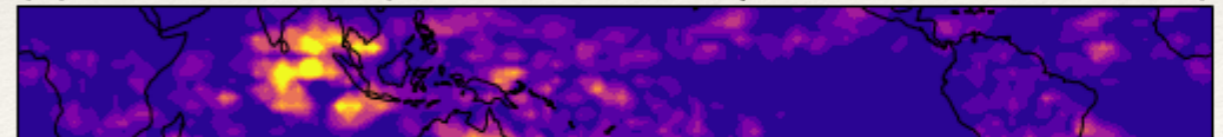
# Machine Learning & the MJO

- ❖ How skillful are ML models at predicting the MJO? How might one frame MJO prediction in an ML context?
  - ❖ ANN approaches can provide skillful MJO prediction out to past 2 weeks, better than traditional statistical models
- ❖ How might ML be useful to study and understand the MJO, in addition to predict it?
  - ❖ ML models computationally efficient, flexible, and explainable
  - ❖ XAI methods & model experimentation might be useful tools to better understand sources & regions of model skill

(g) OLR Input Composite (Phase 5; Lead-10 ANN)



(h) OLR Relevance (Confidence  $\geq$  60 percentile; Lead-10 ANN)



Thanks!

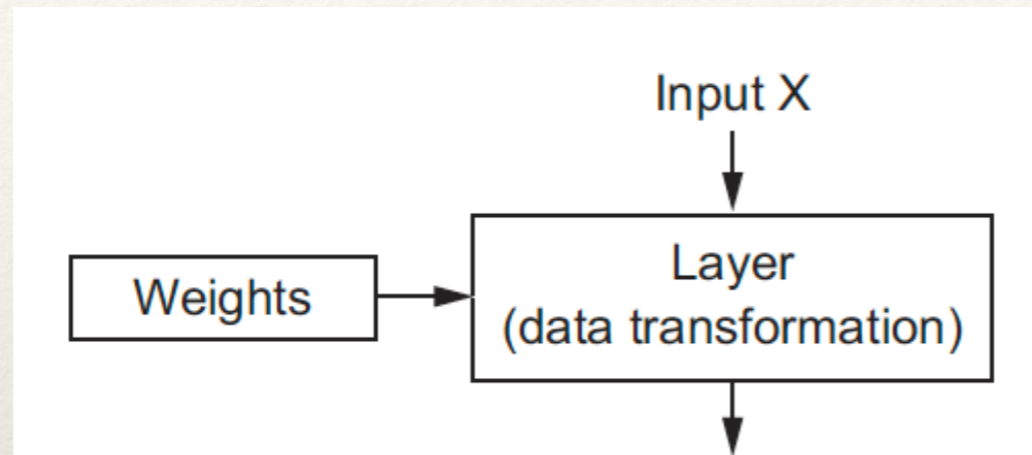
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# Additional Slides

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# Artificial Neural Networks

Fully-connected artificial neural network

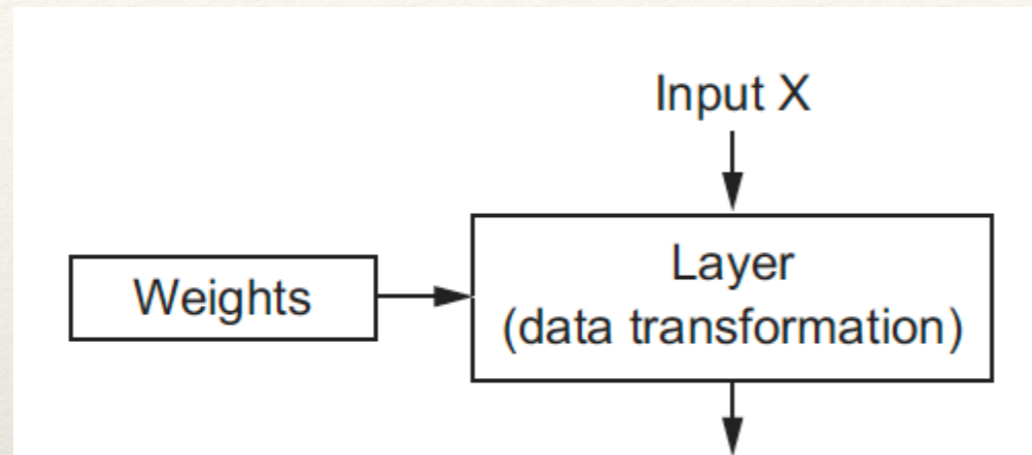


A *linear* data transformation might take the form:

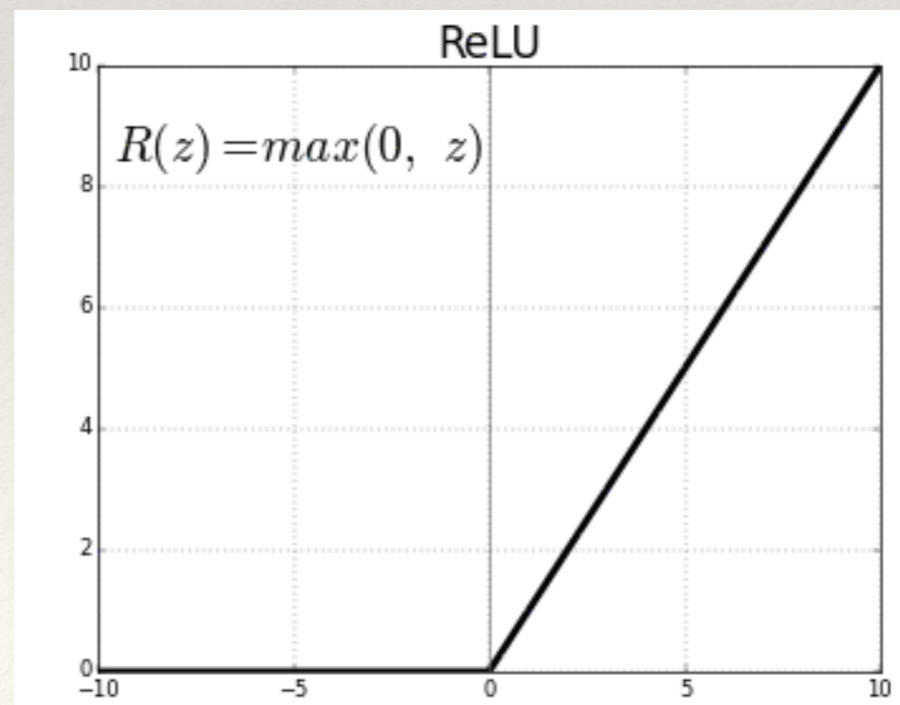
$$W \cdot X + b$$

# Artificial Neural Networks

Fully-connected artificial neural network

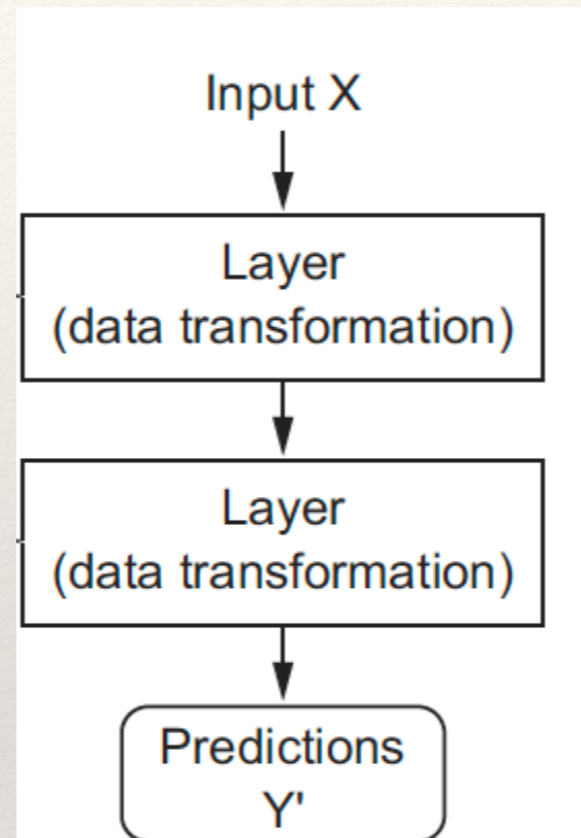


Neural network models introduce *non-linearity* into their transformations

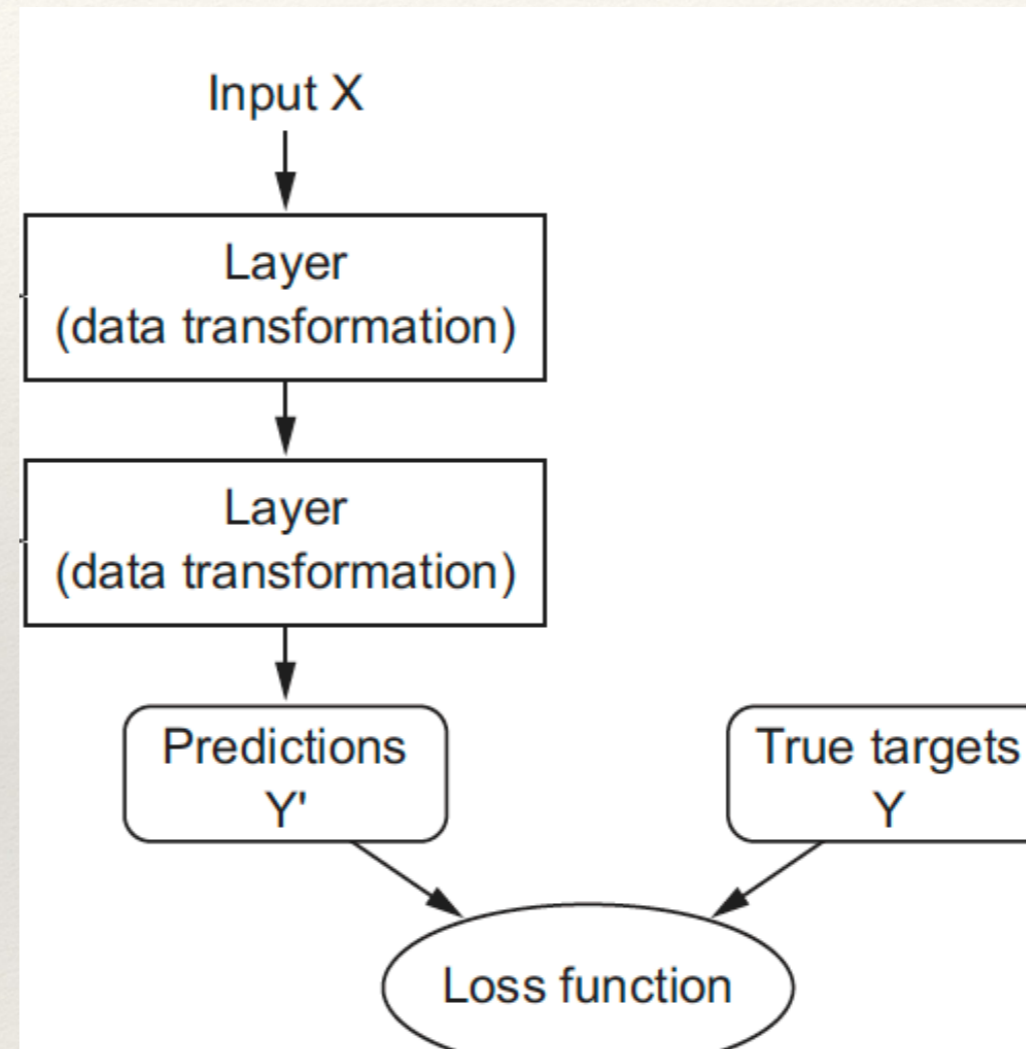




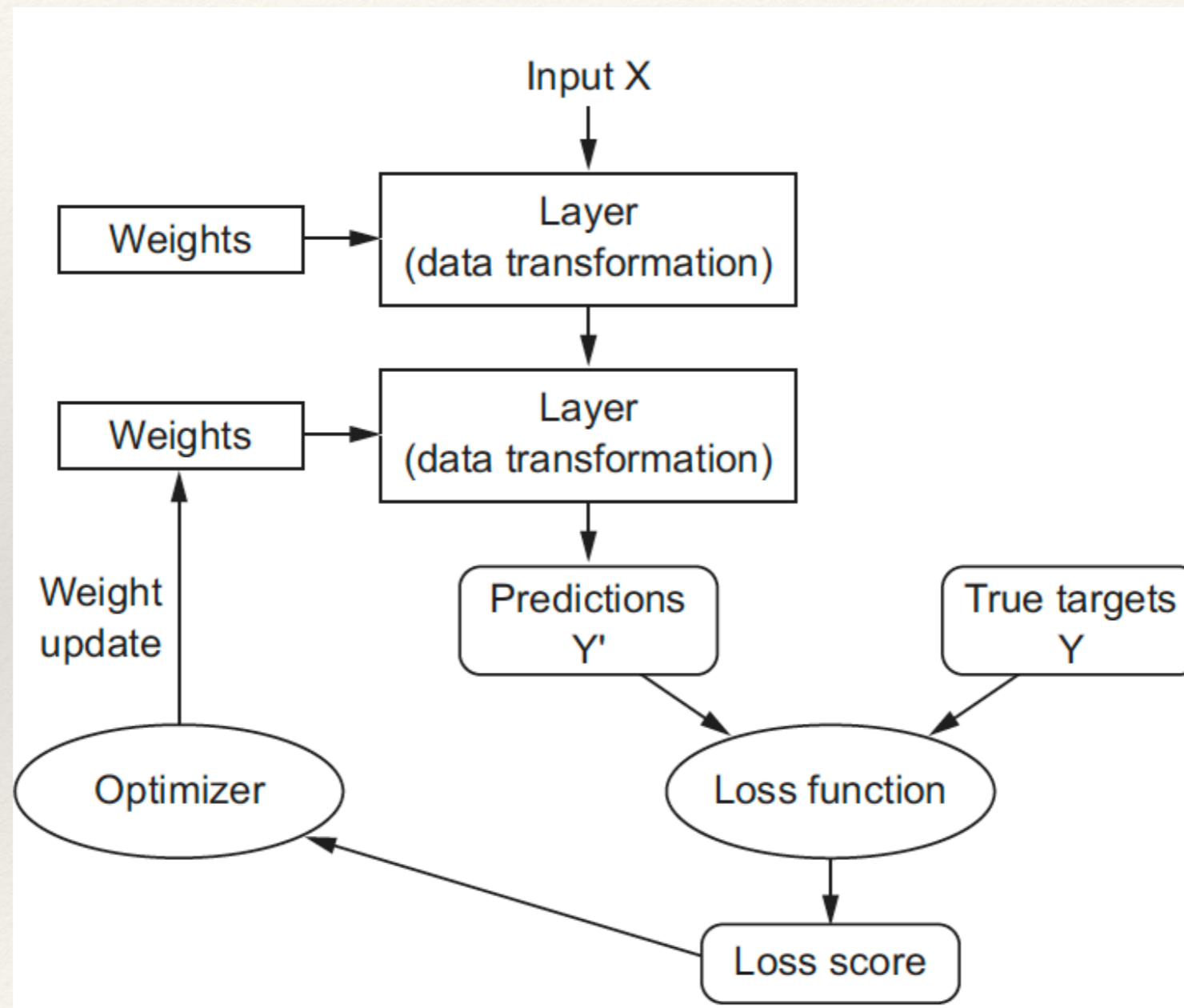
# Artificial Neural Networks



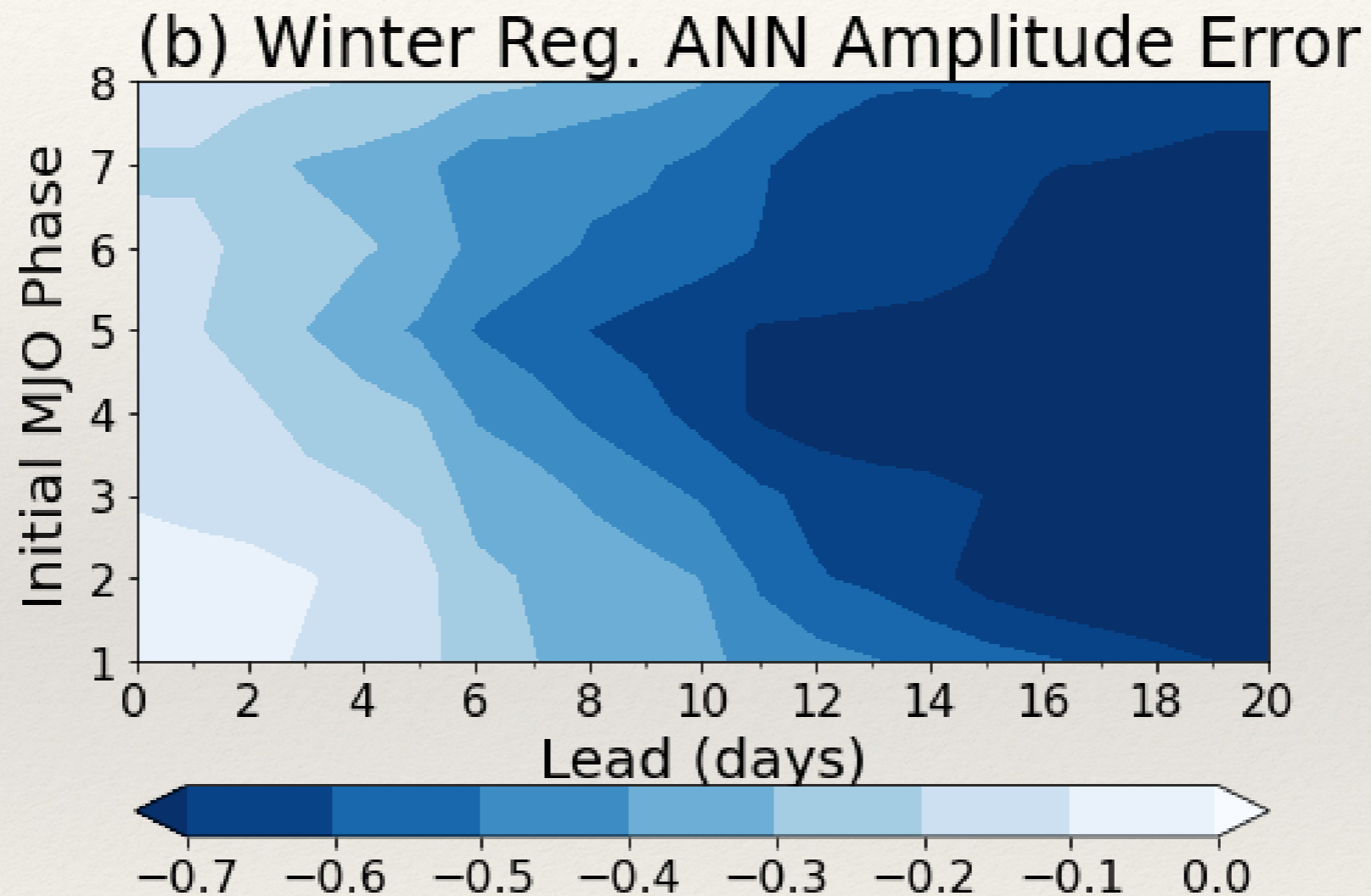
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# Artificial Neural Networks

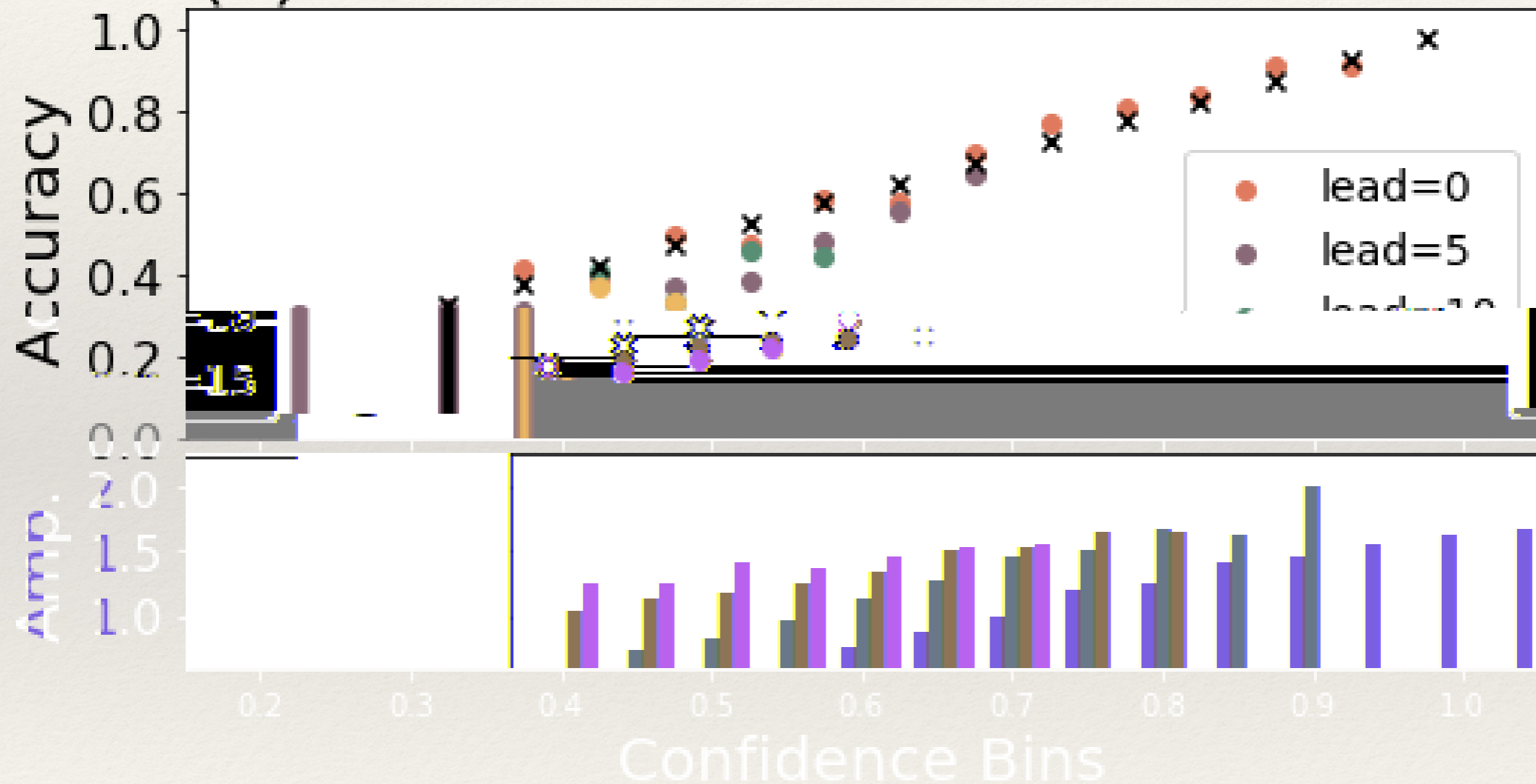


# Regression ANN Model

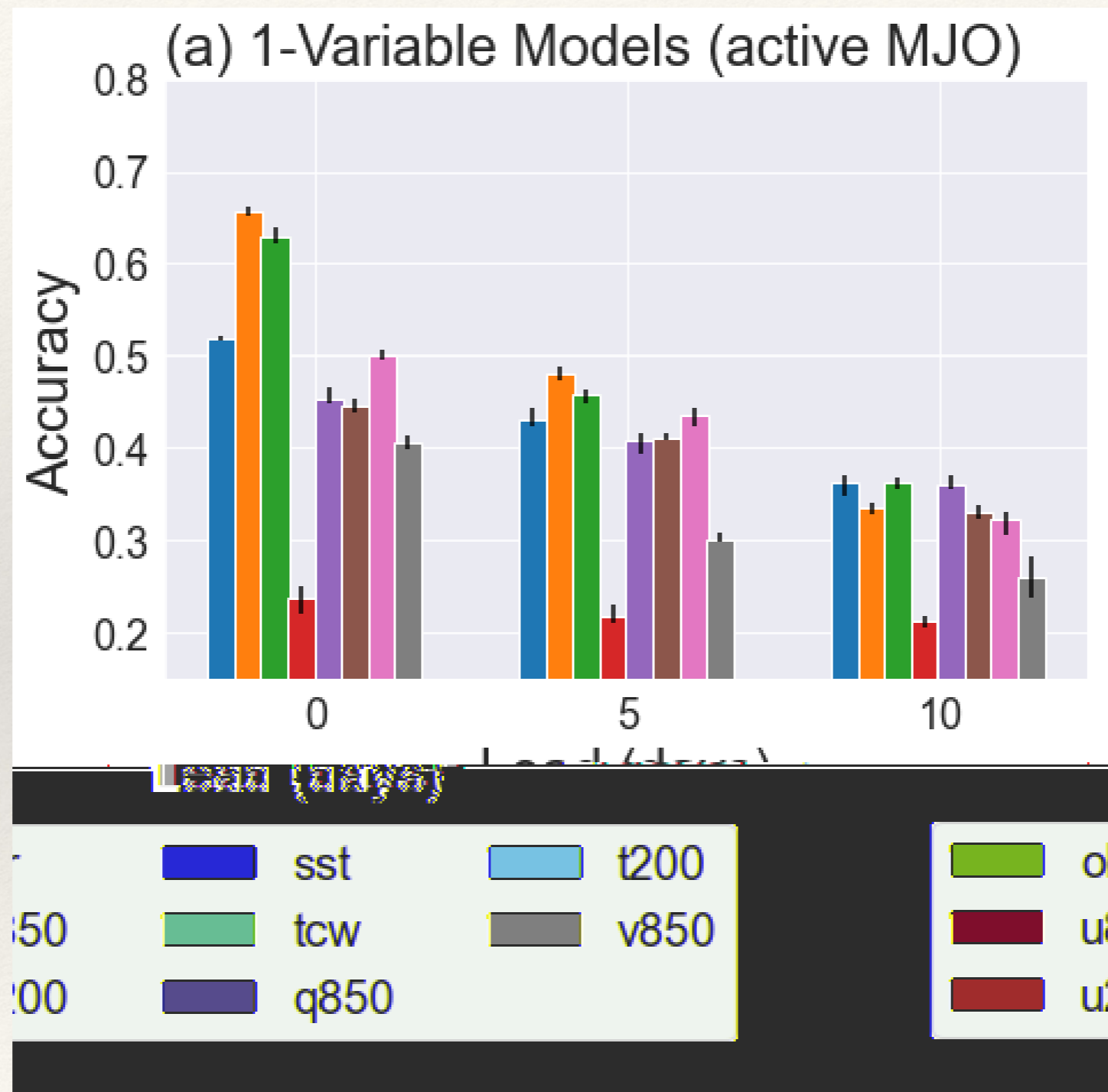


# Classification ANN Model

(b) ANN Performance vs. Confidence



# A Machine-Learning Framework for the MJO

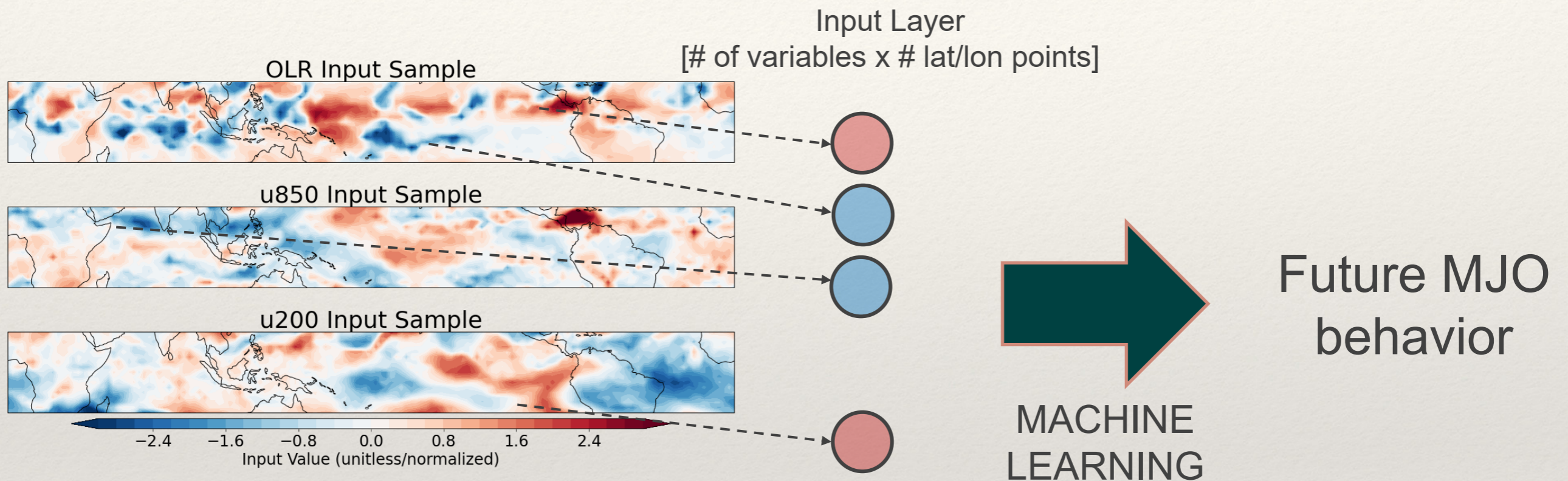




# Machine Learning & the MJO

- ❖ How skillful are machine learning models at predicting the MJO?
- ❖ How might ML be useful to study and understand the MJO?

# Machine Learning & the MJO



*Training Data:* May 1979– Dec. 2010

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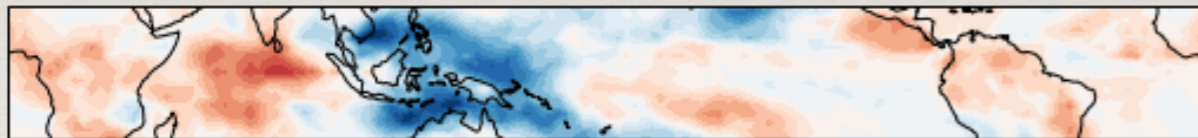
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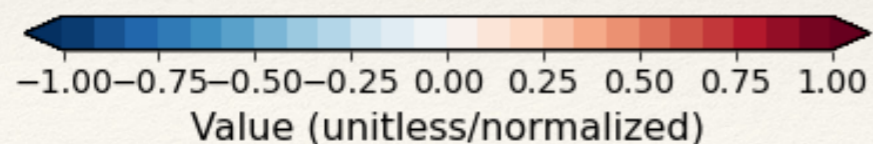
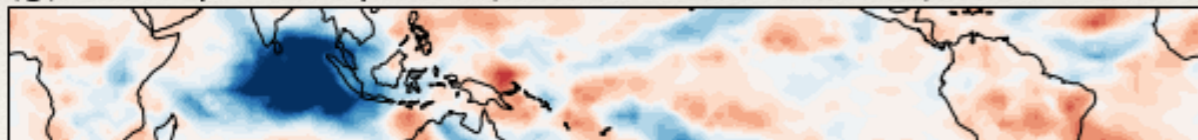
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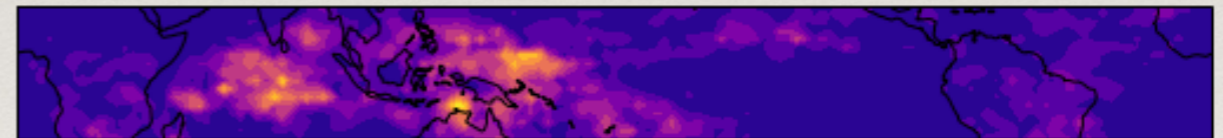
(a) OLR Input Composite (Phase 5; Lead-0 ANN)



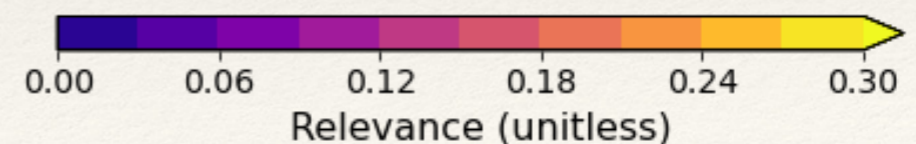
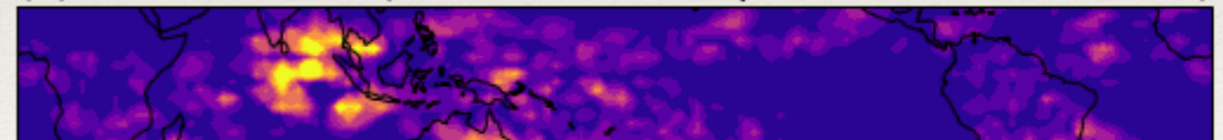
(g) OLR Input Composite (Phase 5; Lead-10 ANN)



(b) OLR Relevance (Confidence  $\geq$  60 percentile; Lead-0 ANN)



(h) OLR Relevance (Confidence  $\geq$  60 percentile; Lead-10 ANN)





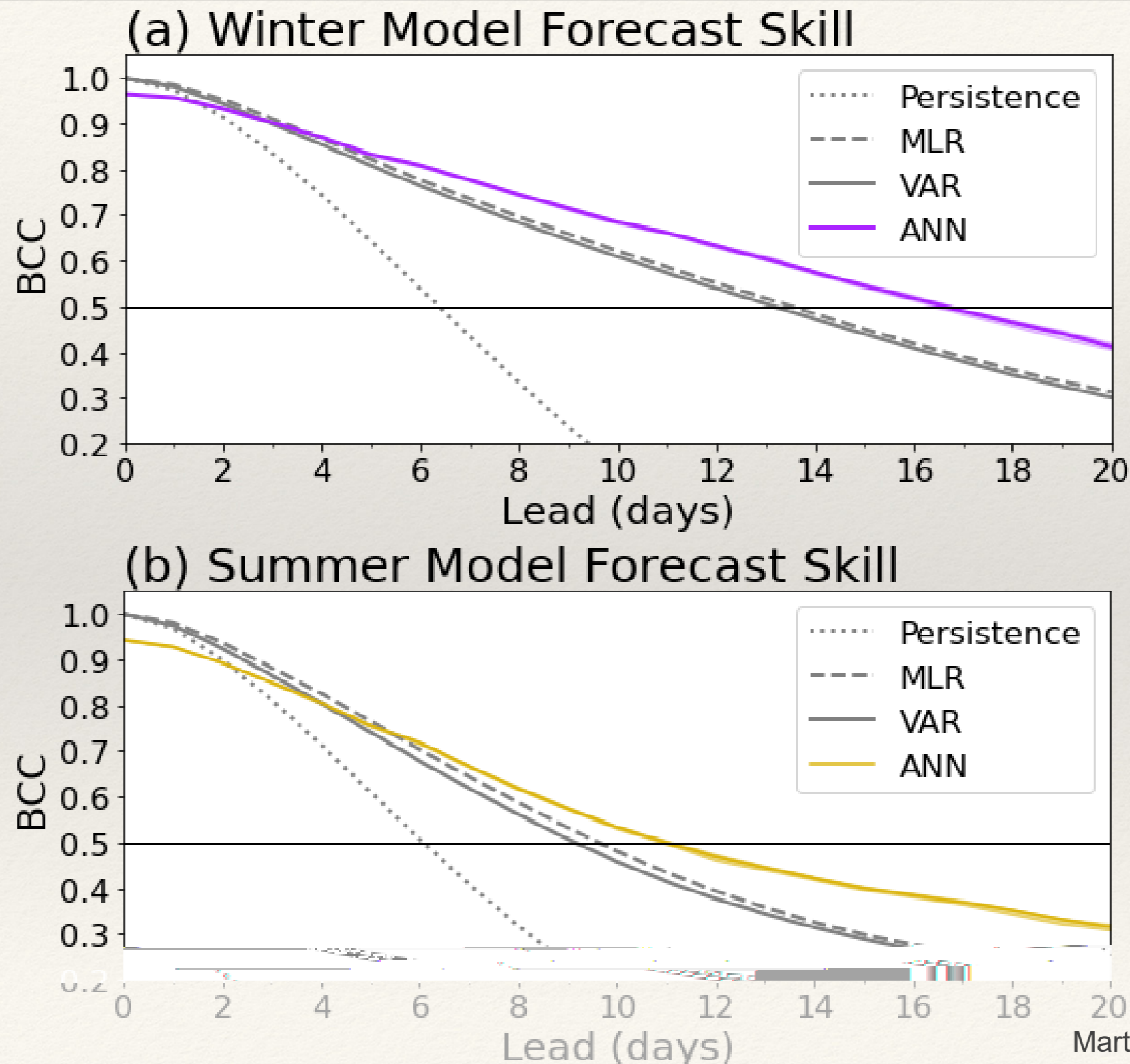
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# Machine Learning & the MJO

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Thanks!

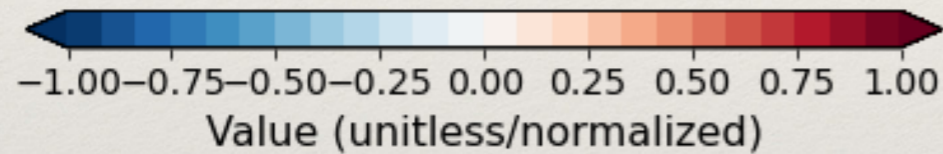
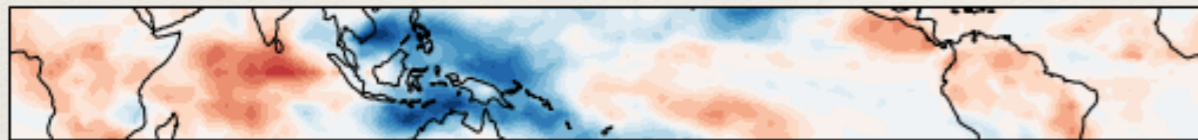
# A Machine-Learning Framework for the MJO



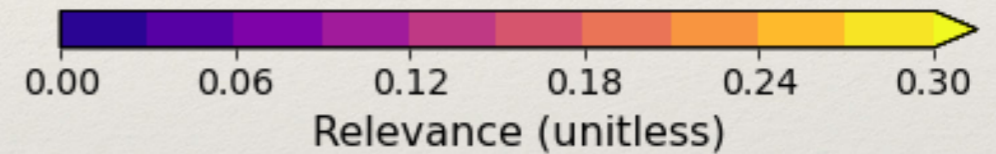
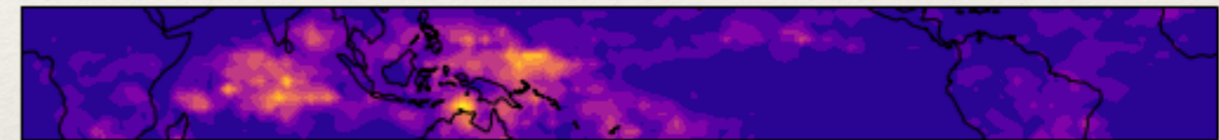
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“Layerwise-relevance propagation” & other tools can help understand how the models work

(a) Lead 0 OLR Composite (Phase 5)

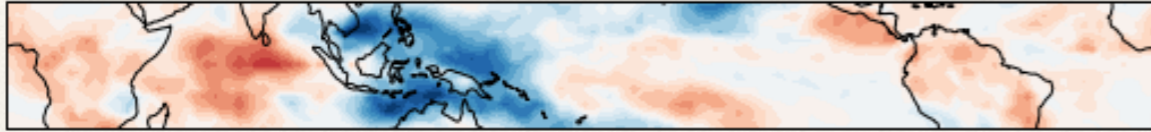


(b) Lead 0 OLR Relevance (Confidence  $\geq$  60 percentile)

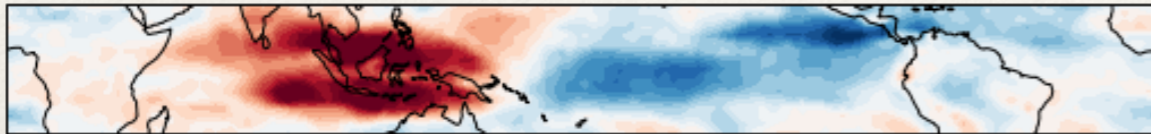


# A Machine-Learning Framework for the MJO

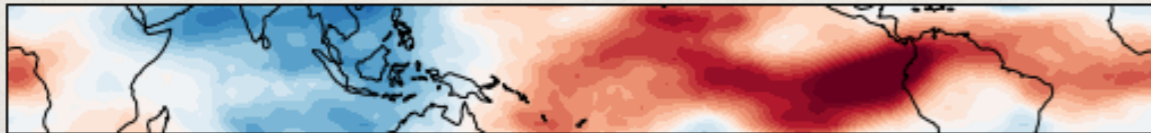
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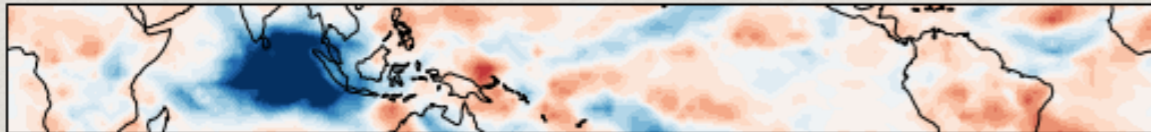
(c) Lead 0 u850 Composite (Phase 5)



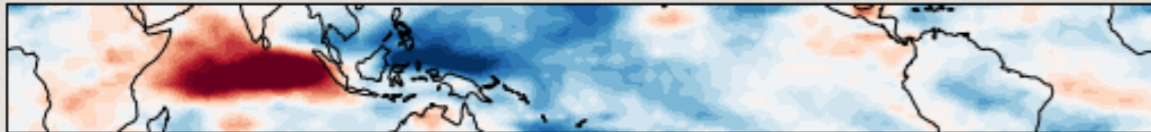
(e) Lead 0 u200 Composite (Phase 5)



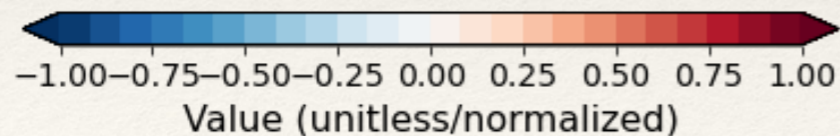
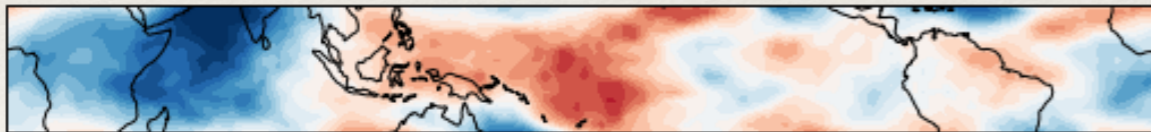
(g) Lead 10 OLR Composite (Phase 5)



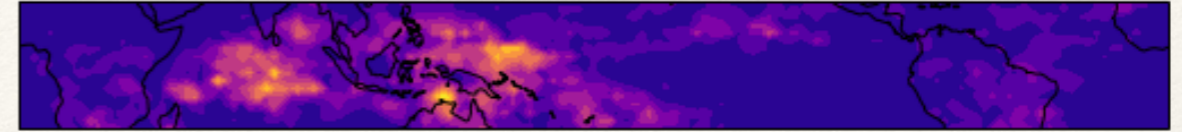
(i) Lead 10 u850 Composite (Phase 5)



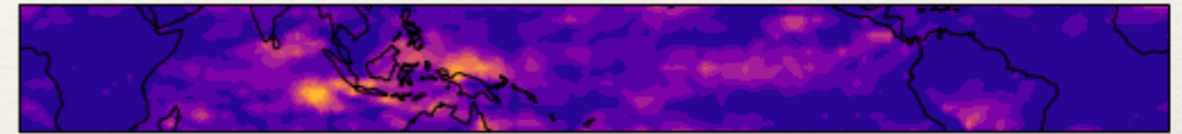
(k) Lead 10 u200 Composite (Phase 5)



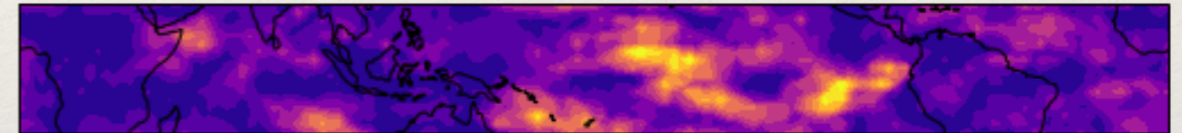
(b) Lead 0 OLR Relevance (Confidence  $\geq$  60 percentile)



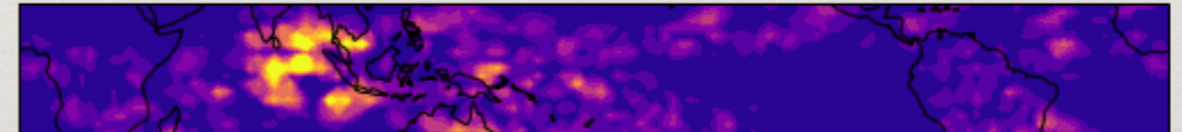
(d) Lead 0 u850 Relevance (Confidence  $\geq$  60 percentile)



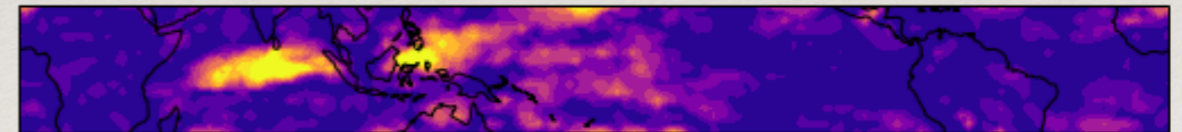
(f) Lead 0 u200 Relevance (Confidence  $\geq$  60 percentile)



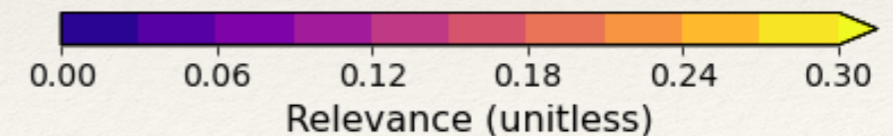
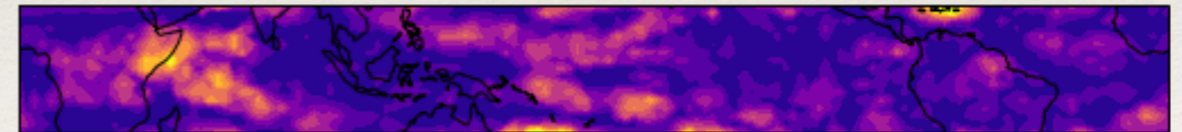
(h) Lead 10 OLR Relevance (Confidence  $\geq$  60 percentile)



(j) Lead 10 u850 Relevance (Confidence  $\geq$  60 percentile)



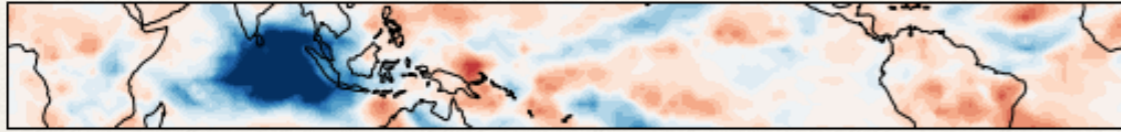
(l) Lead 10 u200 Relevance (Confidence  $\geq$  60 percentile)



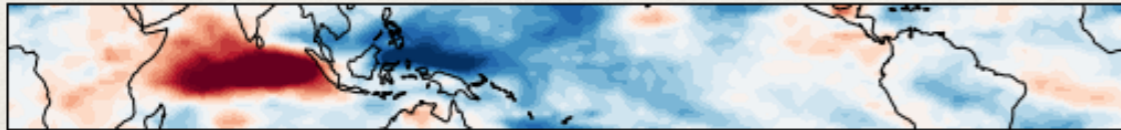
# A Machine-Learning Framework for the MJO

## OLR + u850 + u200 Model

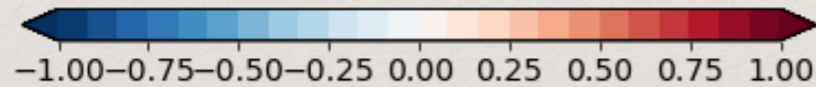
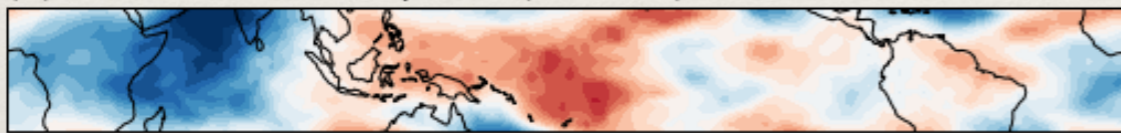
(g) Lead 10 OLR Composite (Phase 5)



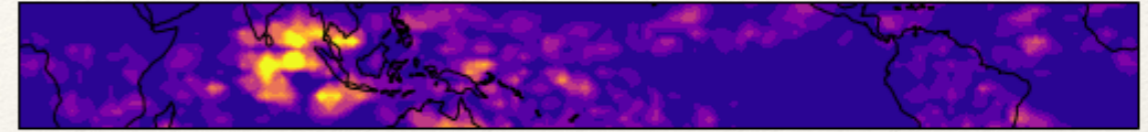
(i) Lead 10 u850 Composite (Phase 5)



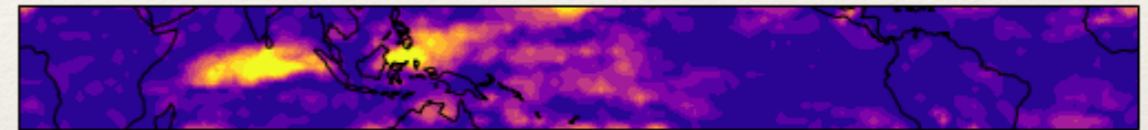
(k) Lead 10 u200 Composite (Phase 5)



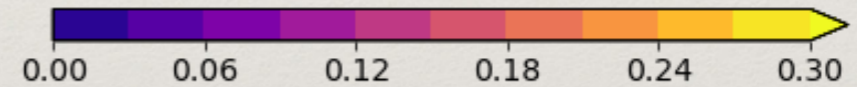
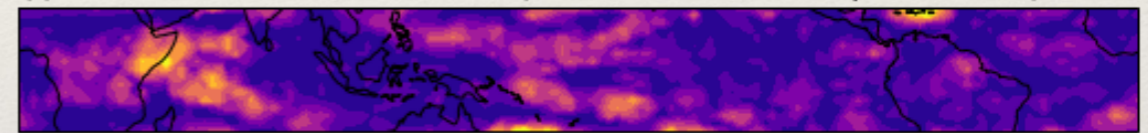
(h) Lead 10 OLR Relevance (Confidence  $\geq$  60 percentile)



(j) Lead 10 u850 Relevance (Confidence  $\geq$  60 percentile)

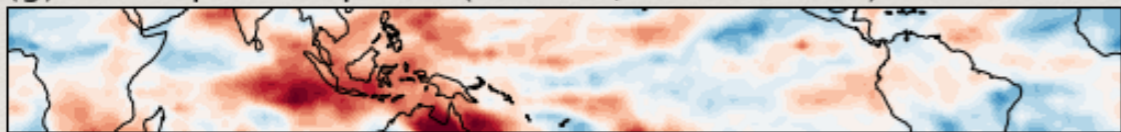


(l) Lead 10 u200 Relevance (Confidence  $\geq$  60 percentile)

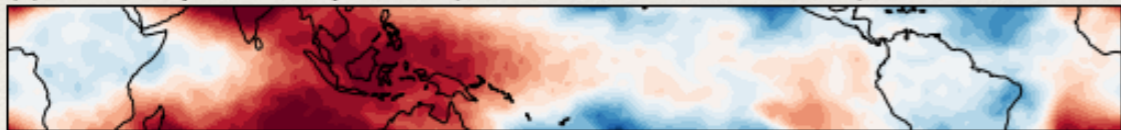


## TCW + t200 + u200 Model

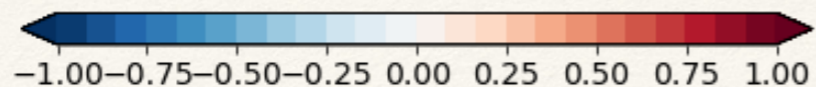
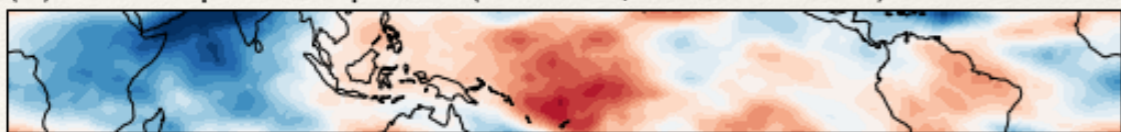
(g) TCW Input Composite (Phase 5; Lead-10 ANN)



(i) t200 Input Composite (Phase 5; Lead-10 ANN)

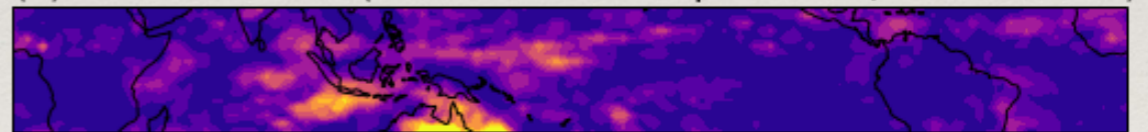


(k) u200 Input Composite (Phase 5; Lead-10 ANN)

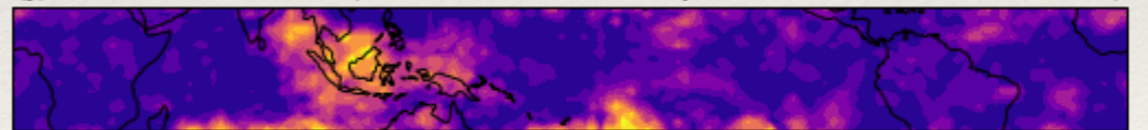


Value (unitless/normalized)

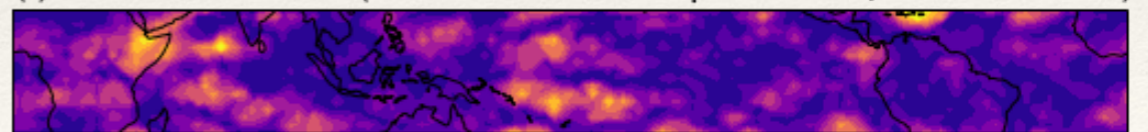
(h) TCW Relevance (Confidence  $\geq$  60 percentile; Lead-10 ANN)



(j) t200 Relevance (Confidence  $\geq$  60 percentile; Lead-10 ANN)



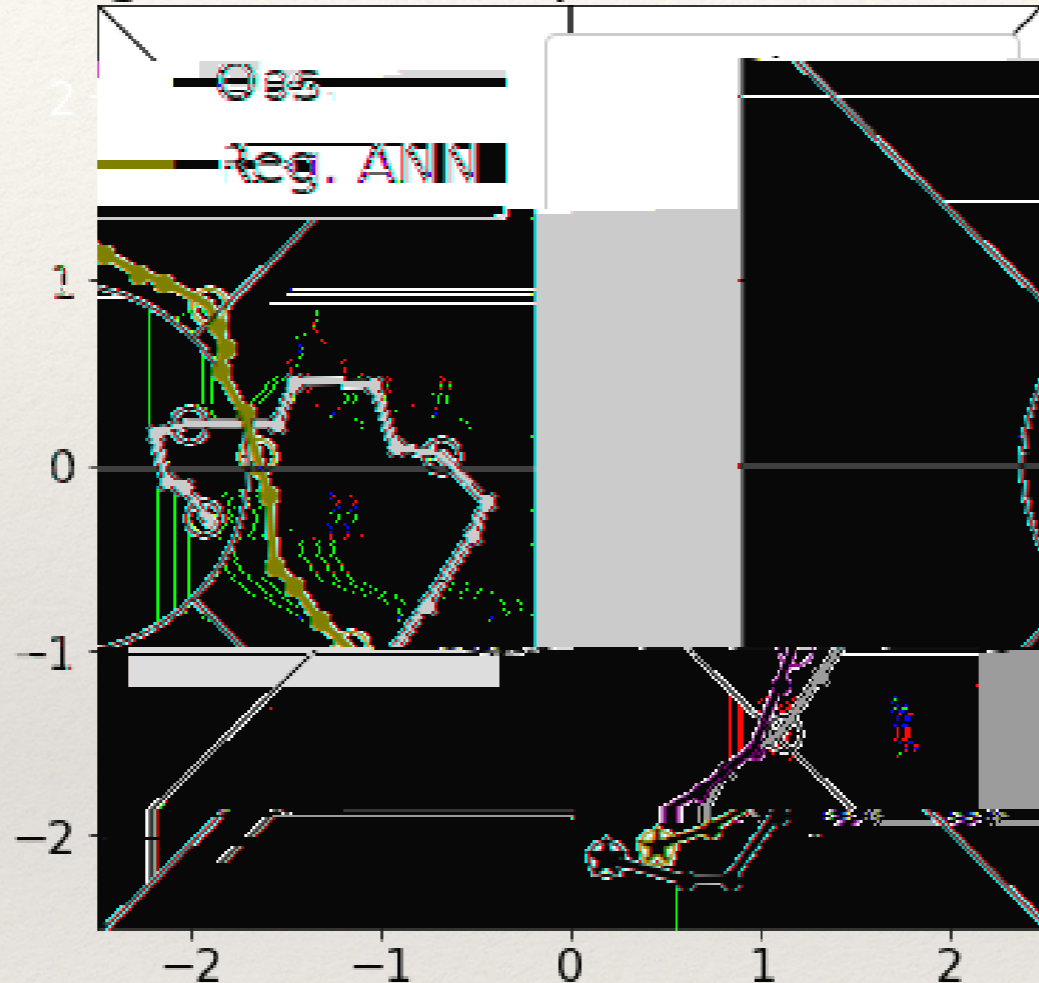
(l) u200 Relevance (Confidence  $\geq$  60 percentile; Lead-10 ANN)



Relevance (unitless) Martin et al. (2021; in prep)

# Machine Learning & the MJO

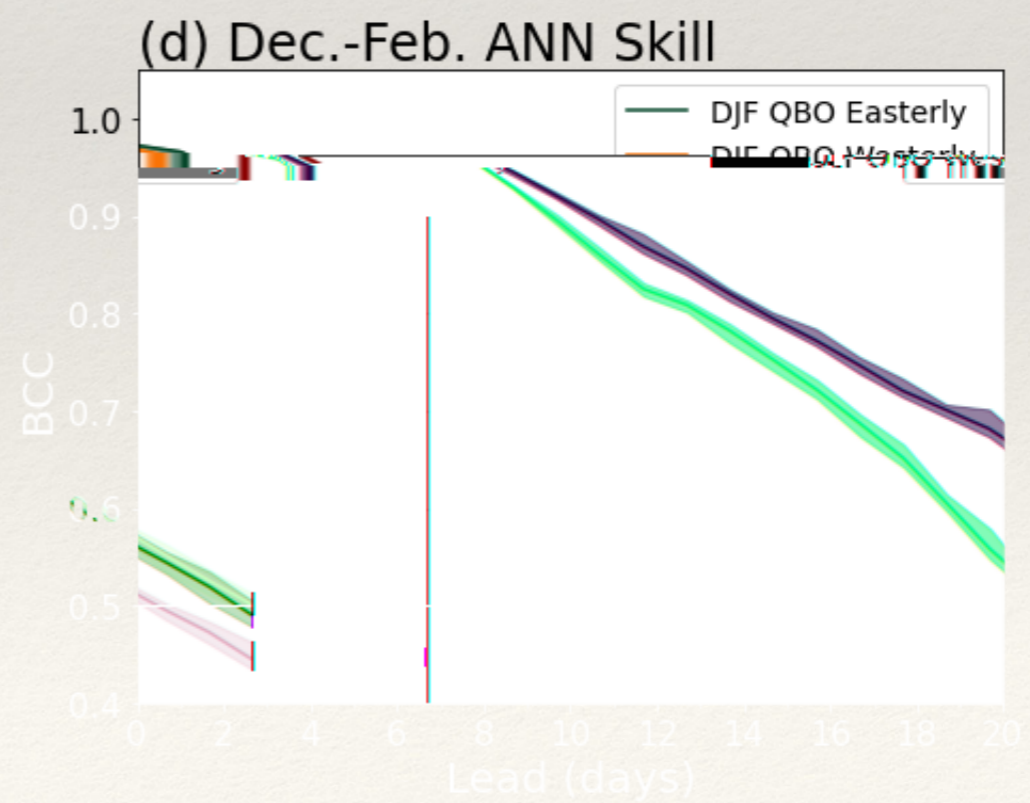
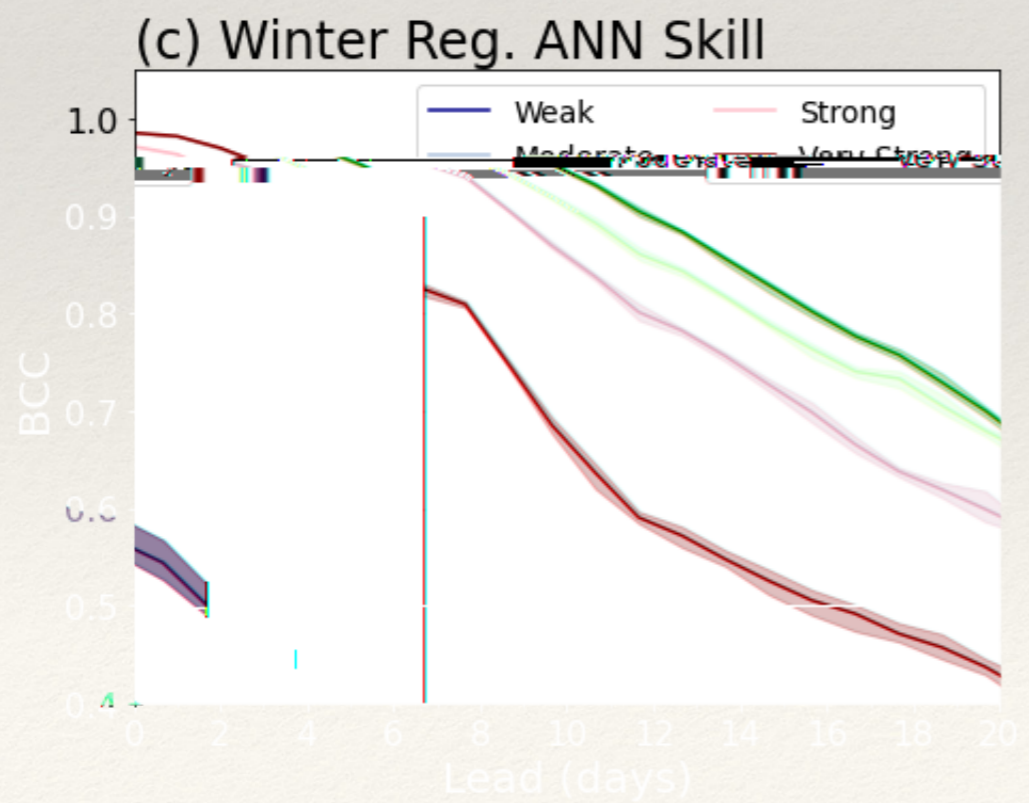
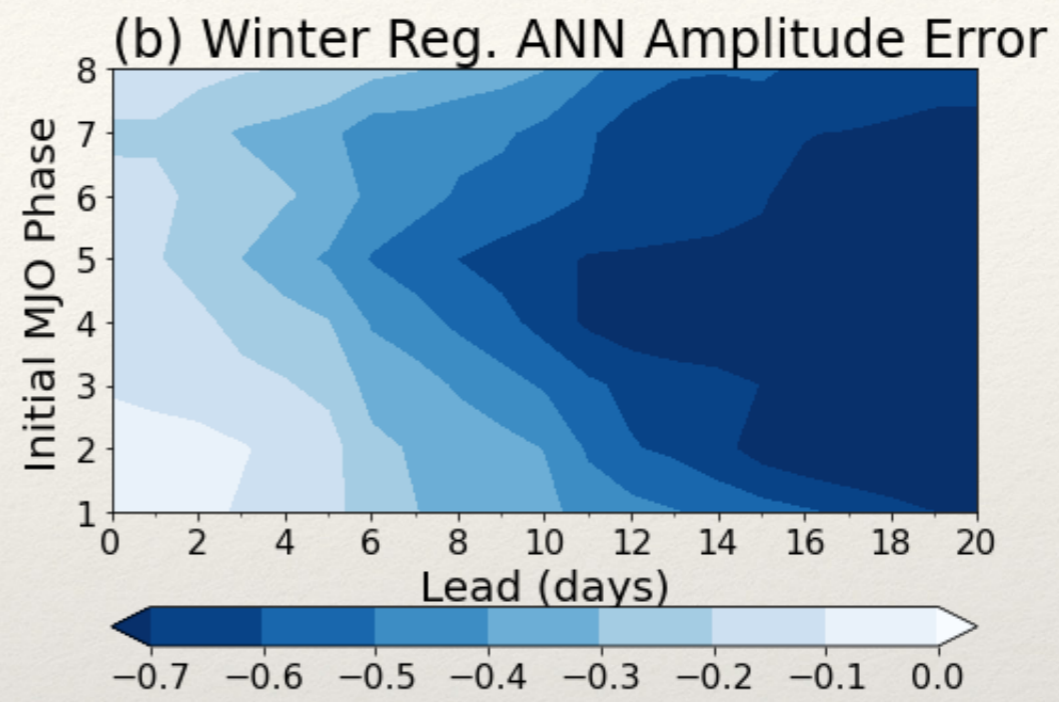
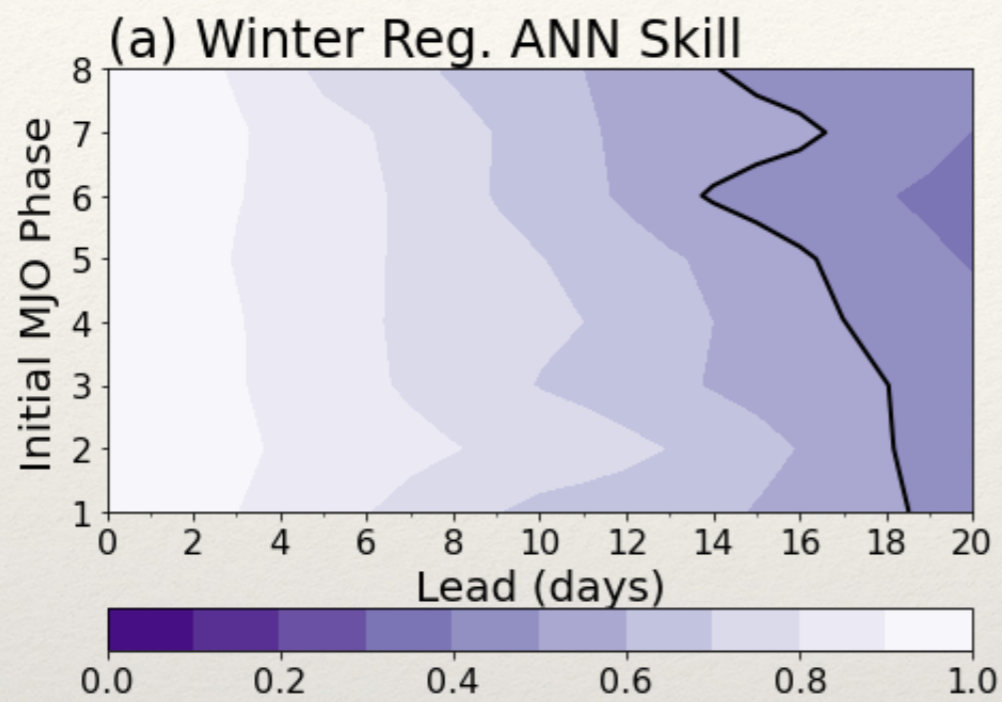
Reg. ANN Example (2011-11-26)



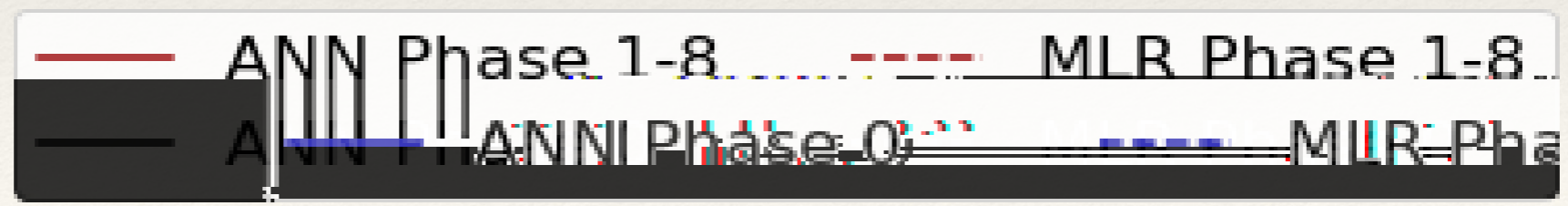
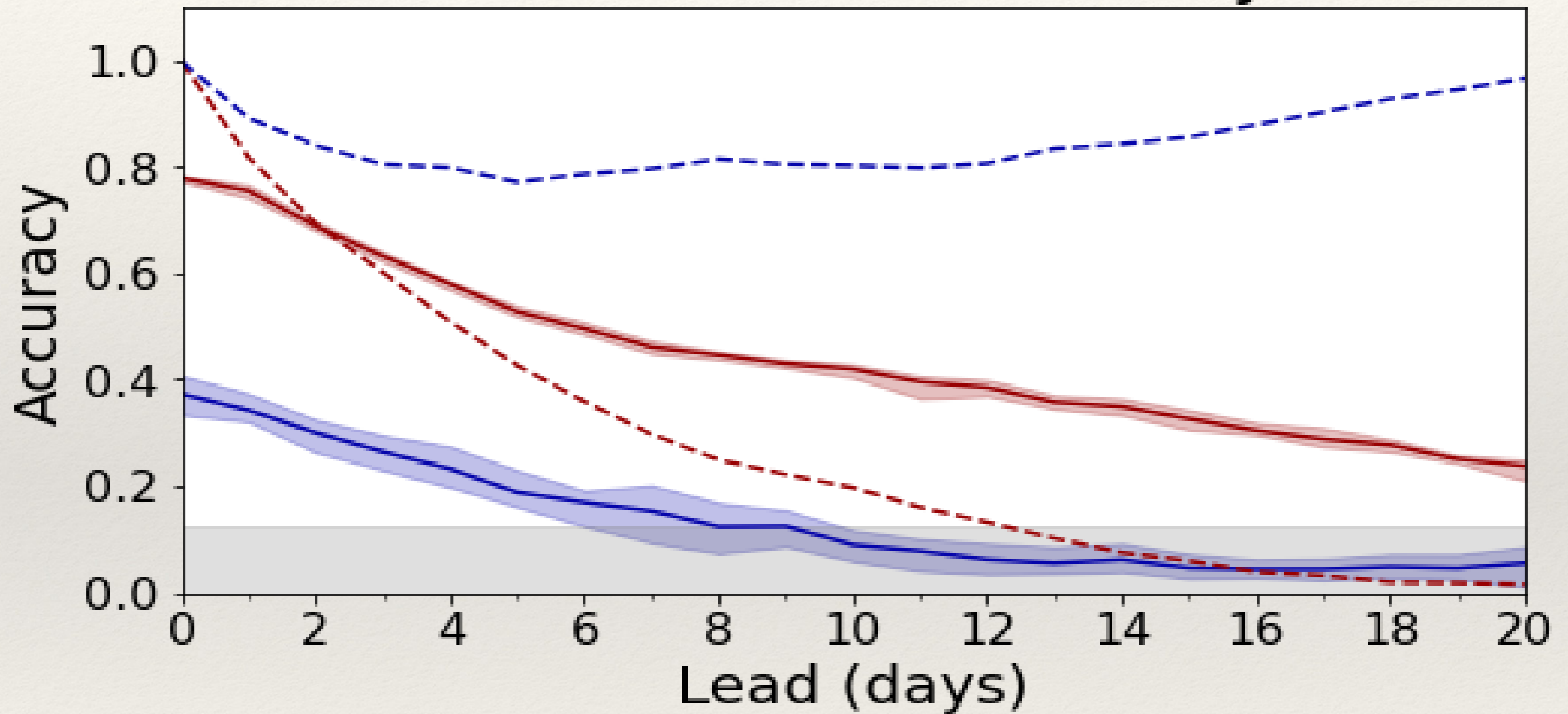
## Regression Model

- ❖ A model which outputs *numerical values*





# Winter Classification Accuracy



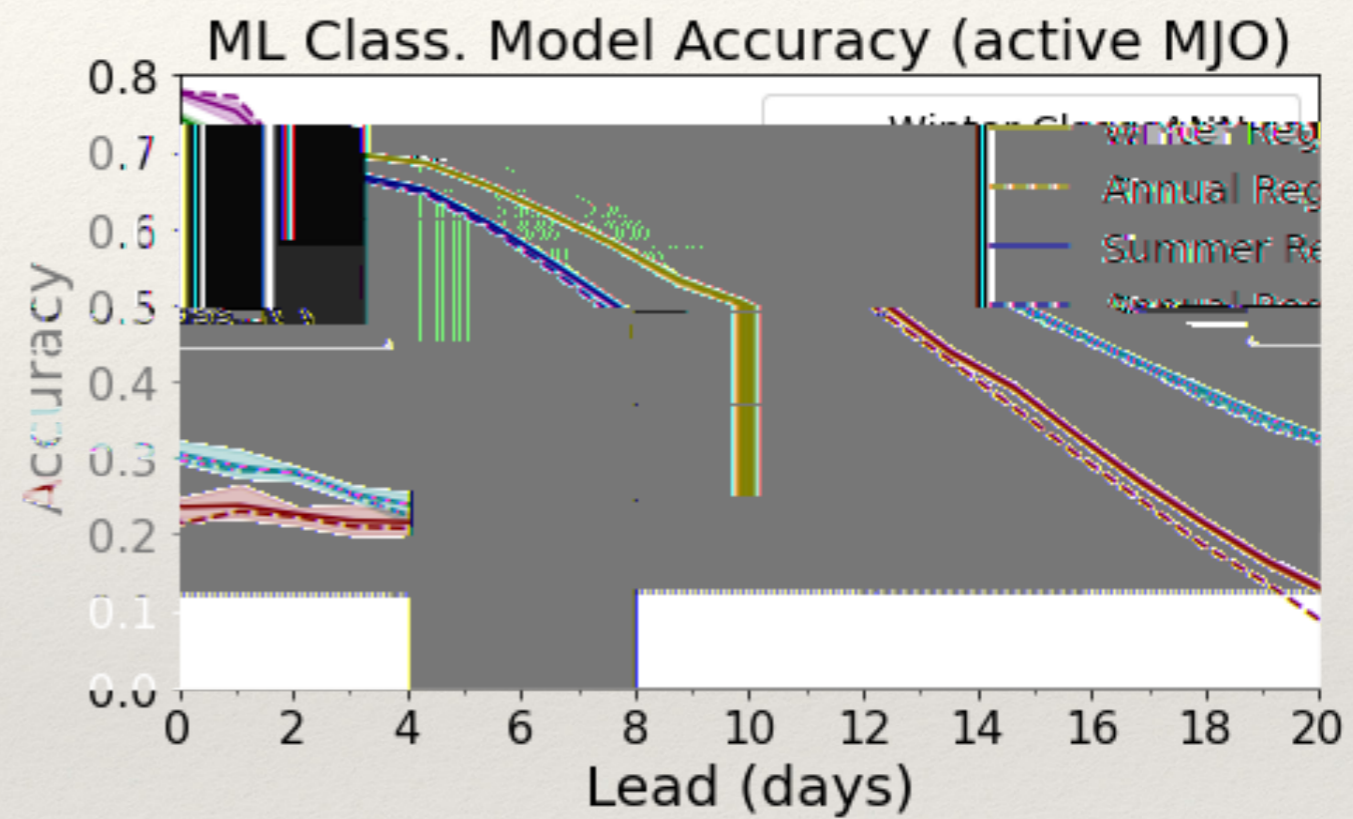
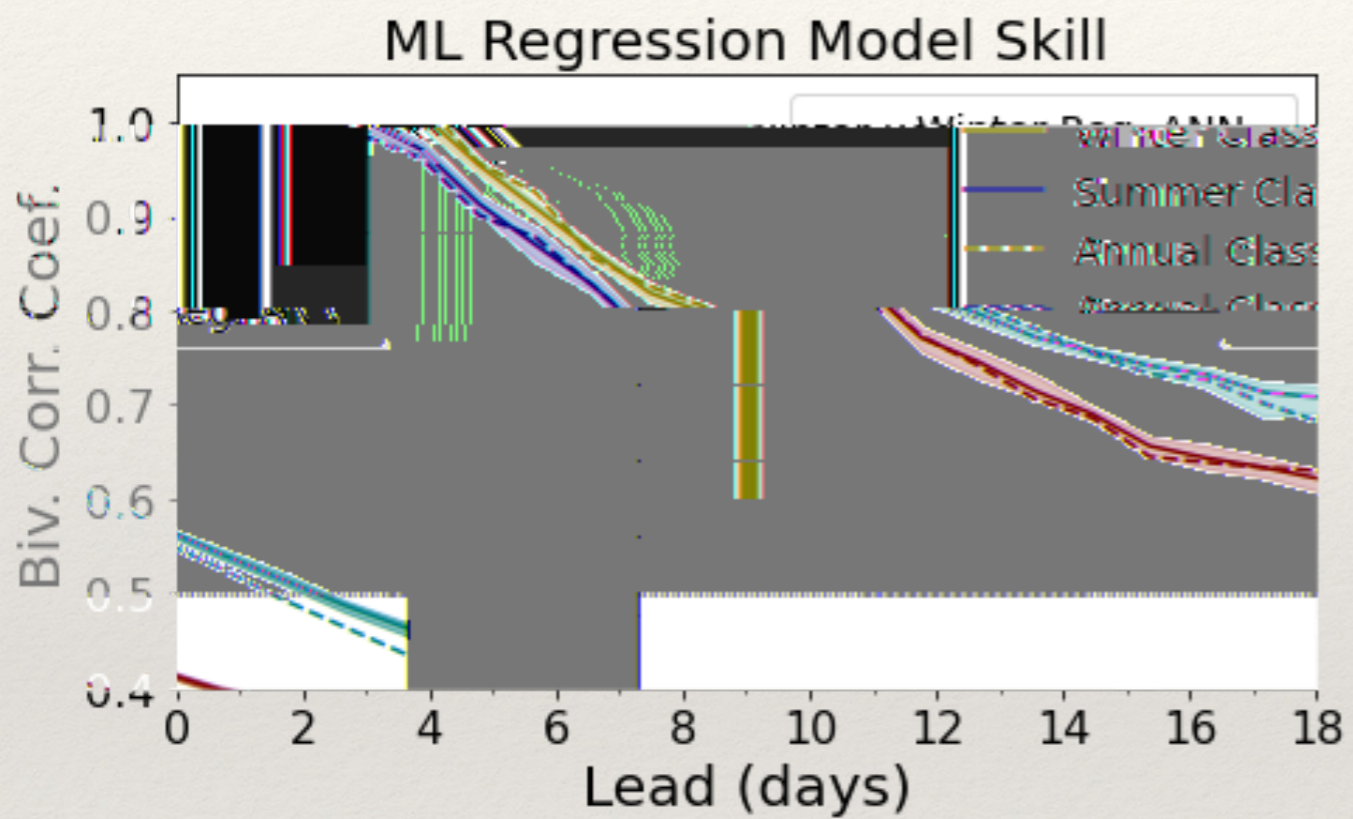


Figure S3

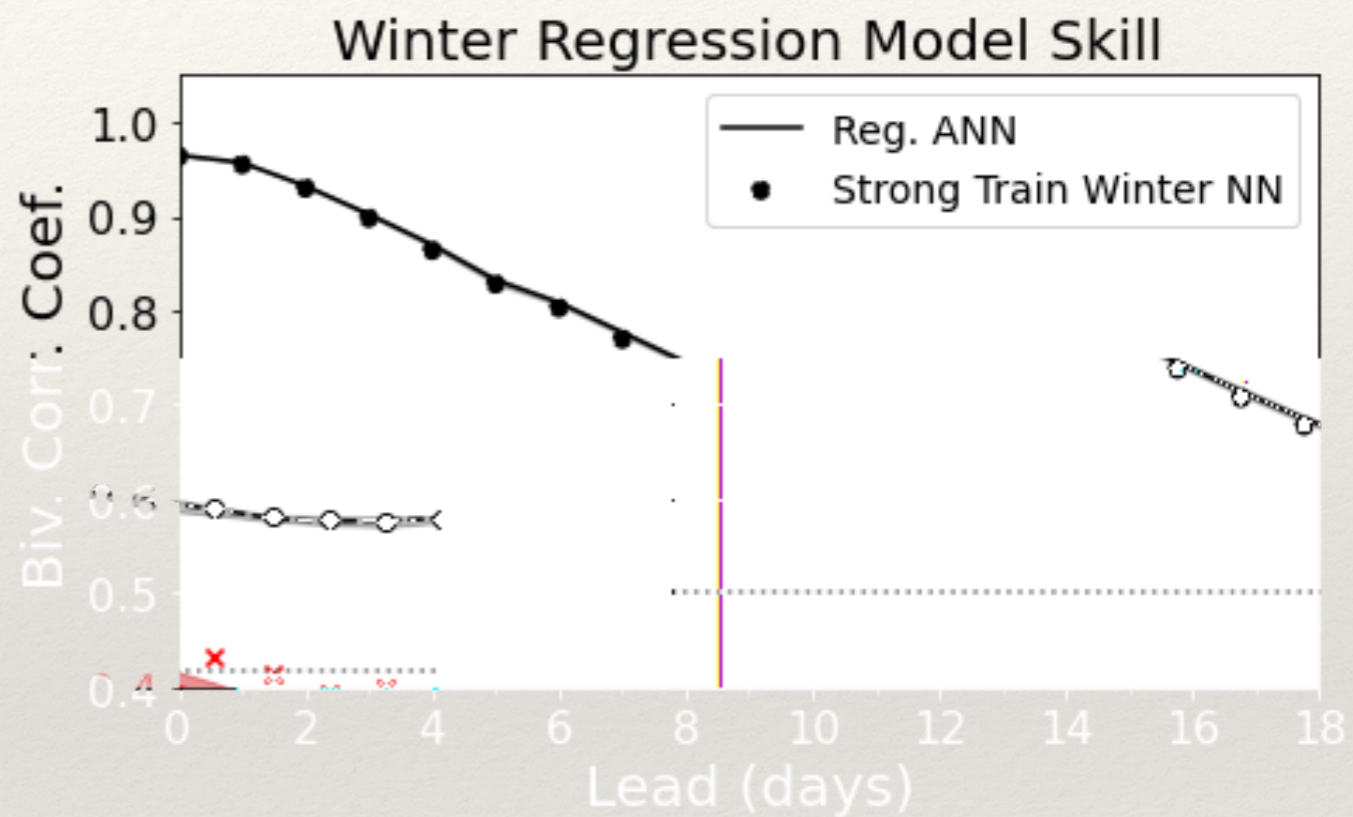
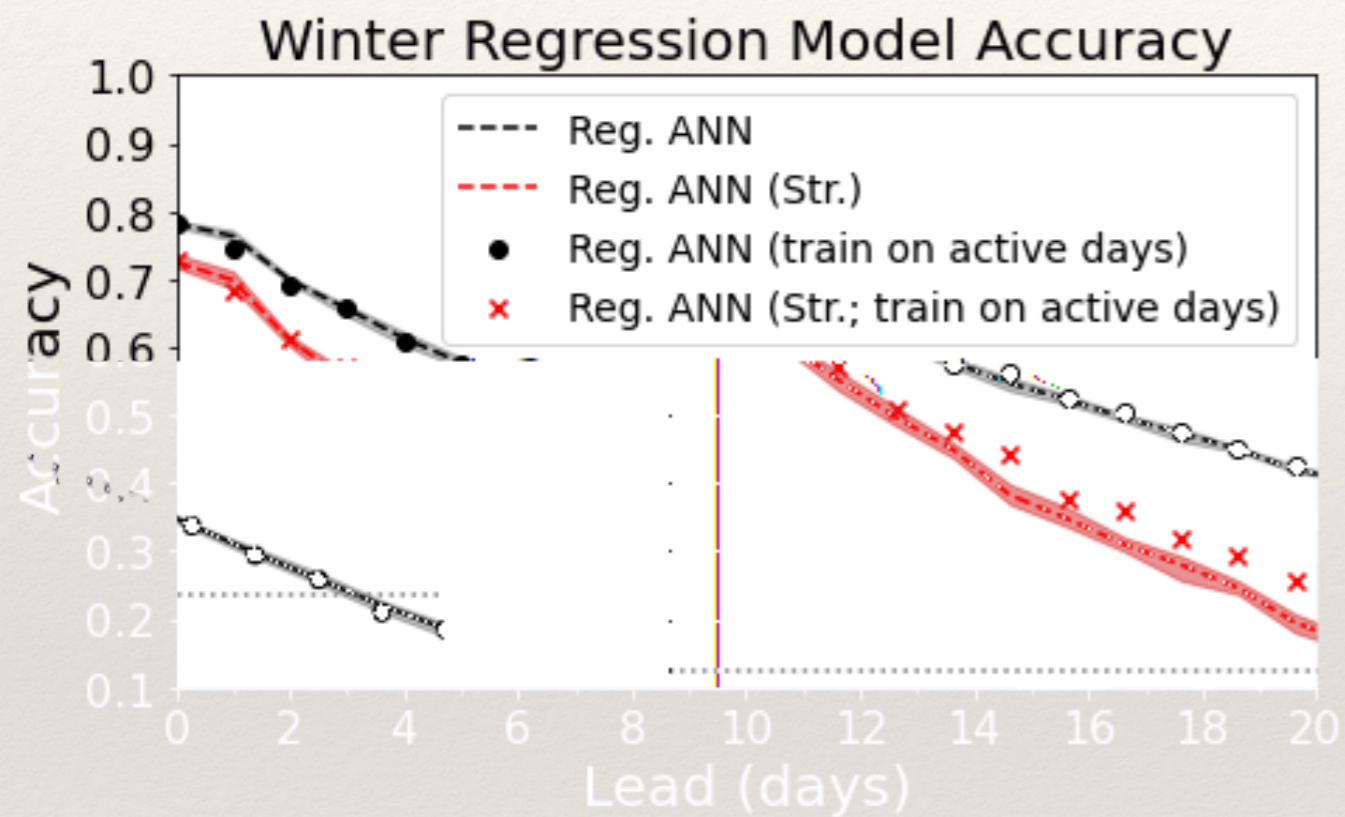
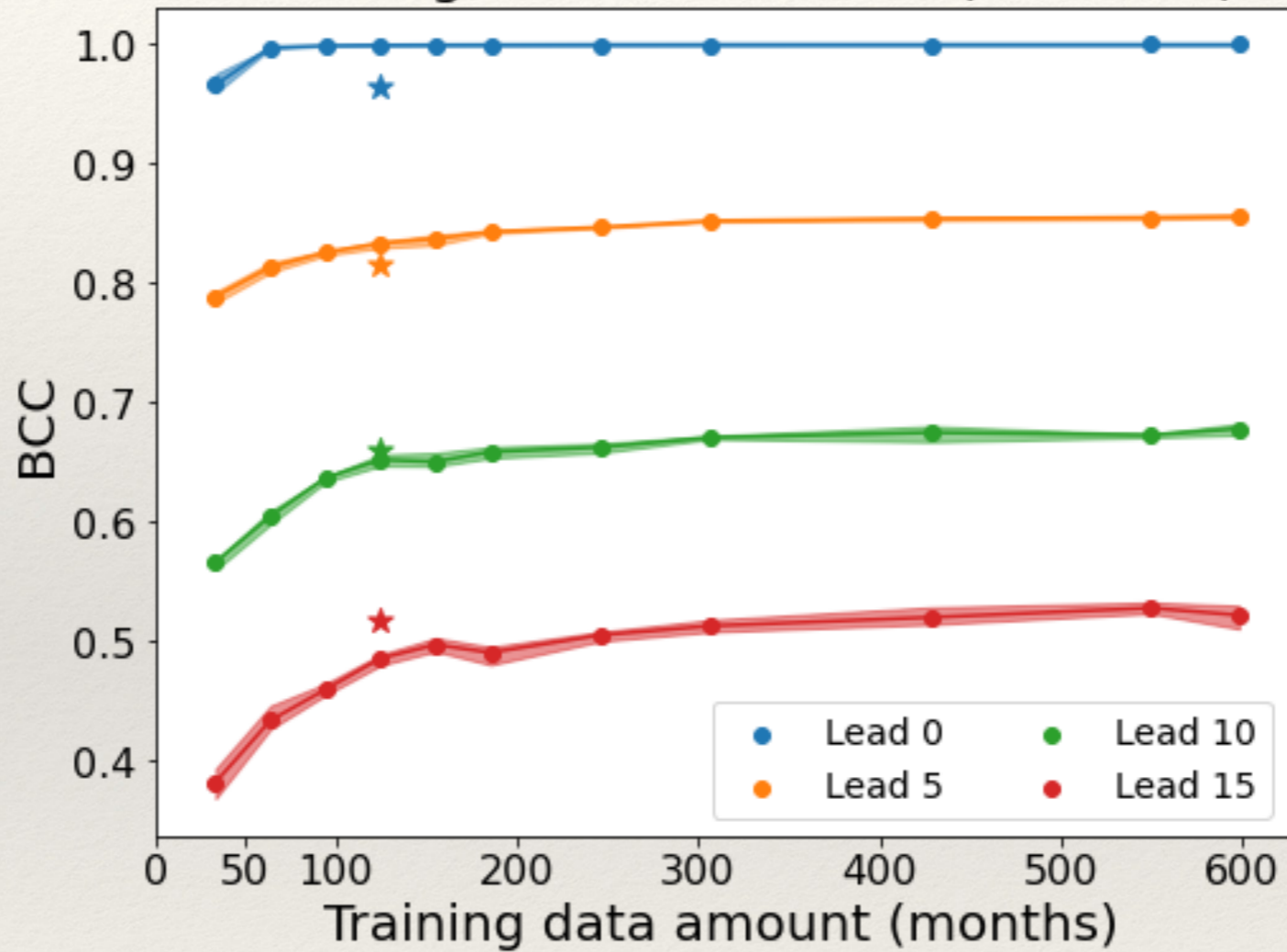


Figure S6: Strong training

Winter Regression ANN Skill (ERA-20C)



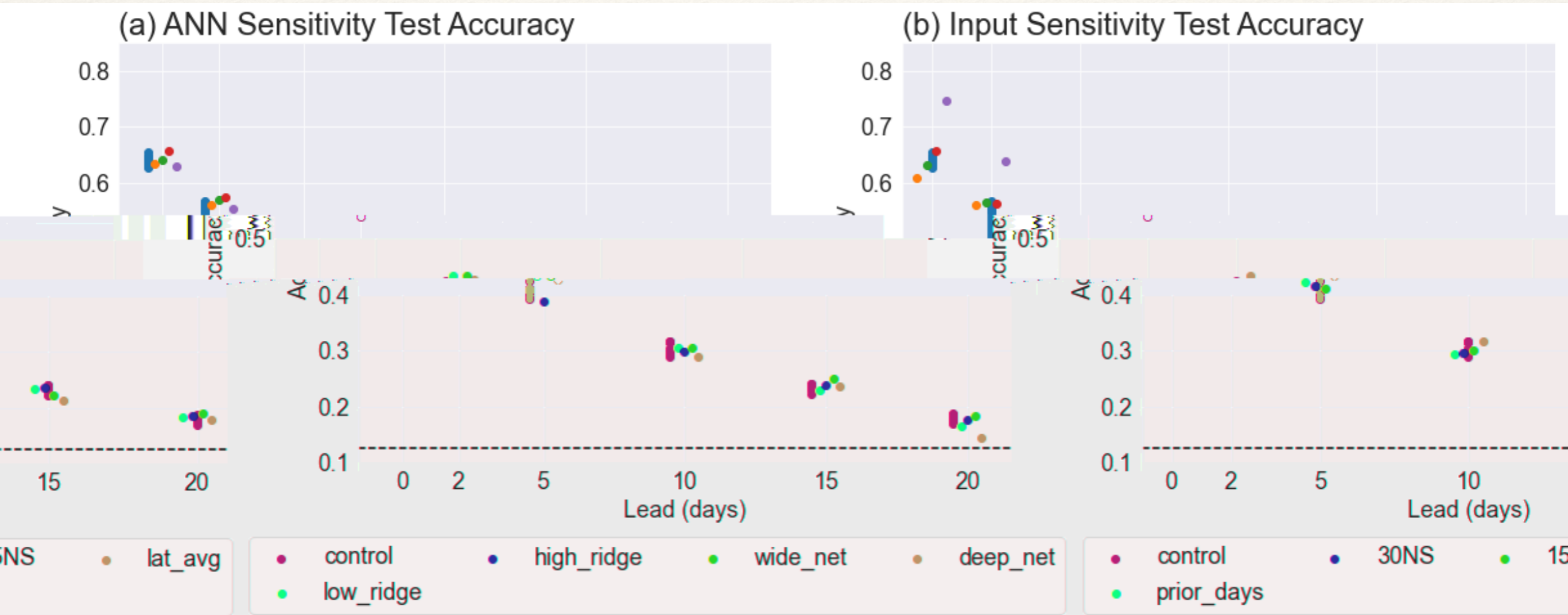


Figure S7: sensitivity tests

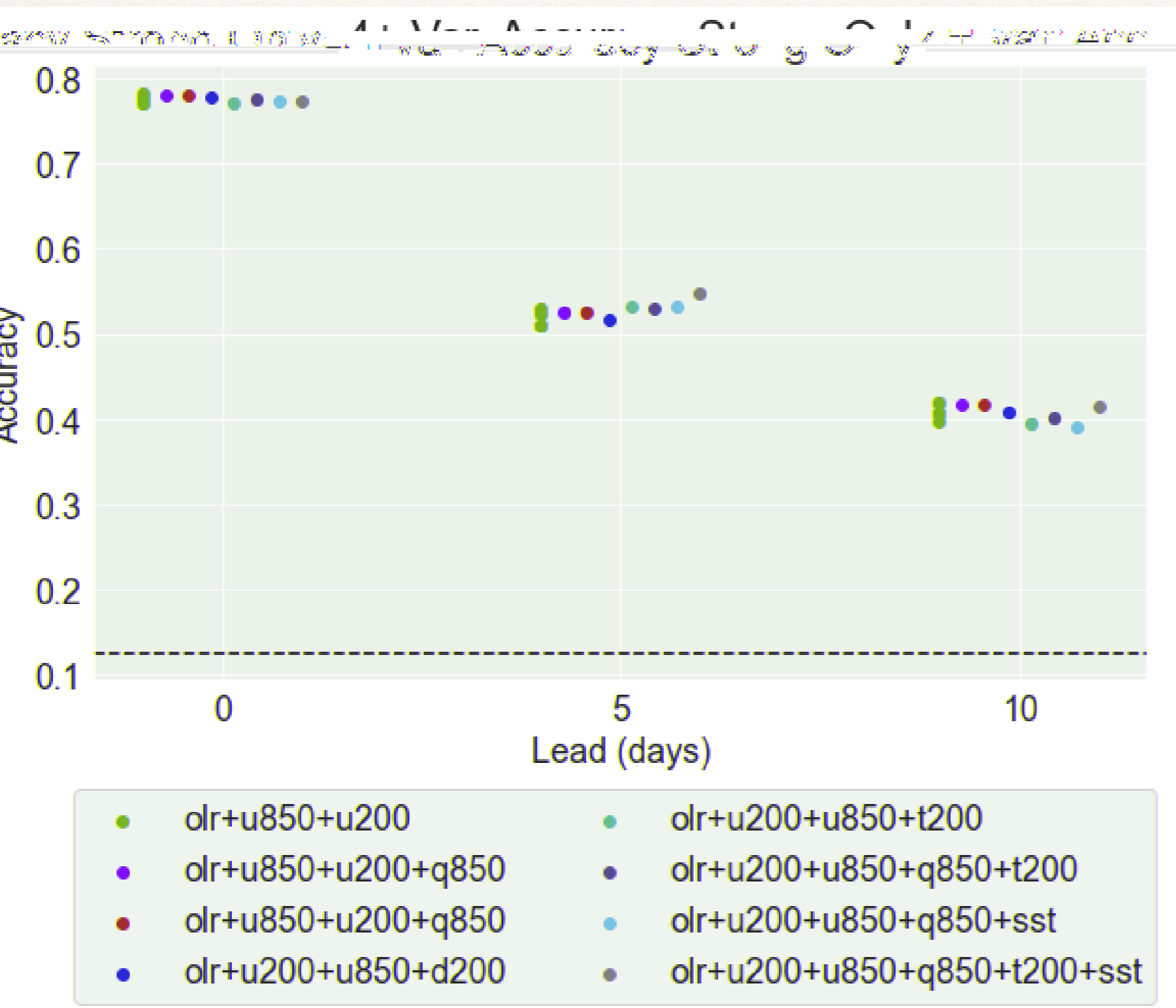


Fig. S11: Additional variable tests of combinations of 4, 5, or 6 inputs

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1. “Persistence” model which simple persists the initial condition

$$\begin{aligned}RMM1(t_0 + \tau) &= RMM1(t_0) \\RMM2(t_0 + \tau) &= RMM2(t_0)\end{aligned}$$



---

2. **Vector autoregressive (VAR) scheme** (Maharaj & Wheeler 2005; Marshall et al. 2016)

Statistical bivariate forecast which captures 1-day typical change in RMM and steps forward (essentially akin to our prior “persistence” model)

$$\begin{bmatrix} RMM1(t) \\ RMM2(t) \end{bmatrix} = \mathbf{L} \begin{bmatrix} RMM1(t-1) \\ RMM2(t-1) \end{bmatrix}$$

MLR used to calculate  $\mathbf{L}$   
in each season

Marshall et al. 2016:

$$RMM1_t = 0.9616 (RMM1_{t-1}) - 0.1135 (RMM2_{t-1})$$

$$RMM2_t = 0.1257 (RMM1_{t-1}) + 0.9875 (RMM2_{t-1})$$

M21 “ $\mathbf{L}$ ”:

```
LR.coef_
```

```
array([[ 0.96745844, -0.11490354],  
       [ 0.12136748,  0.98466266]])
```

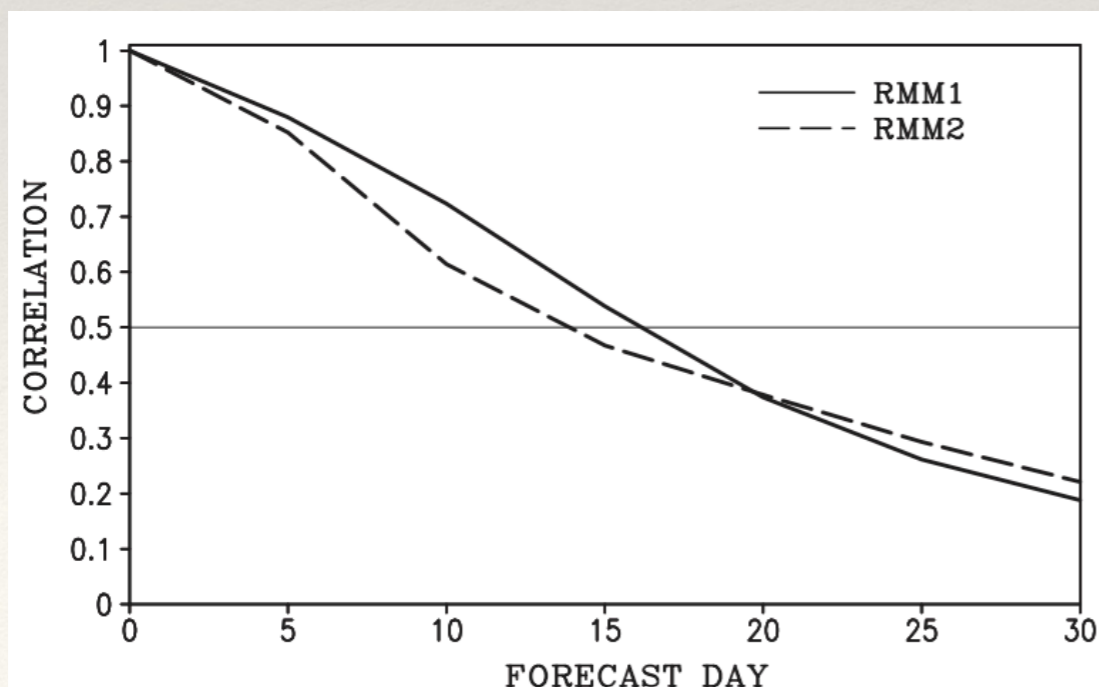
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### 3. Multiple linear regression (MLR) scheme (Kim 2008; Jiang et al. 2008; Kang & Kim 2010; Seo et al. 2009, Wang et al. 2019)

Predicts RMM at lead  $\tau$  given RMM at initial time and on prior days. Follow Kim & Kang (2010) who found  $j=2$  (e.g. day 0 and day -1) is ok (Seo et al. 2009 used pentad data and retained more days, but change seemed relatively small).

$$\begin{bmatrix} RMM1(t_0 + \tau) \\ RMM2(t_0 + \tau) \end{bmatrix} = L_\tau \sum_{j=1} \begin{bmatrix} RMM1(t_0 - j + 1) \\ RMM2(t_0 - j + 1) \end{bmatrix}$$

Kang & Kim 2010



Present MLR model  
(different train/validation period)

