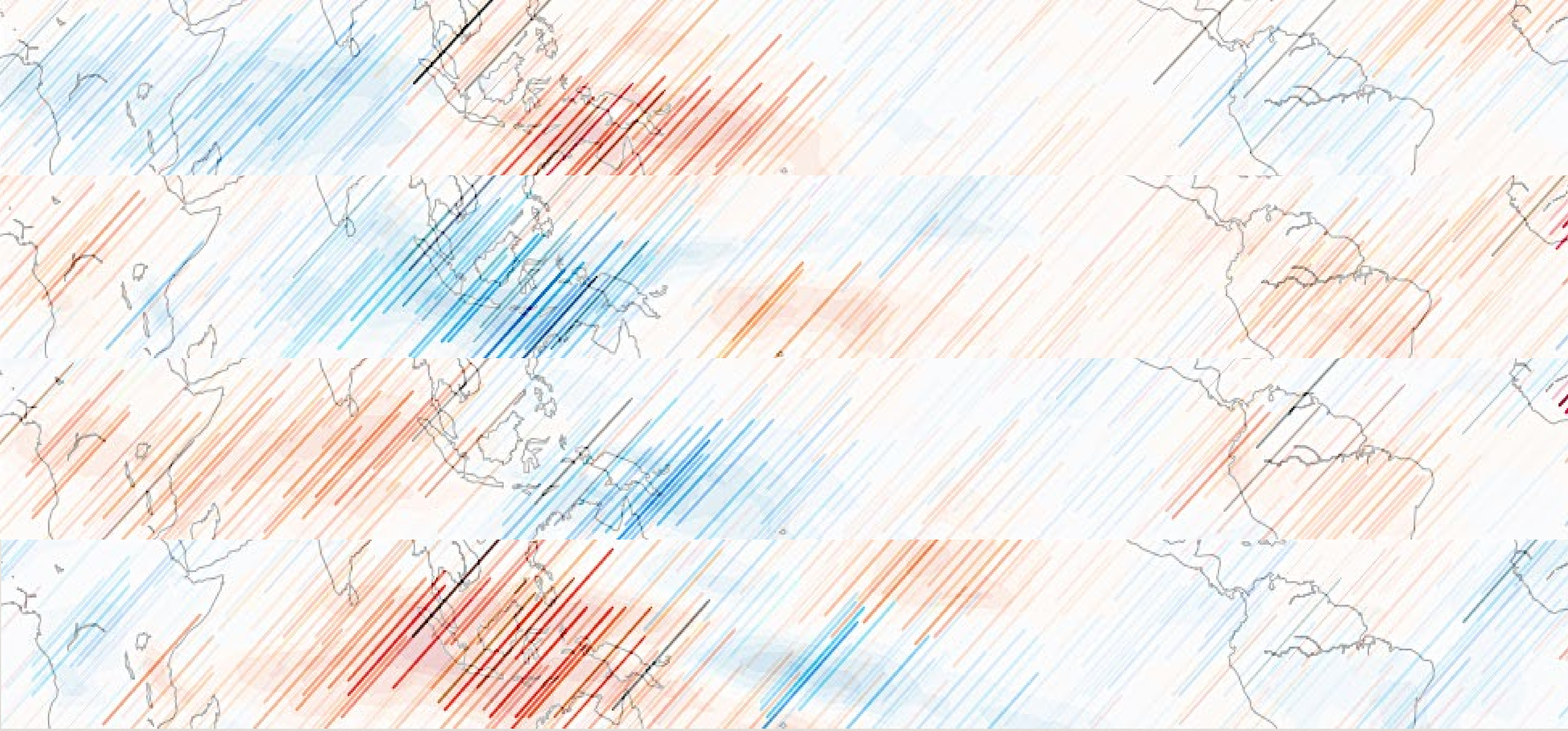


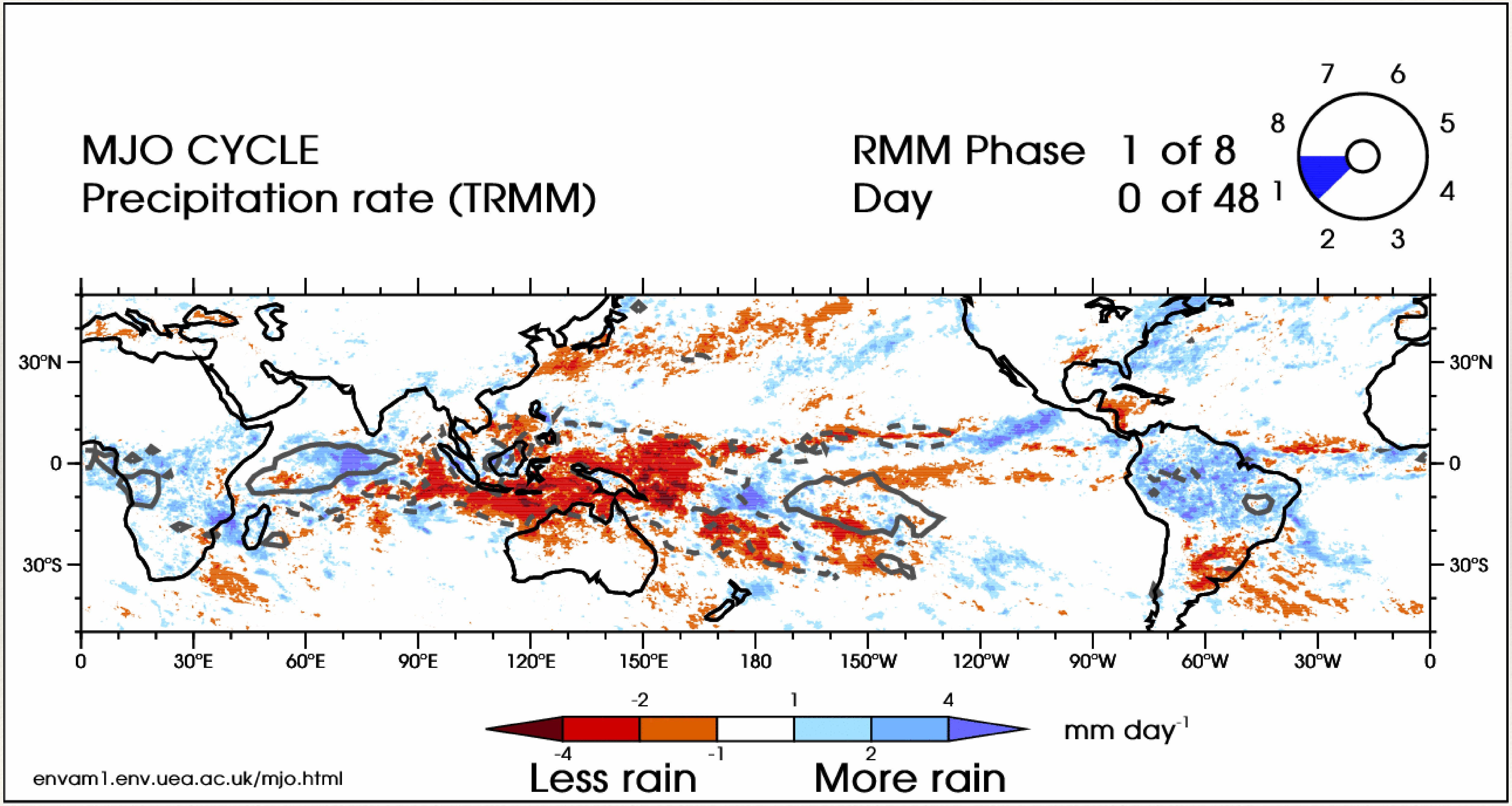
NOAA Weeks 3-4 & S2S Webinar

October 4, 2021

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

Zane Martin
Elizabeth Barnes
Eric Maloney

The Madden-Julian Oscillation



Summary of MJO Prediction

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

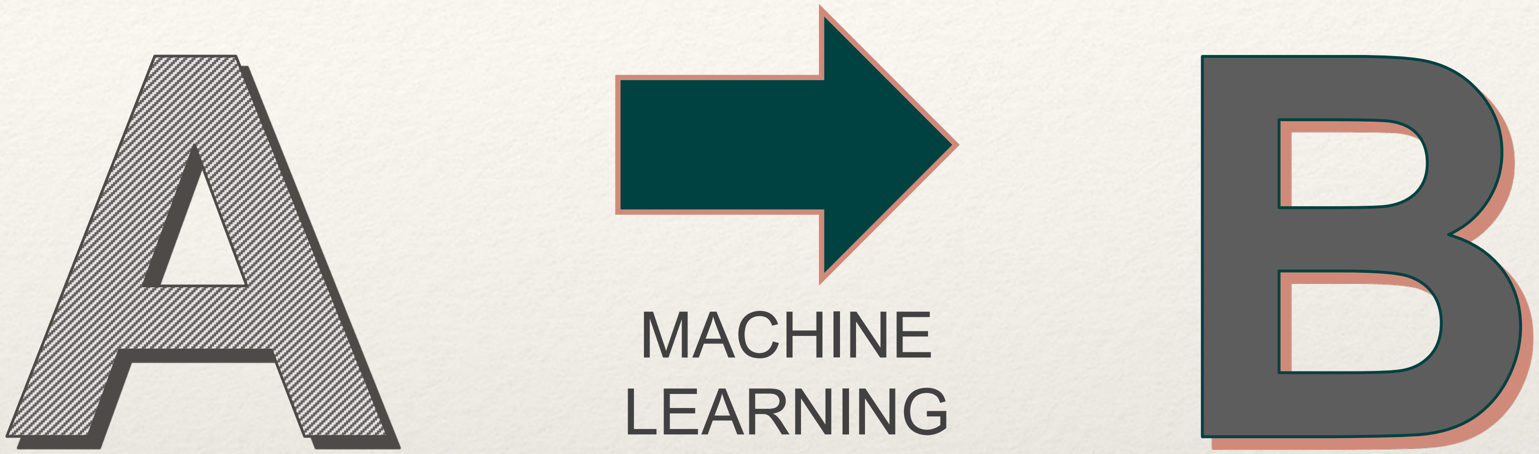
- 3-5 weeks of skill
- Since 2000s, model processes improved, ensembles grew, intercomparisons developed

Summary of MJO Prediction

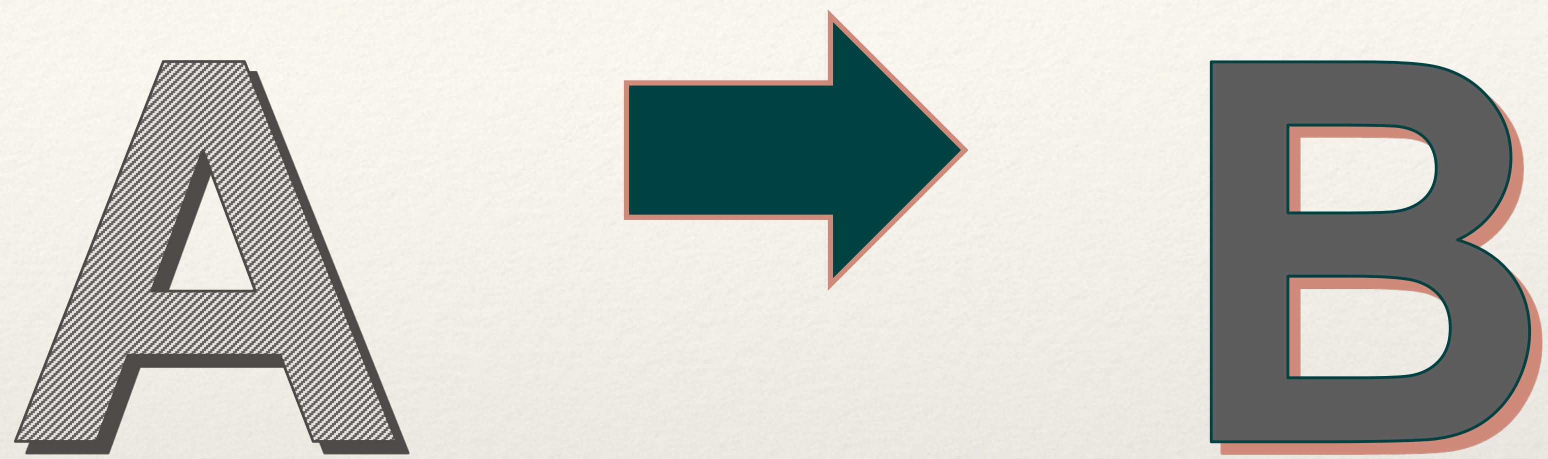
The future of statistical MJO prediction…

Non-linear methods and machine learning!

Machine Learning



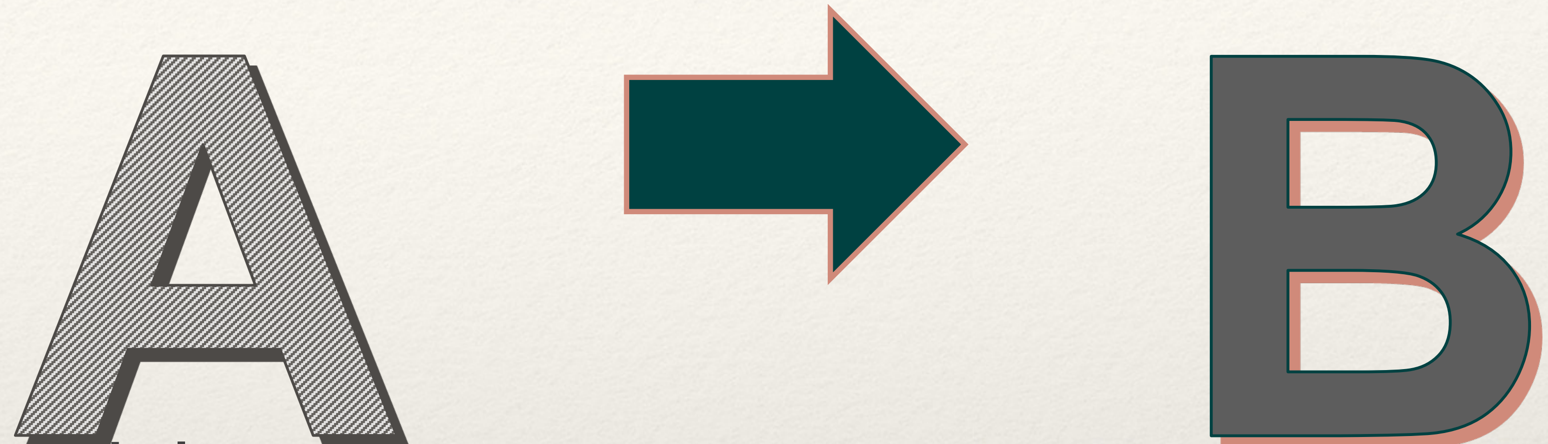
Machine Learning



A *linear* data transformation might take the form:

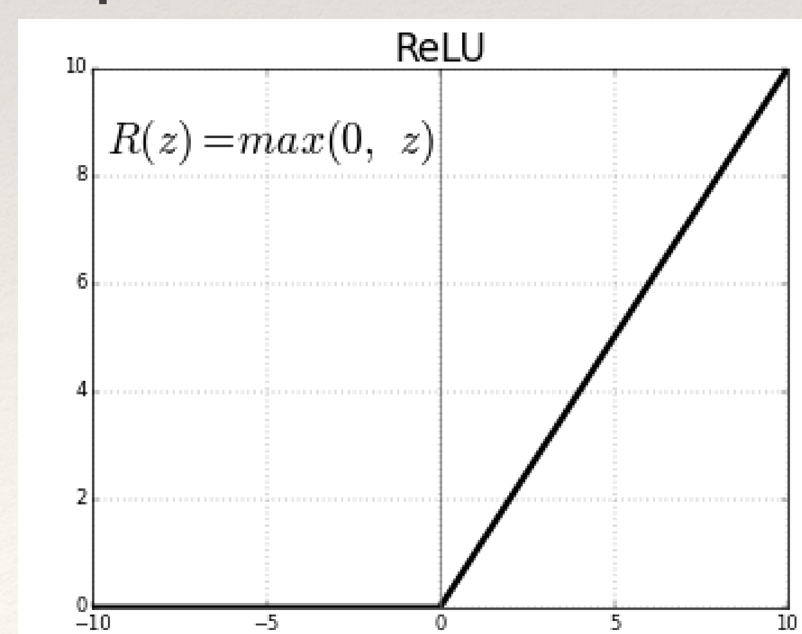
$$X \cdot A + y$$

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 tropical variables (pre-processed)

MACHINE LEARNING

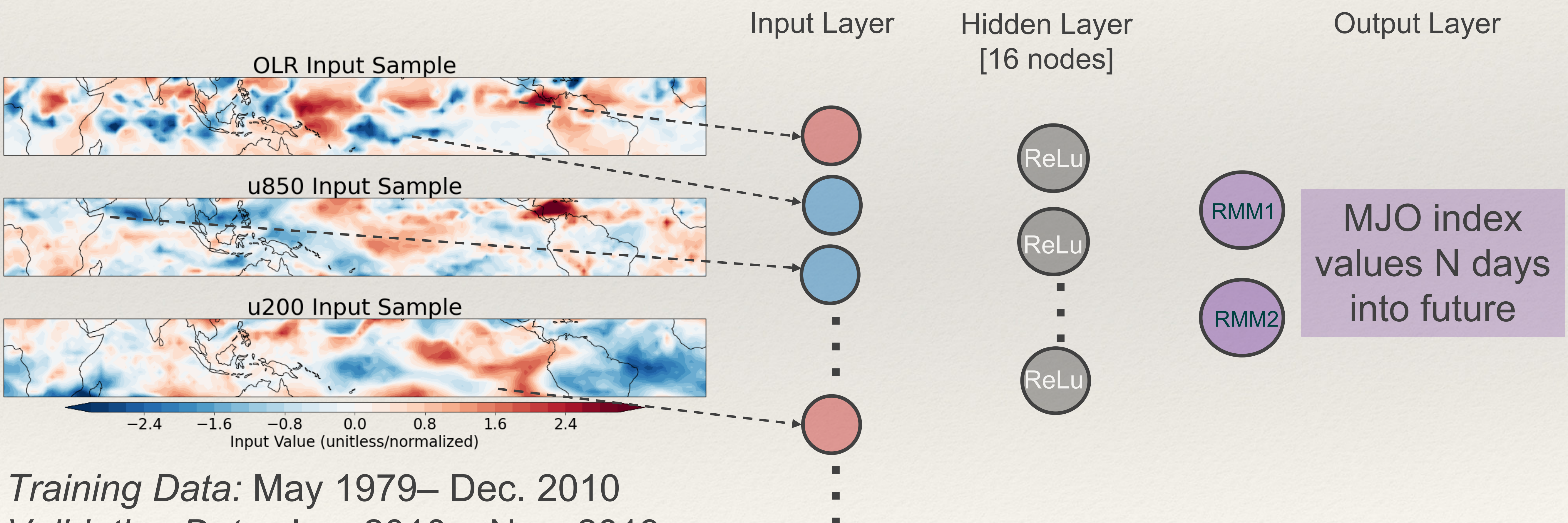
Information about an **MJO index** at various leads

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

Machine Learning & the MJO

Regression Model

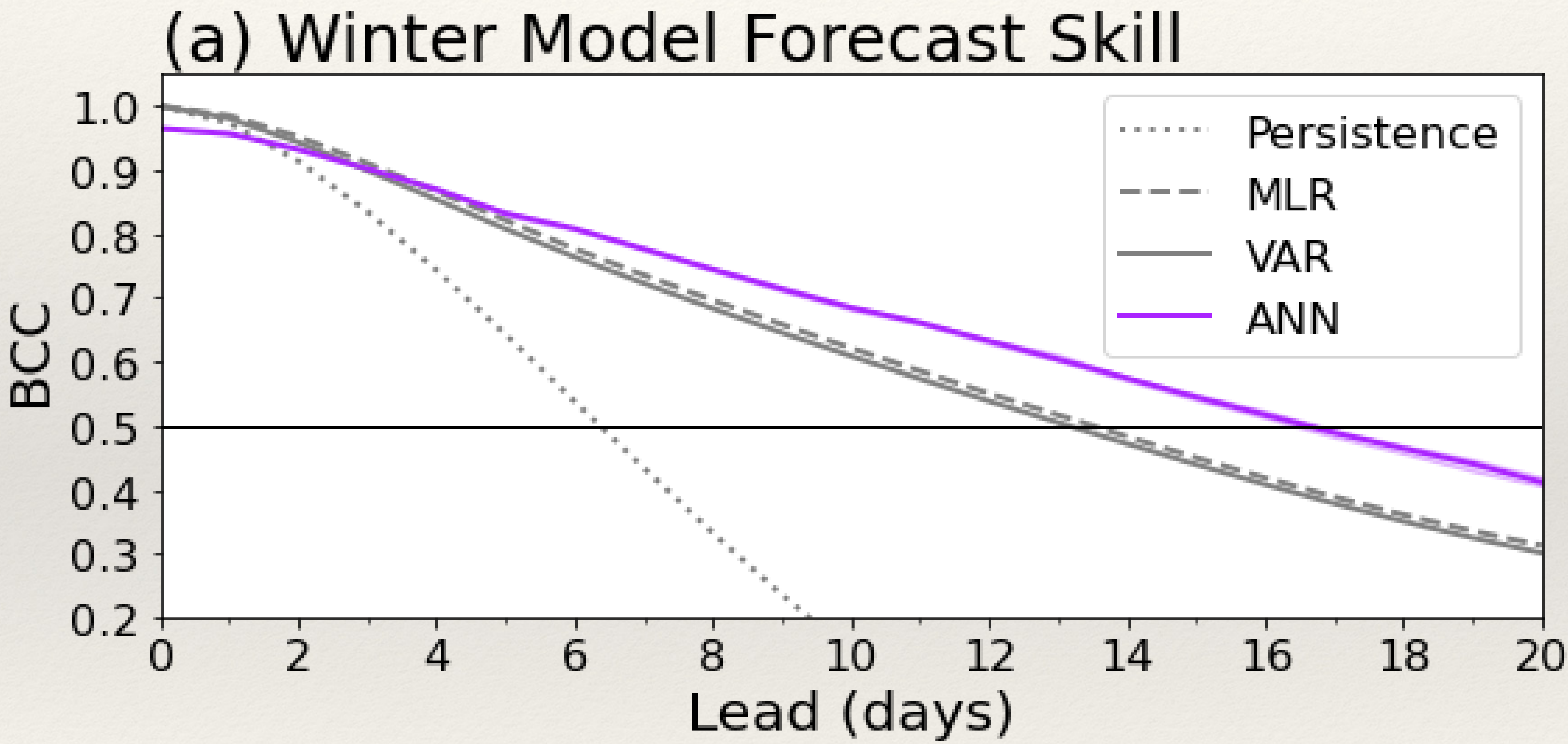
- Deterministic model which outputs *numerical values*



Training Data: May 1979– Dec. 2010
Validation Data: Jan. 2010 – Nov. 2019

Martin et al. (2021; submitted)

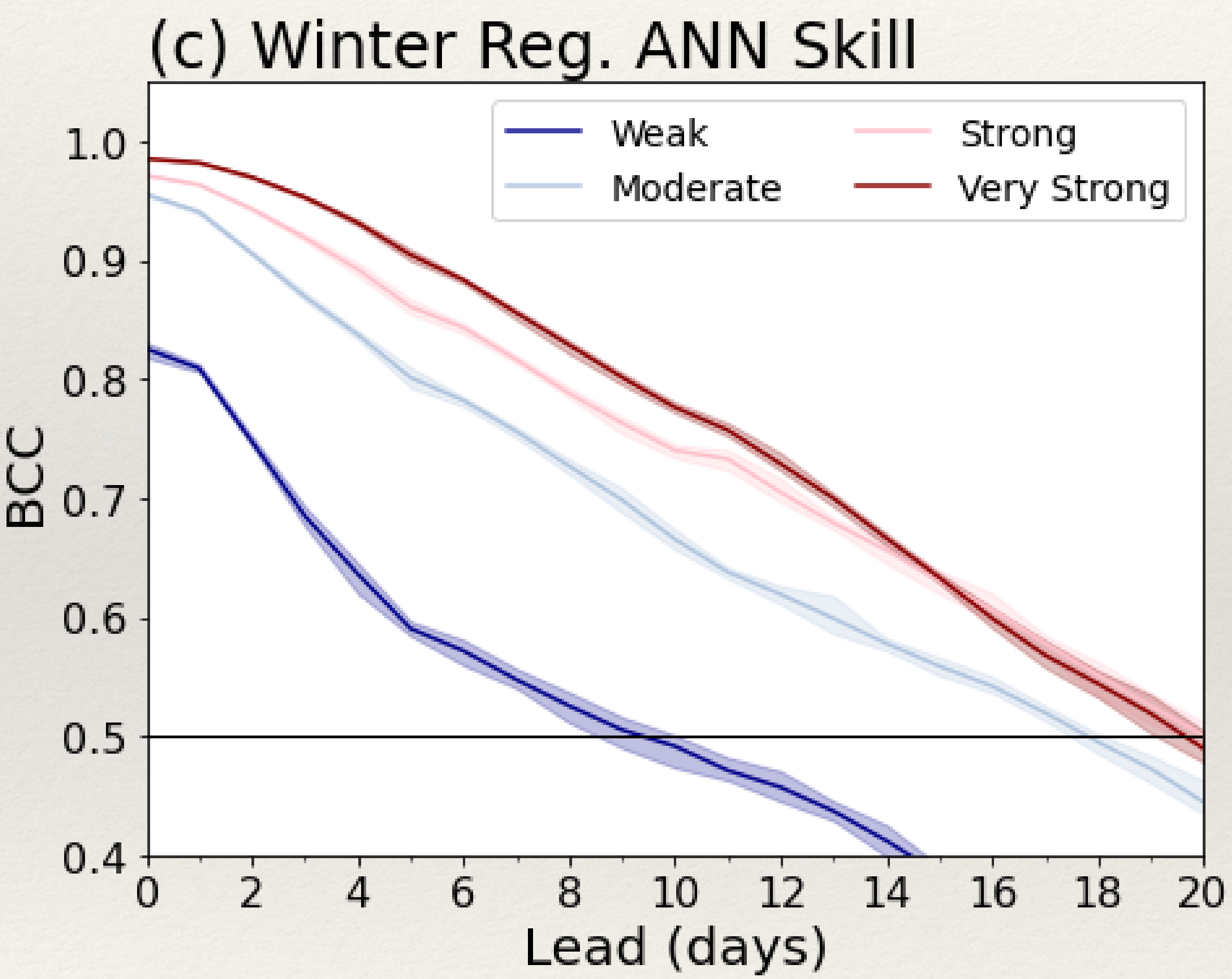
Regression ANN Model



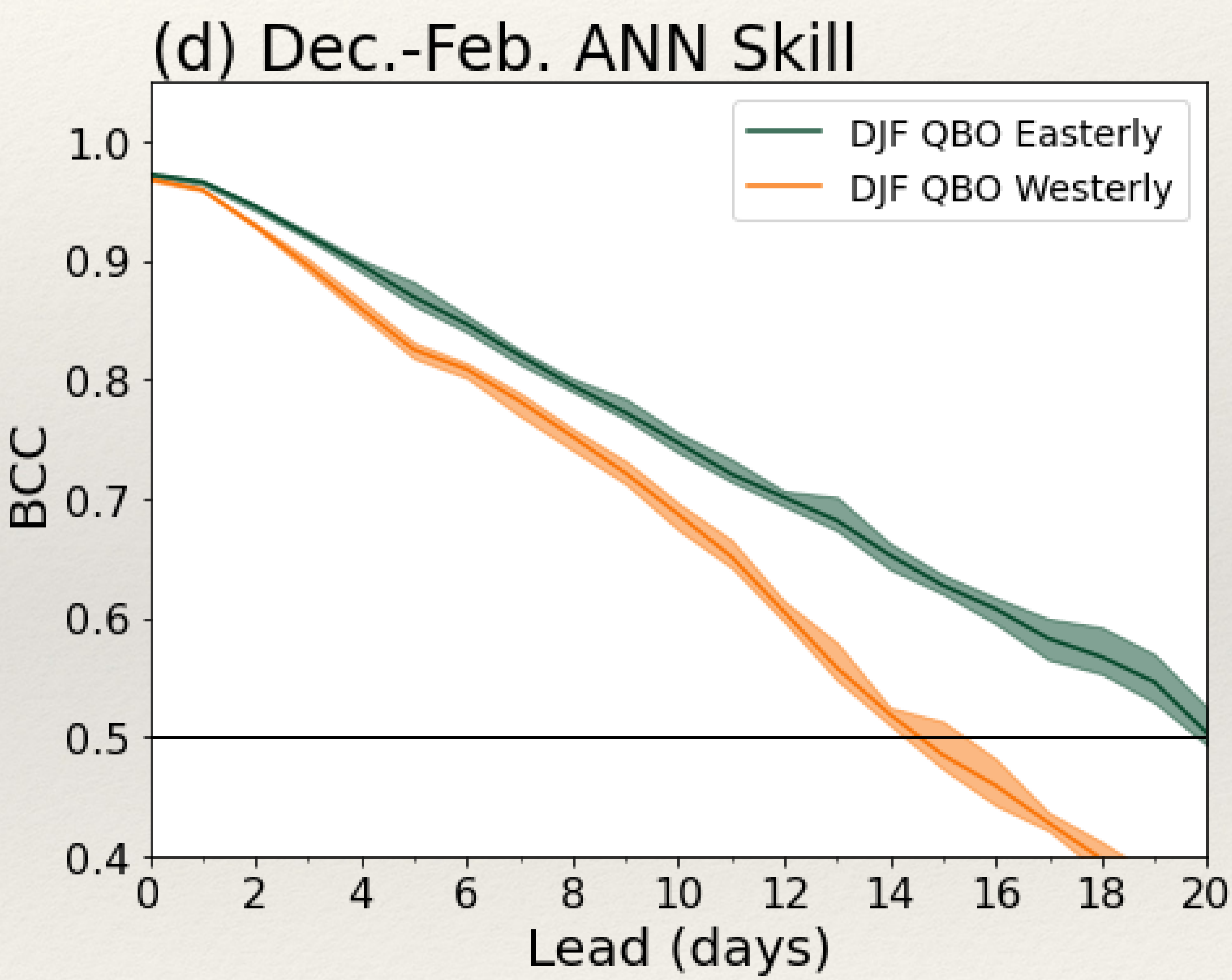
Martin et al. (2021; submitted)

Regression ANN Model

Skill vs. Initial MJO Amplitude



MJO Skill vs. Stratospheric State

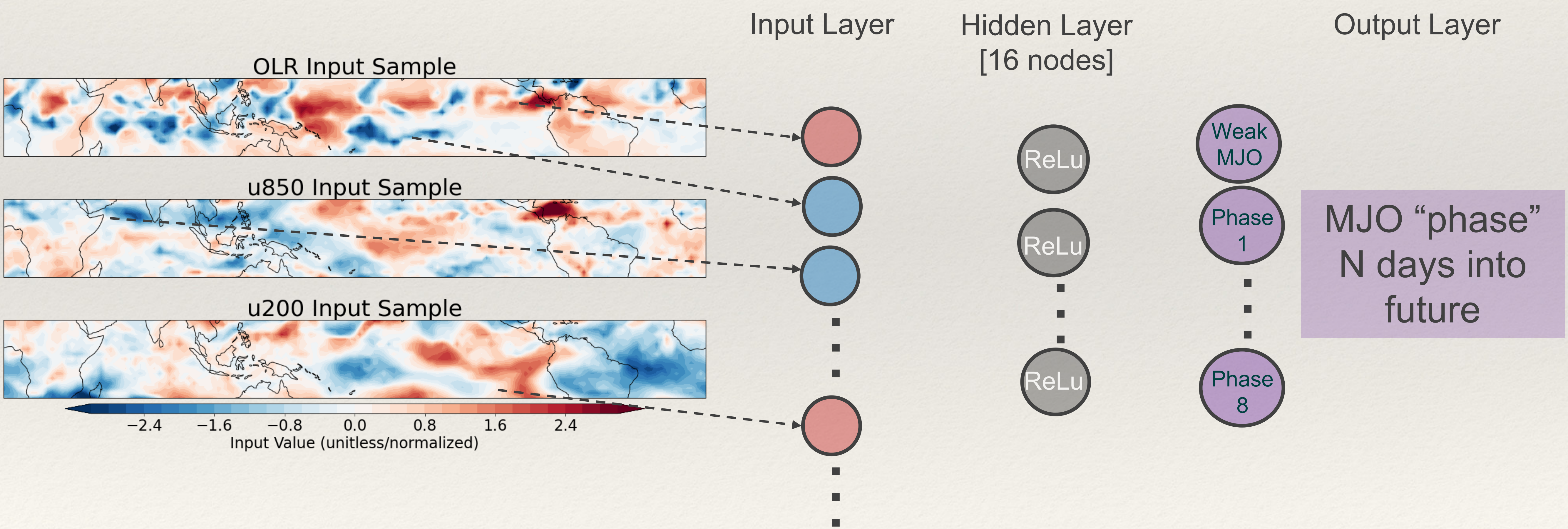


Martin et al. (2021; submitted)

Classification ANN Model

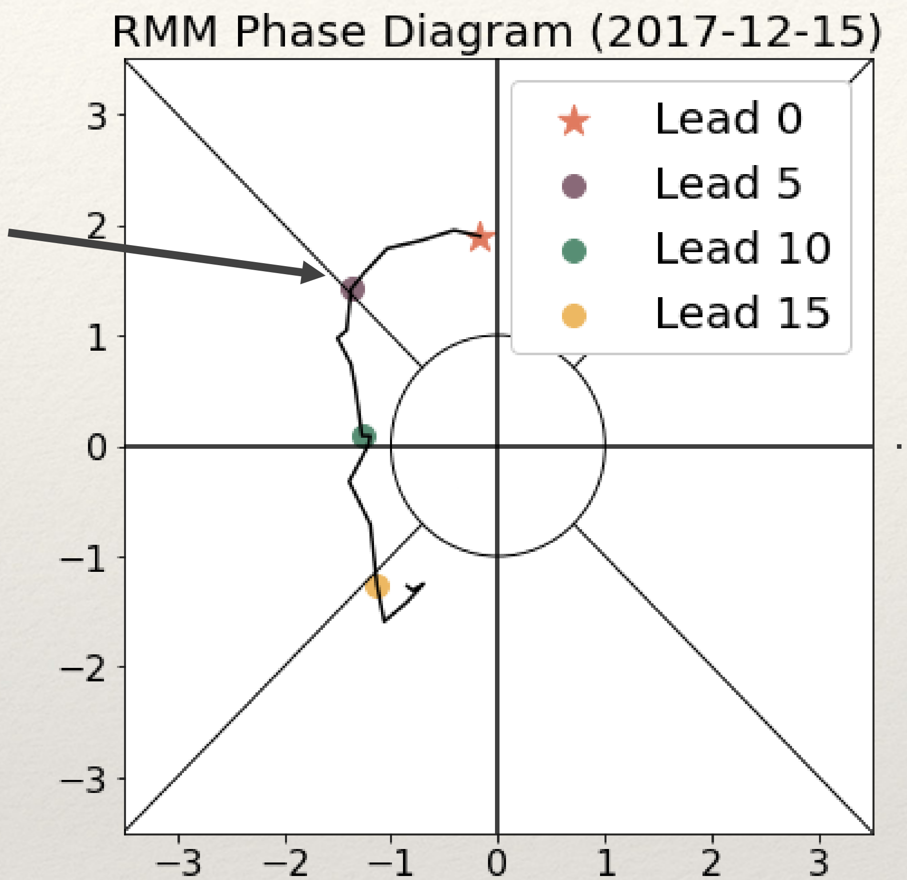
Classification Model

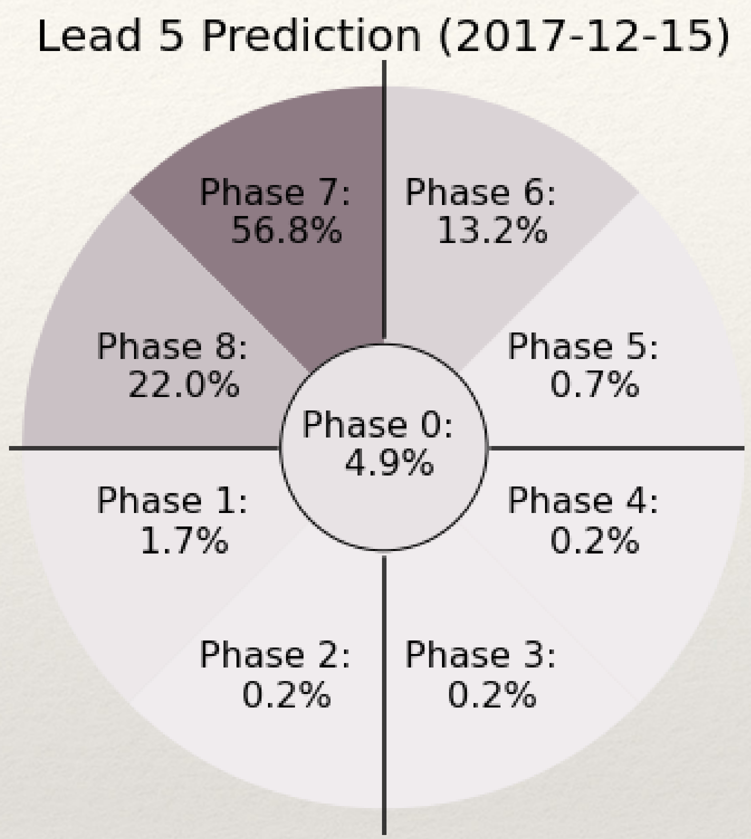
- Model which outputs the *probability* across various categories



Martin et al. (2021; submitted)

Classification ANN Model



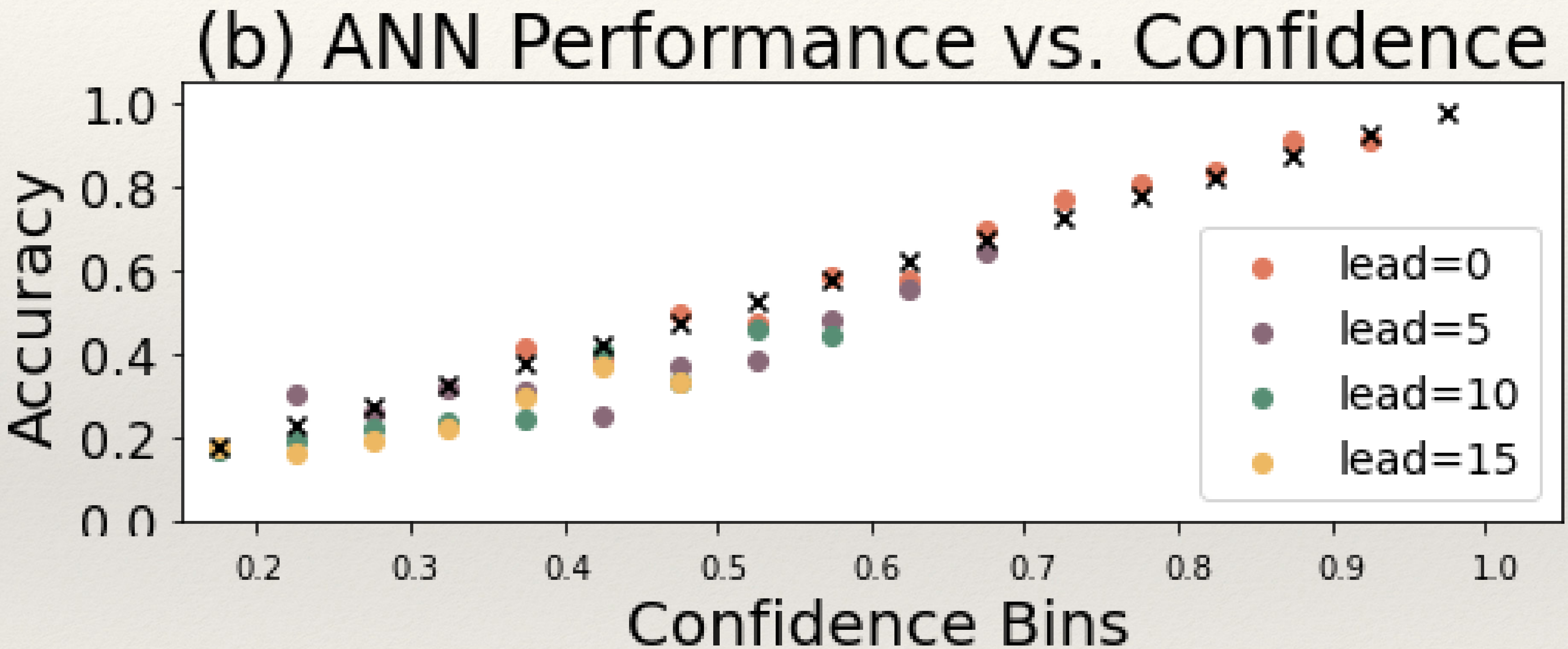


Classification Model

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

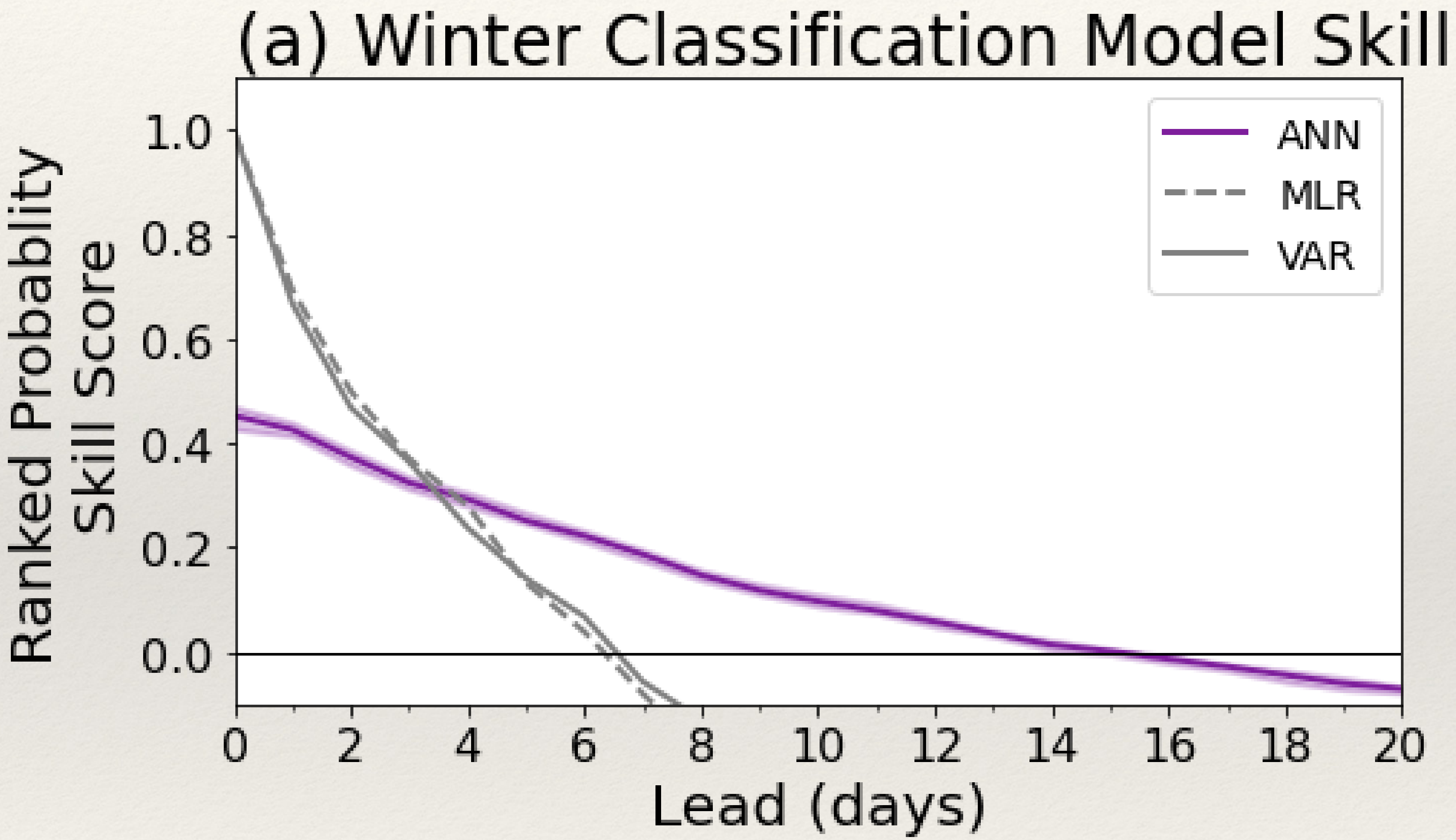
Martin et al. (2021; submitted)

Classification ANN Model



Martin et al. (2021; submitted)

Classification ANN Model



Martin et al. (2021; submitted)

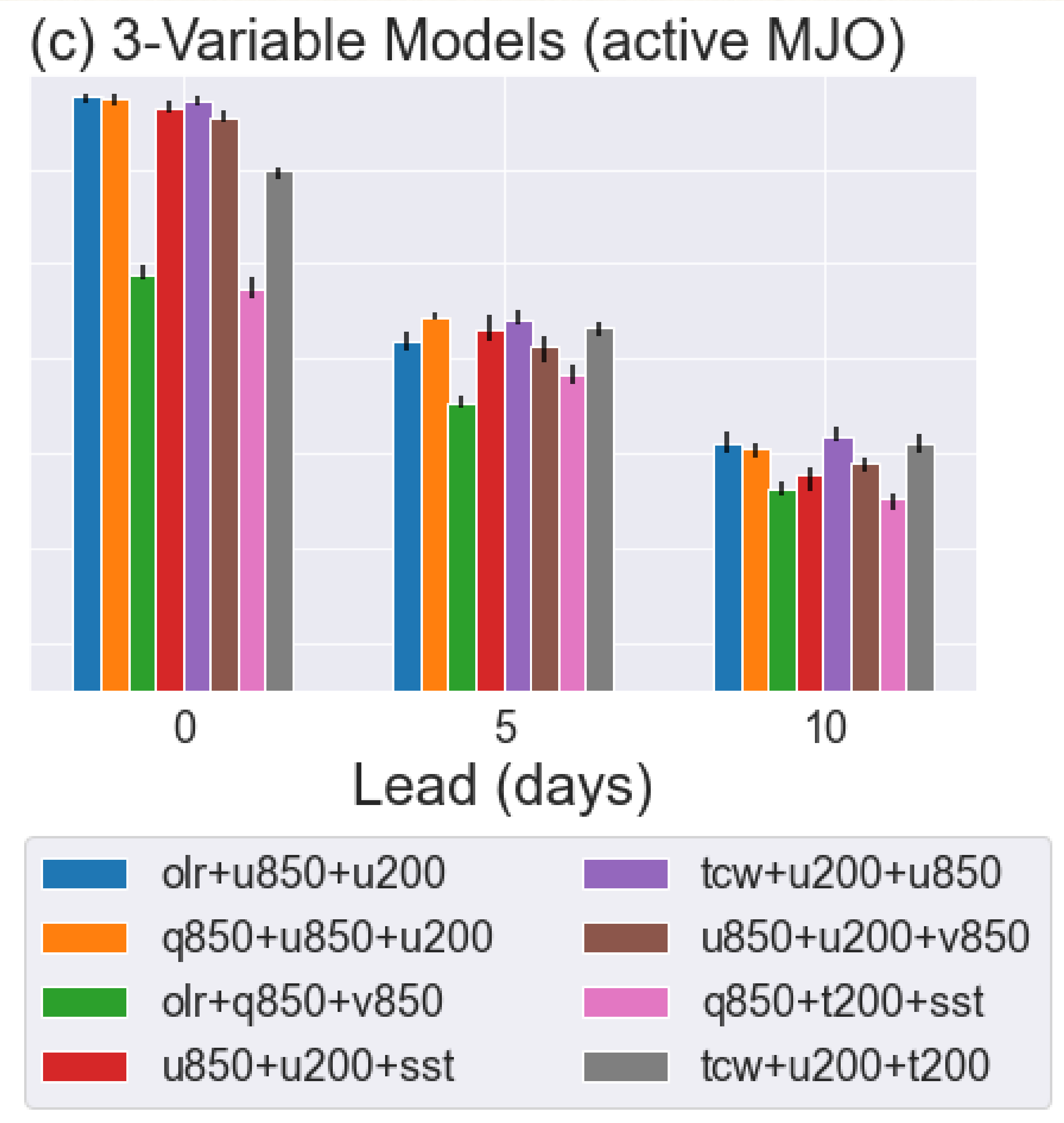
Machine Learning & the MJO

- **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!

Martin et al. (2021; submitted)

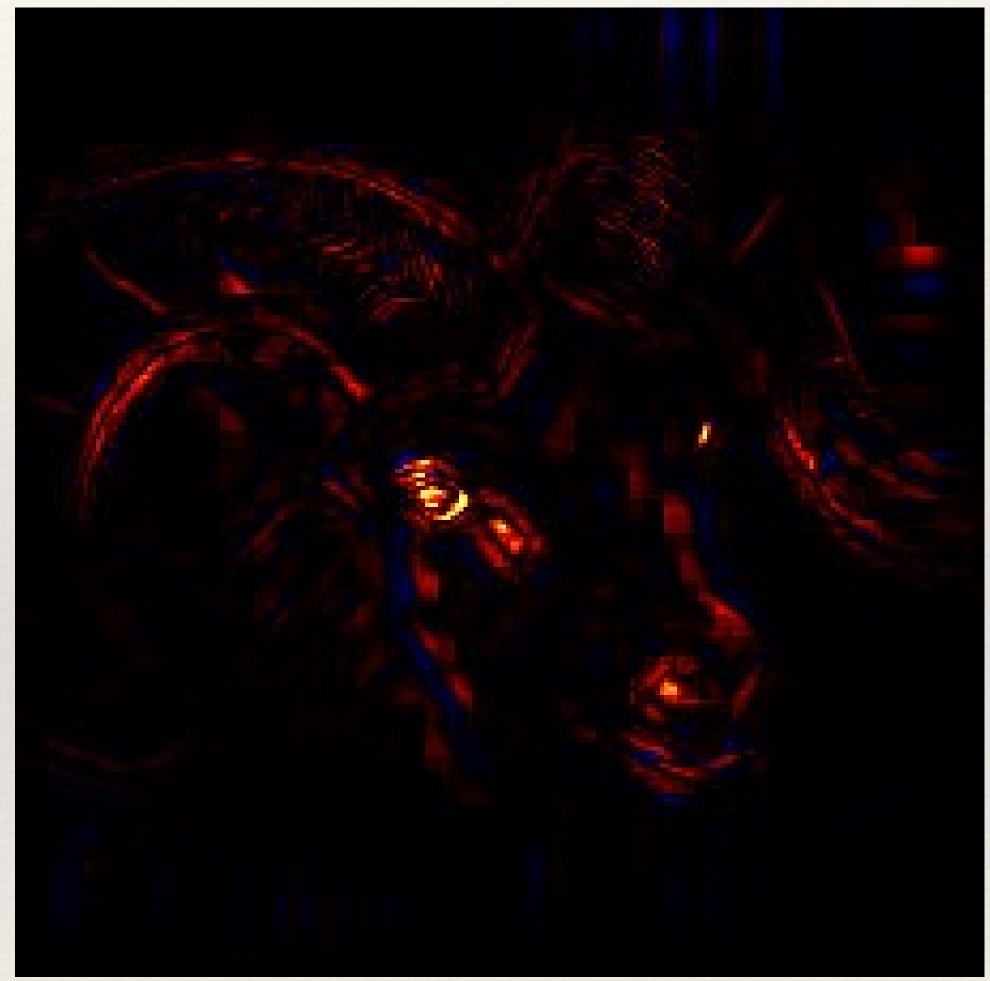
A Machine-Learning Framework for the MJO

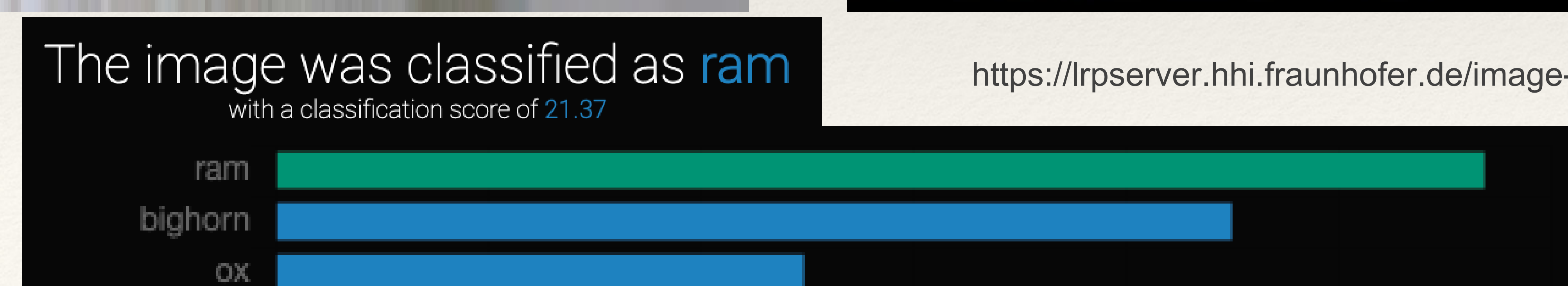


Martin et al. (2021; submitted)

A Machine-Learning Framework for the MJO

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

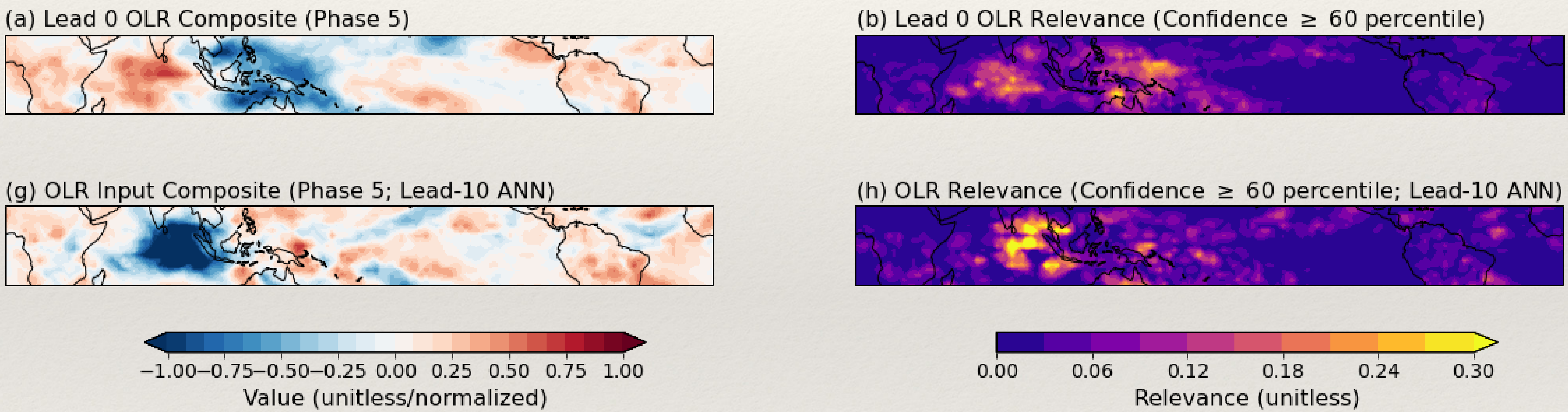




https://lrpserver.hhi.fraunhofer.de/image-classification

A Machine-Learning Framework for the MJO

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

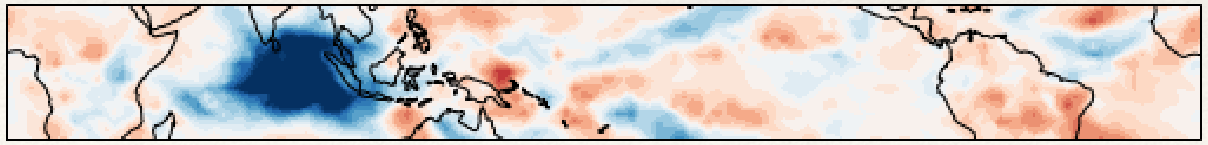


Martin et al. (2021; submitted)

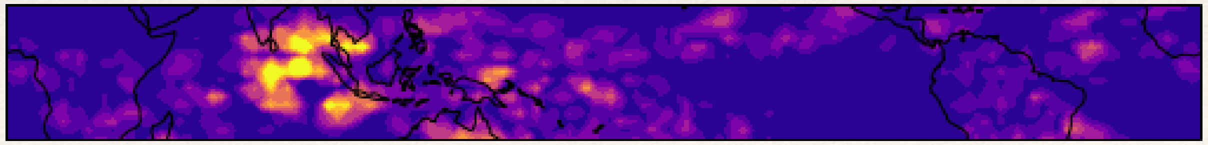
Machine Learning & the MJO

- **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 ≥ 60 percentile; Lead-10 ANN)



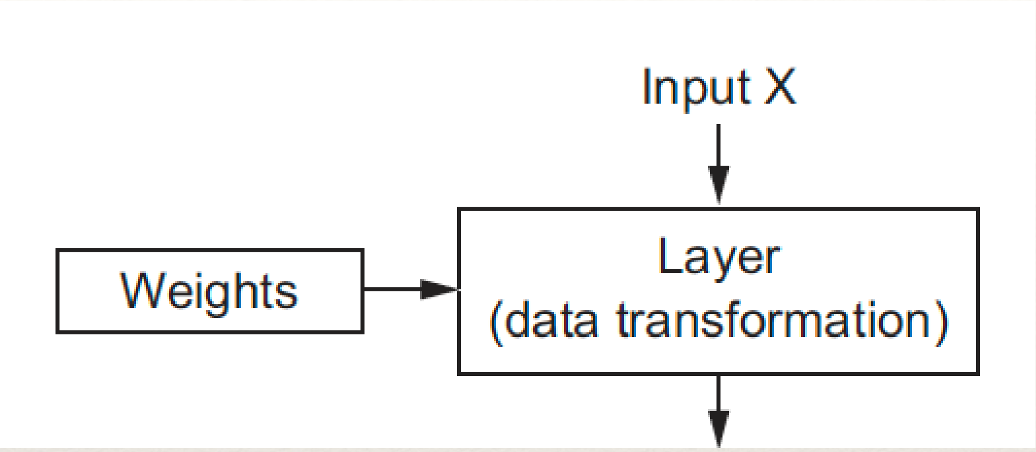
Thanks!

Martin et al. (2021; submitted)

Additional Slides

Artificial Neural Networks

Fully-connected artificial neural network



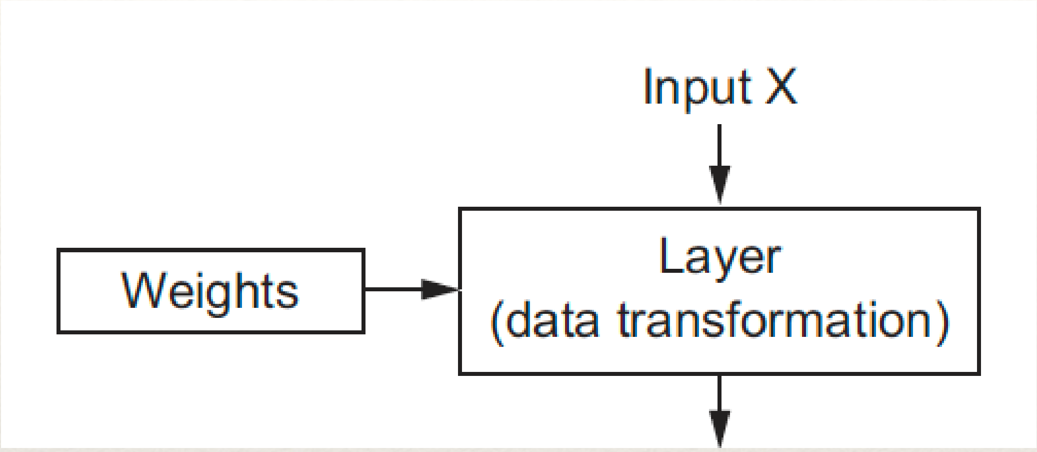
A *linear* data transformation might take the form:

$$W \cdot X + b$$

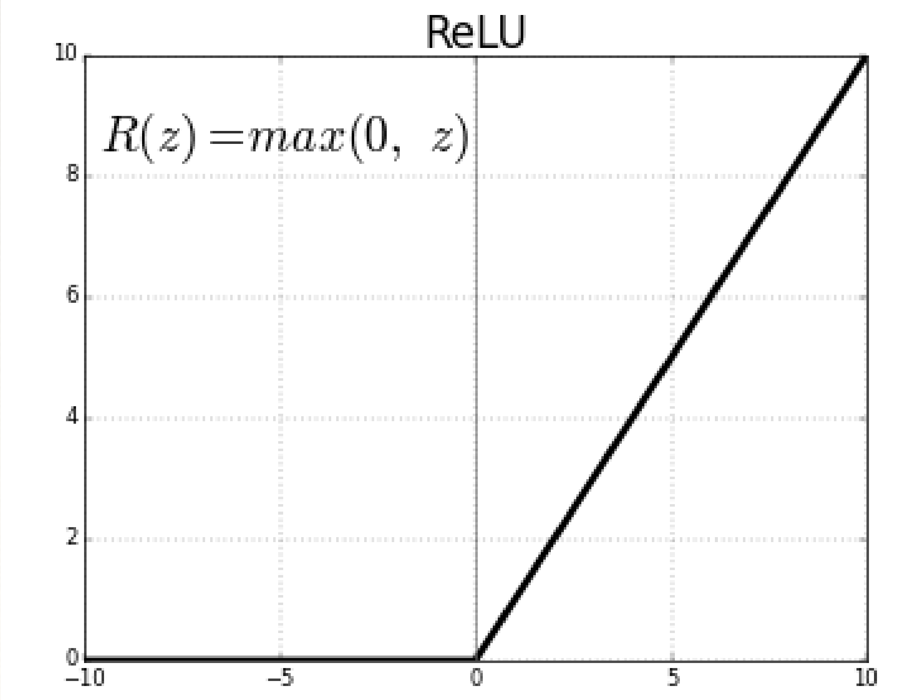
Chollet 2018

Artificial Neural Networks

Fully-connected artificial neural network

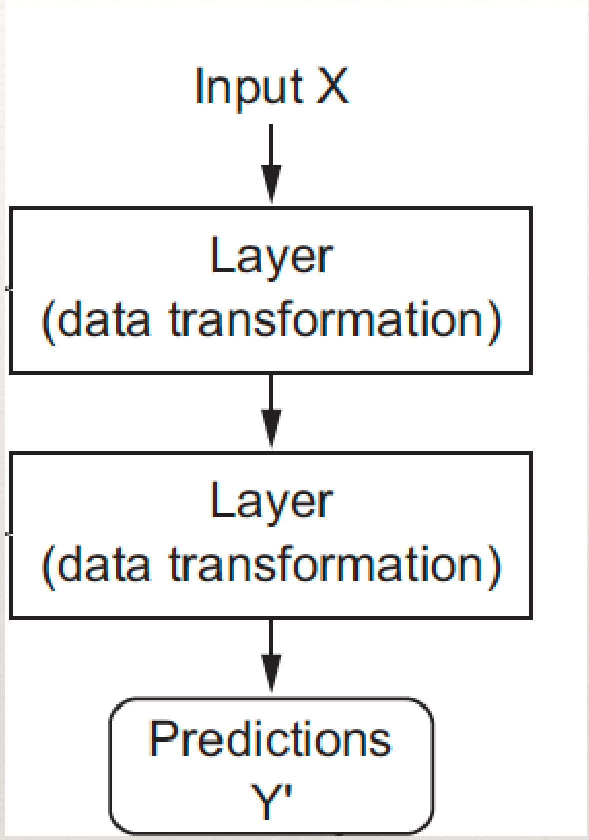


Neural network models introduce *non-linearity* into their transformations



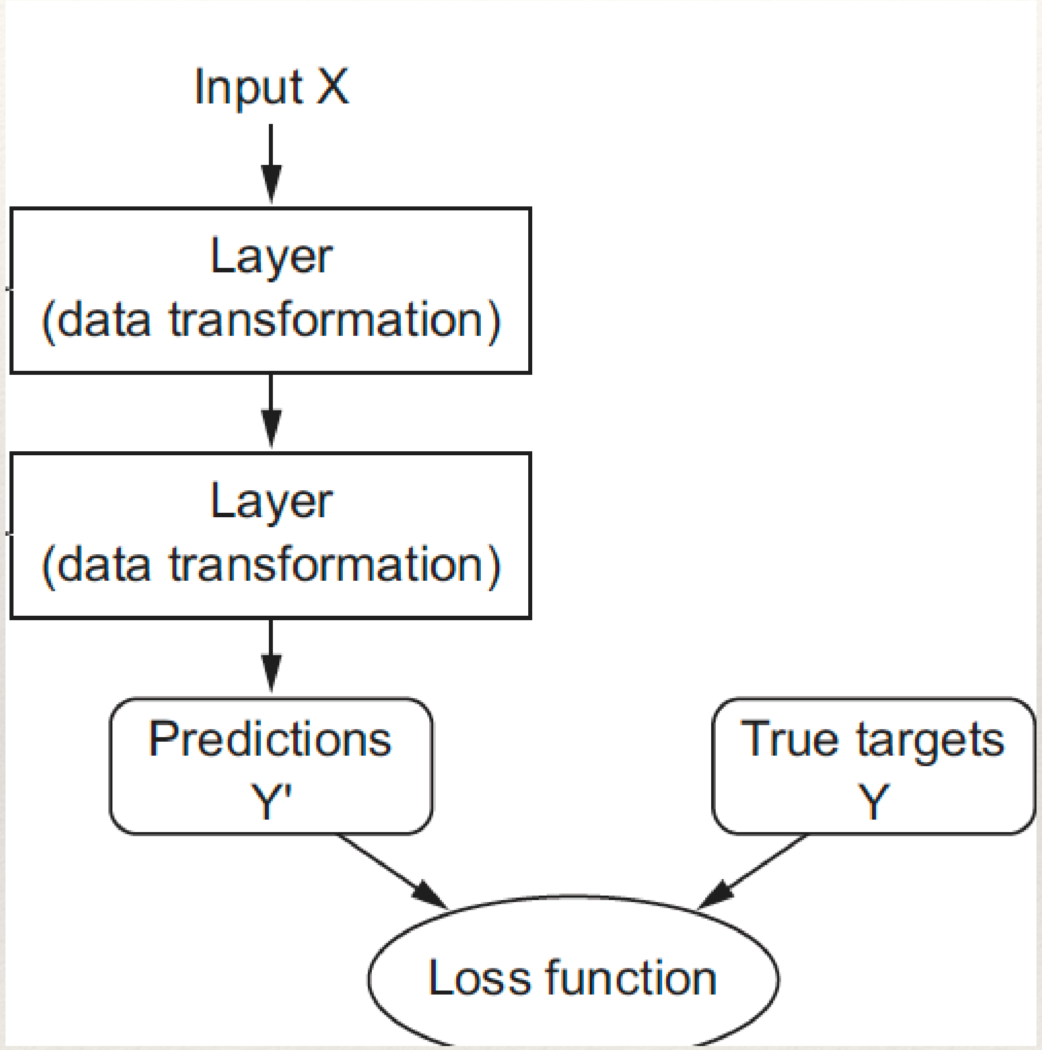
Chollet 2018

Artificial Neural Networks



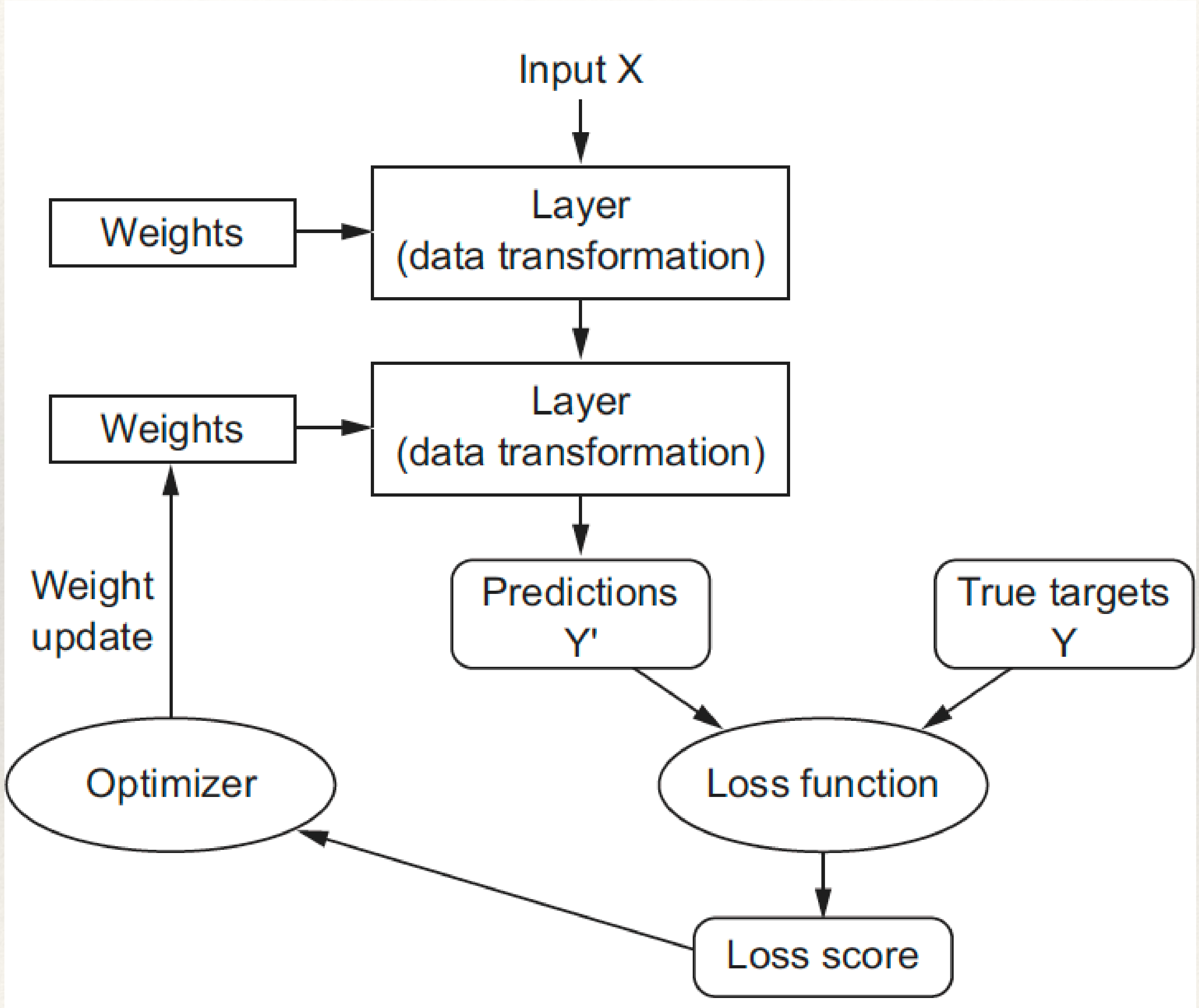
Chollet 2018

Artificial Neural Networks



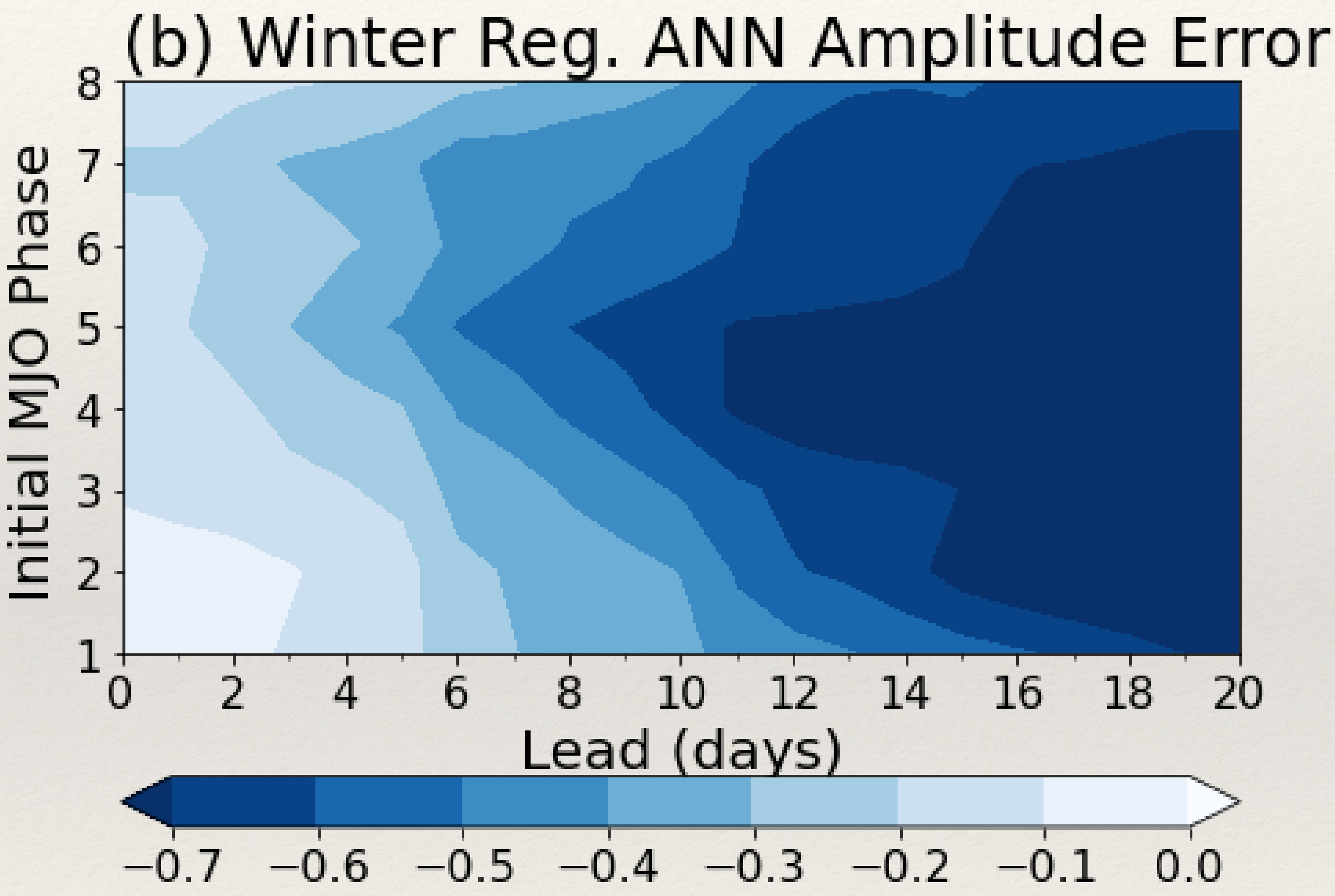
Chollet 2018

Artificial Neural Networks



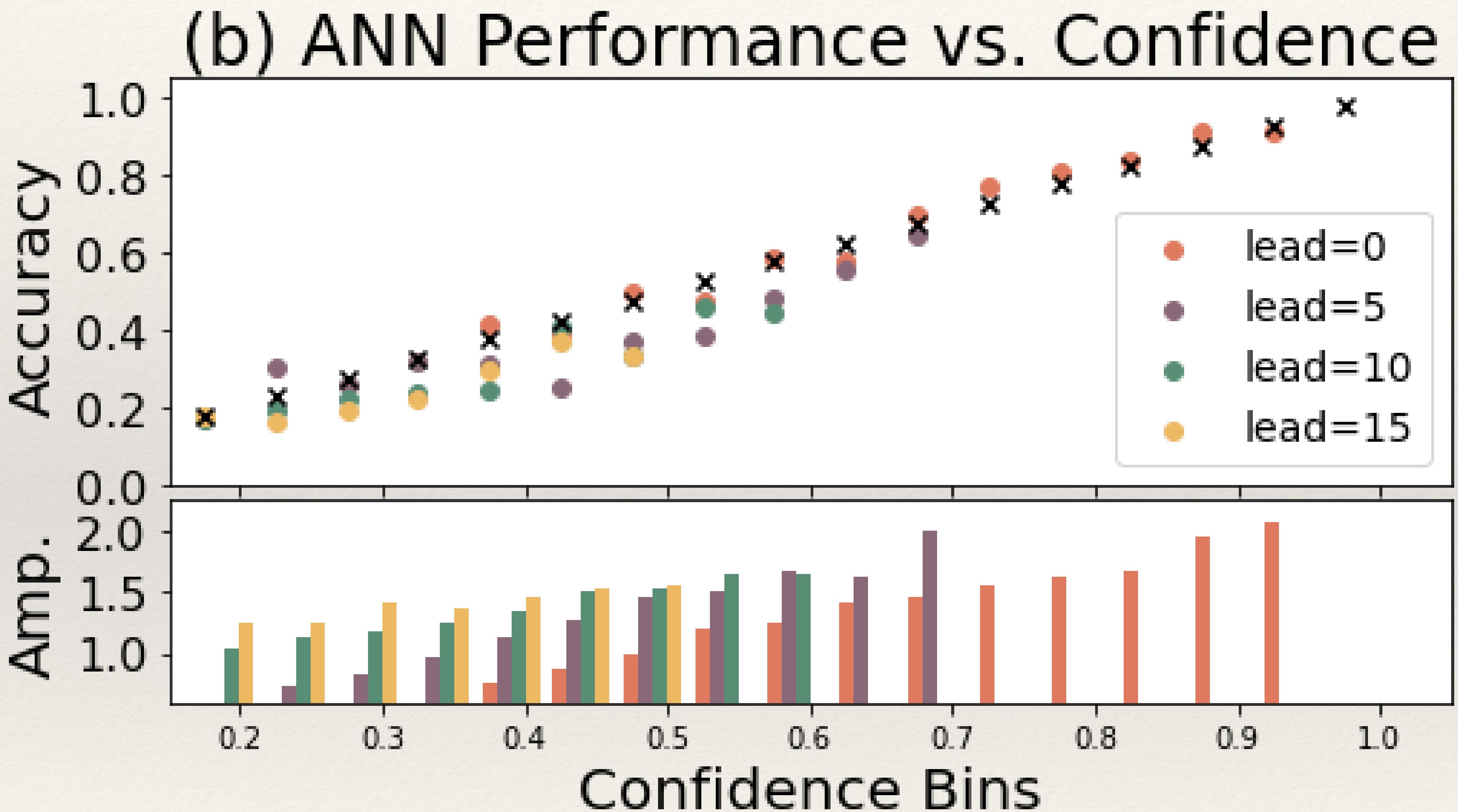
Chollet 2018

Regression ANN Model



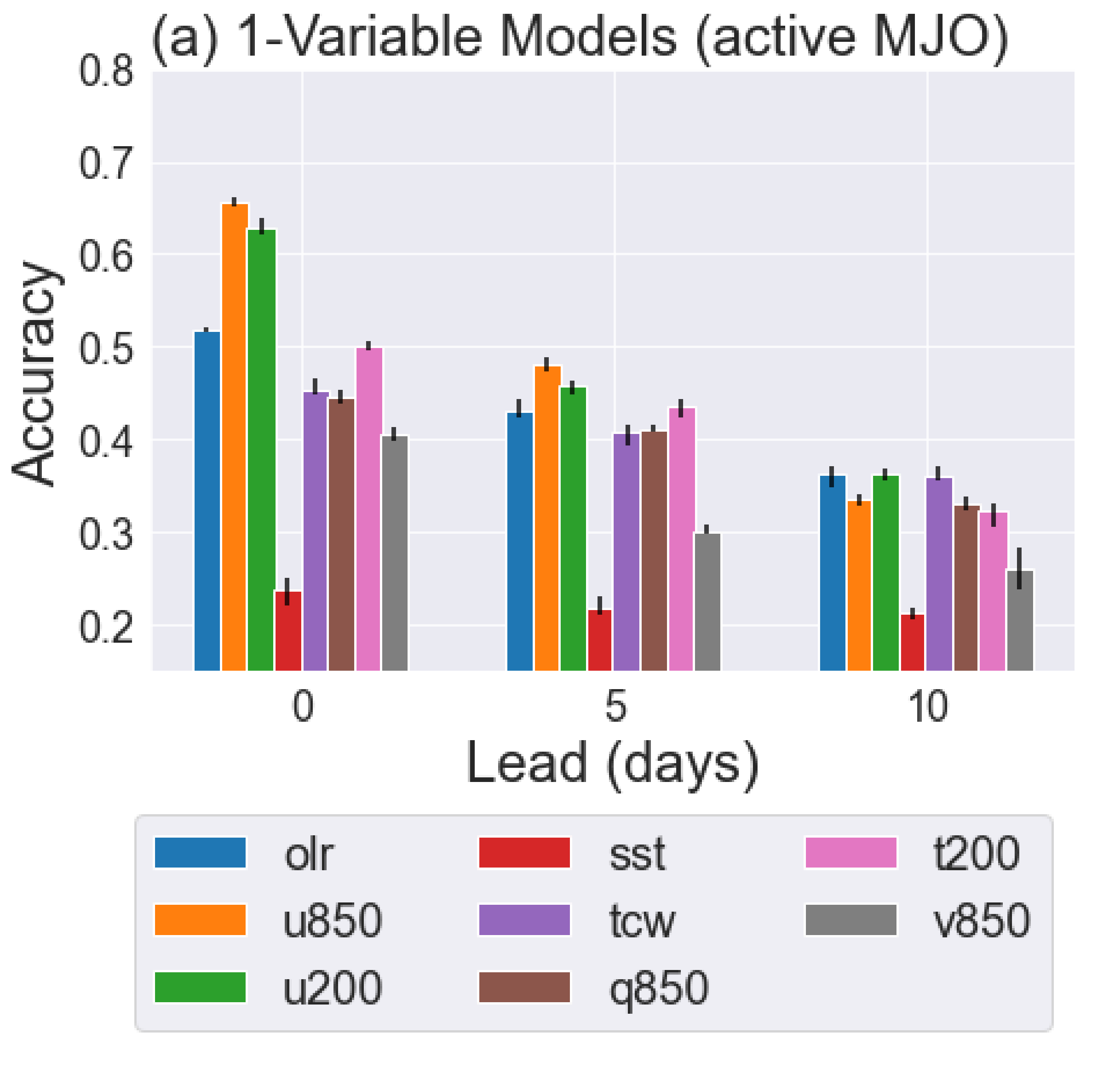
Martin et al. (2021; submitted)

Classification ANN Model



Martin et al. (2021; submitted)

A Machine-Learning Framework for the MJO

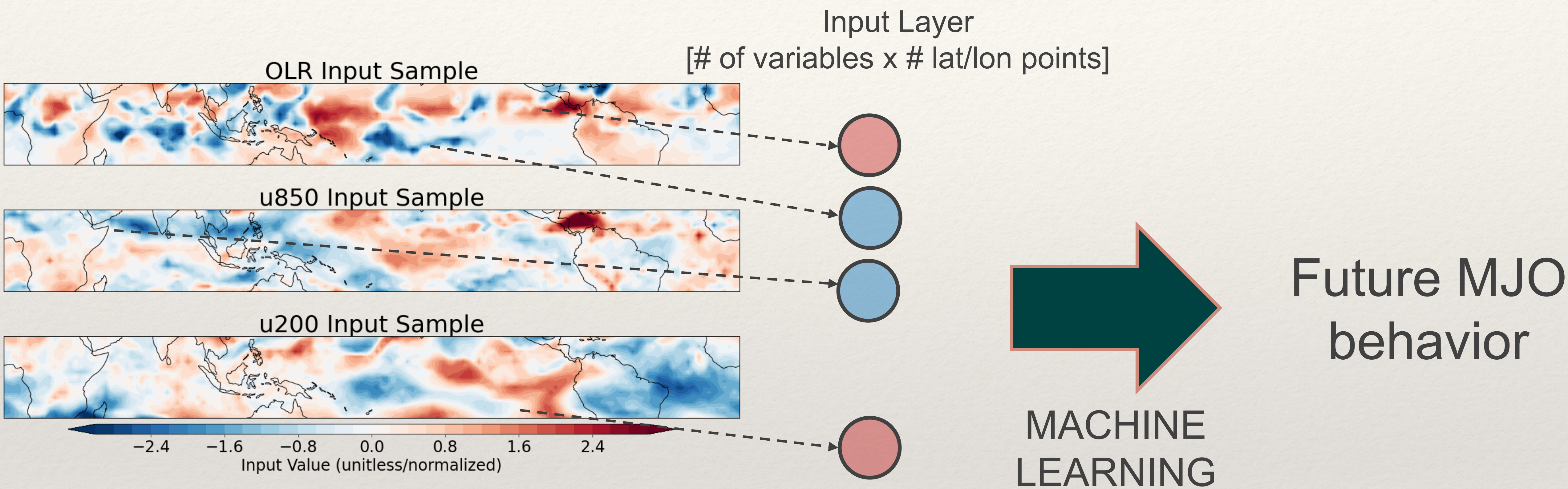


Martin et al. (2021; submitted)

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
Validation Data: Jan. 2010 – Nov. 2019

Machine Learning & the MJO

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Machine Learning & the MJO

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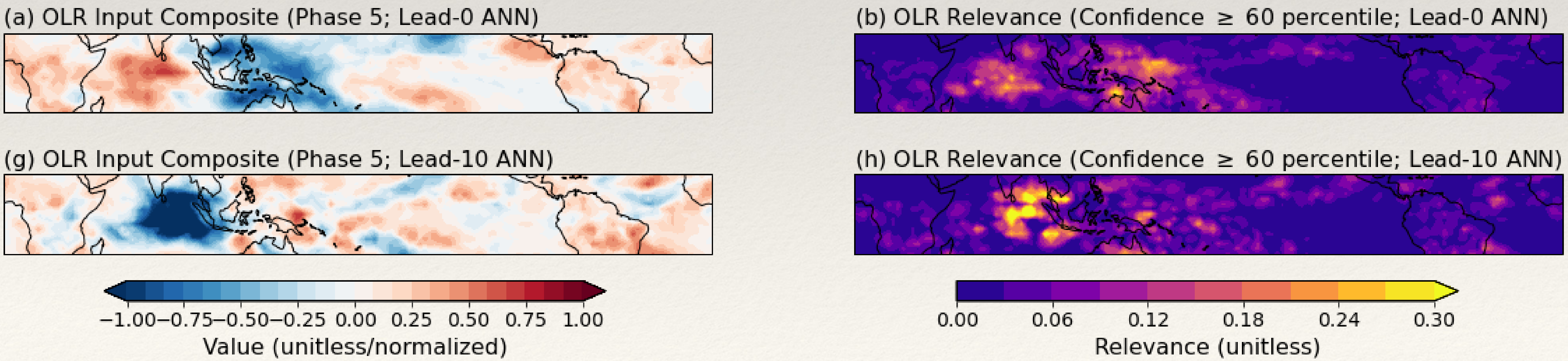
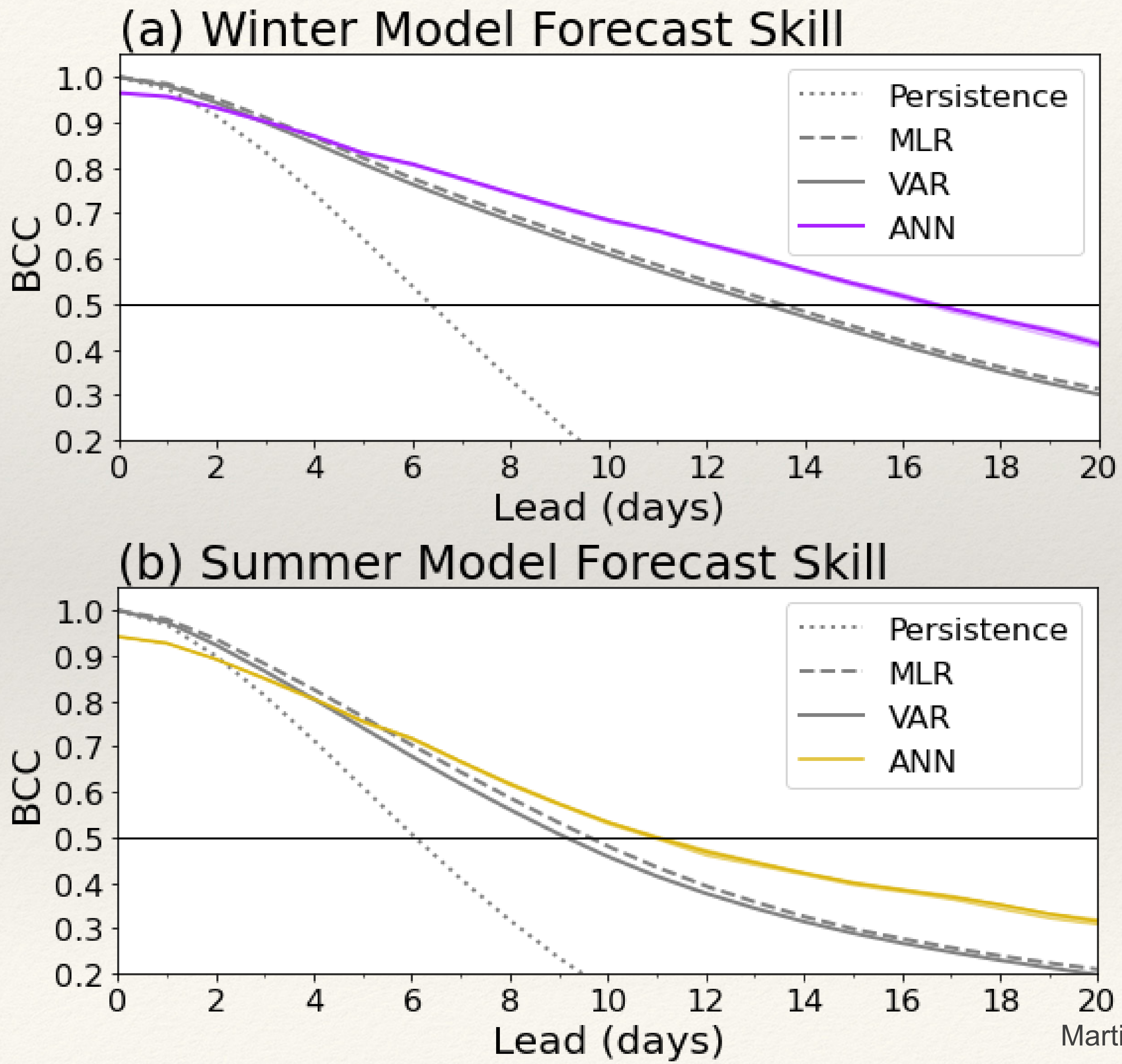


Machine Learning & the MJO

Thanks!

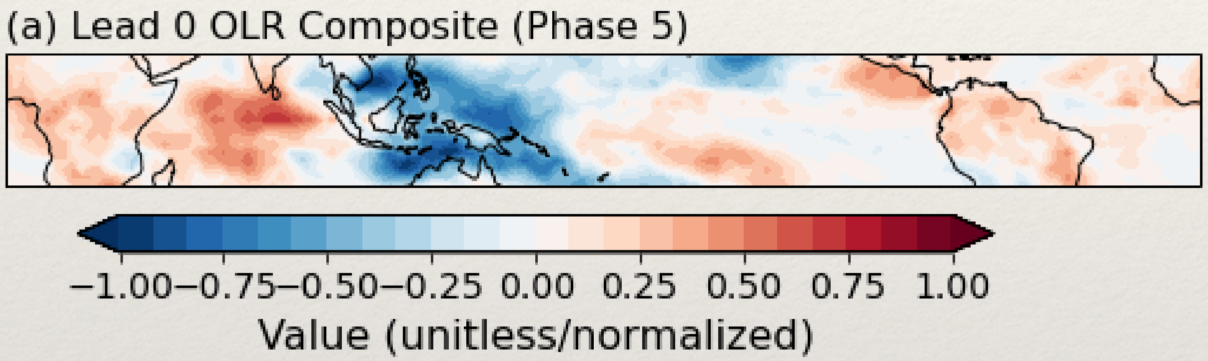
A Machine-Learning Framework for the MJO

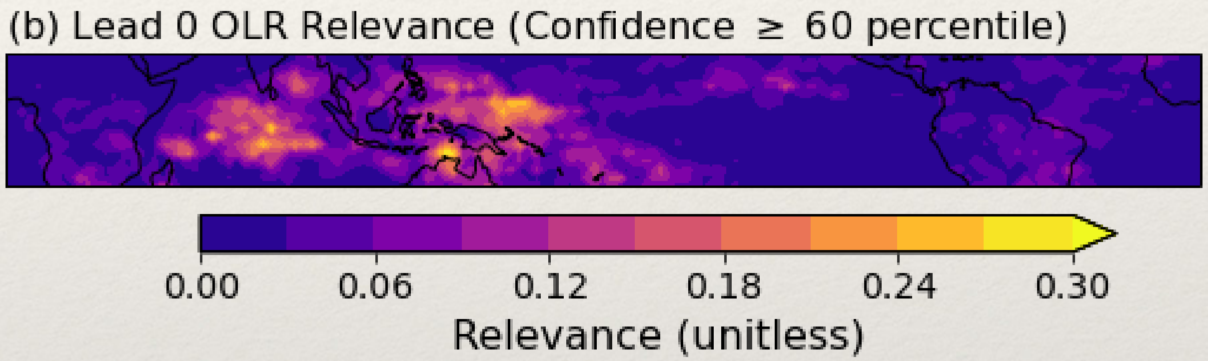


Martin et al. (2021; submitted)

A Machine-Learning Framework for the MJO

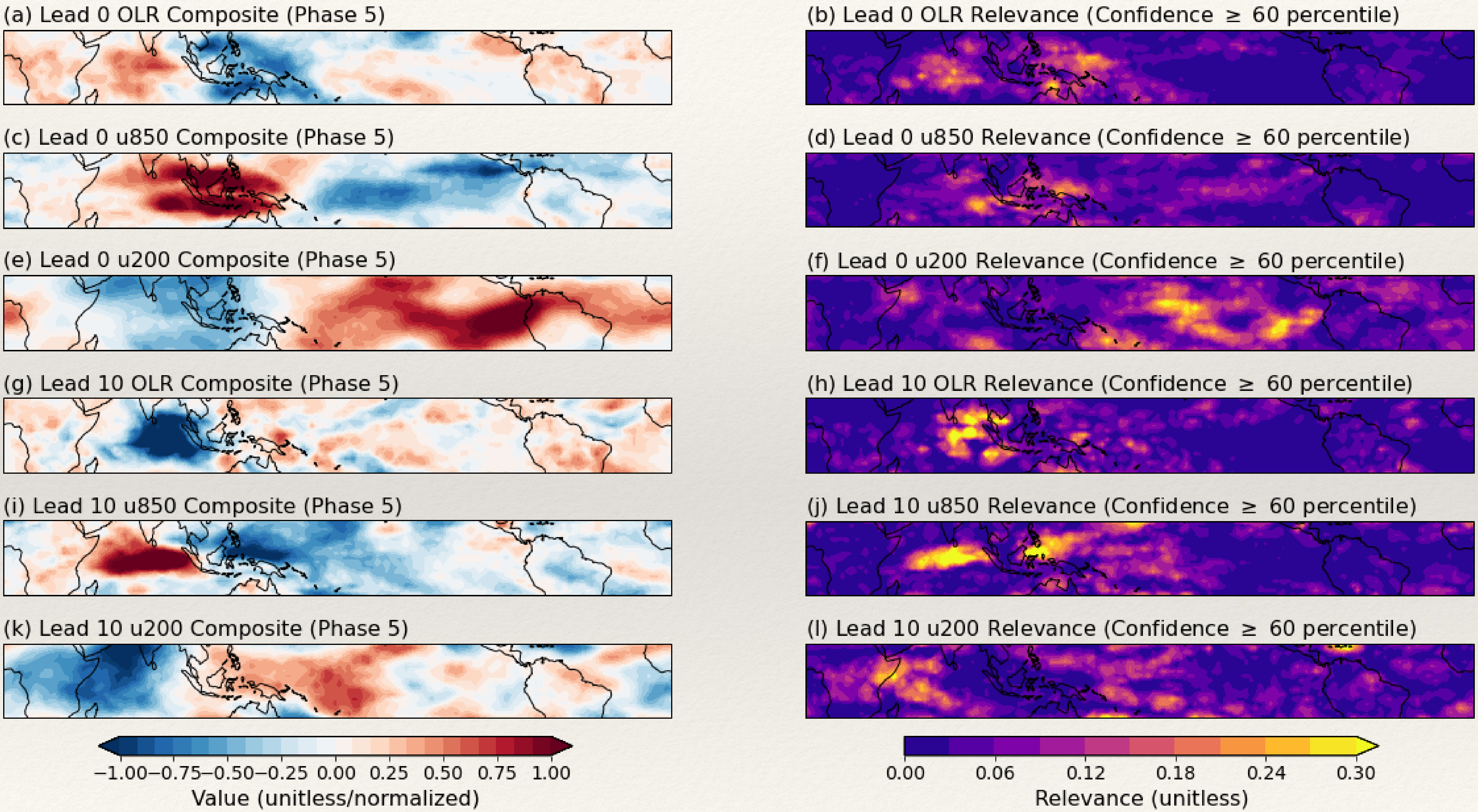
“Layerwise-relevance propagation” & other tools can help understand how the models work





Martin et al. (2021; submitted)

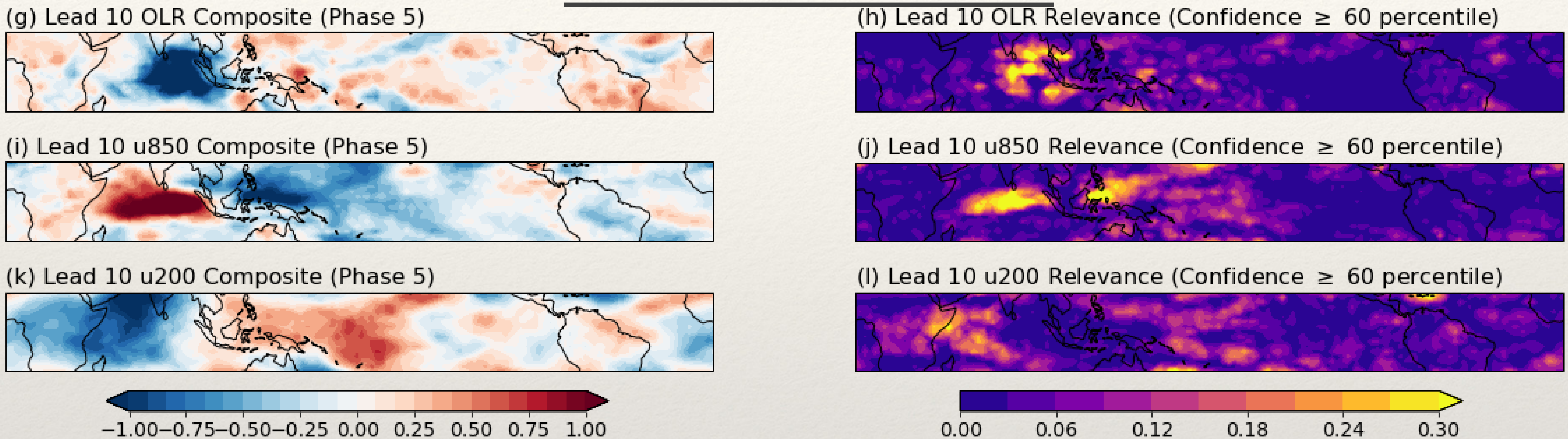
A Machine-Learning Framework for the MJO



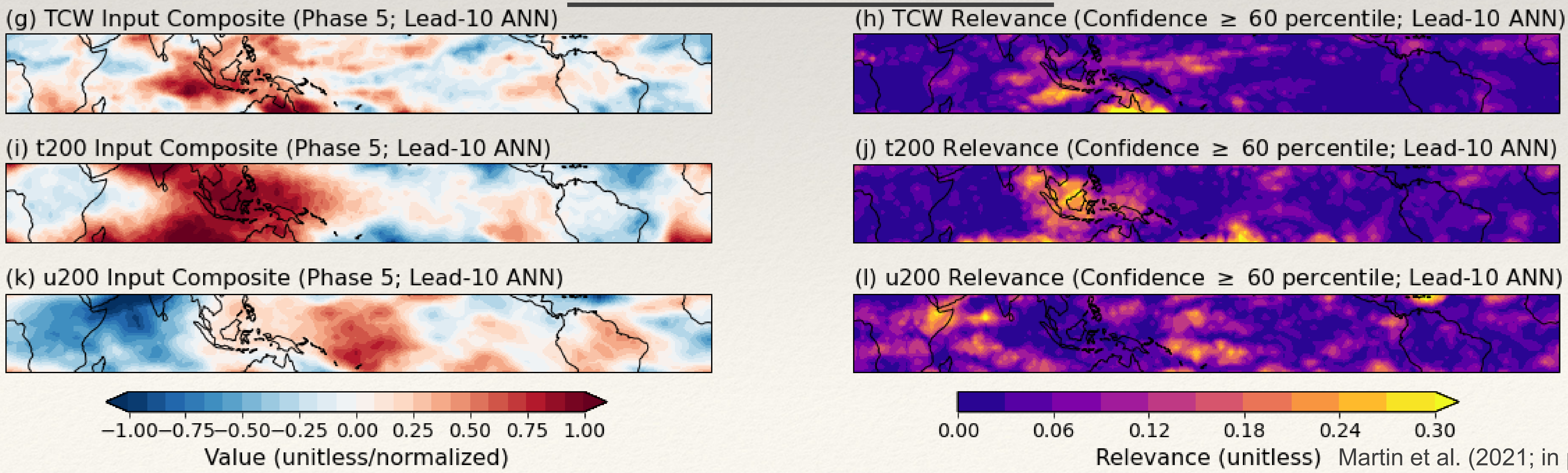
Martin et al. (2021; in prep)

A Machine-Learning Framework for the MJO

OLR + u850 + u200 Model

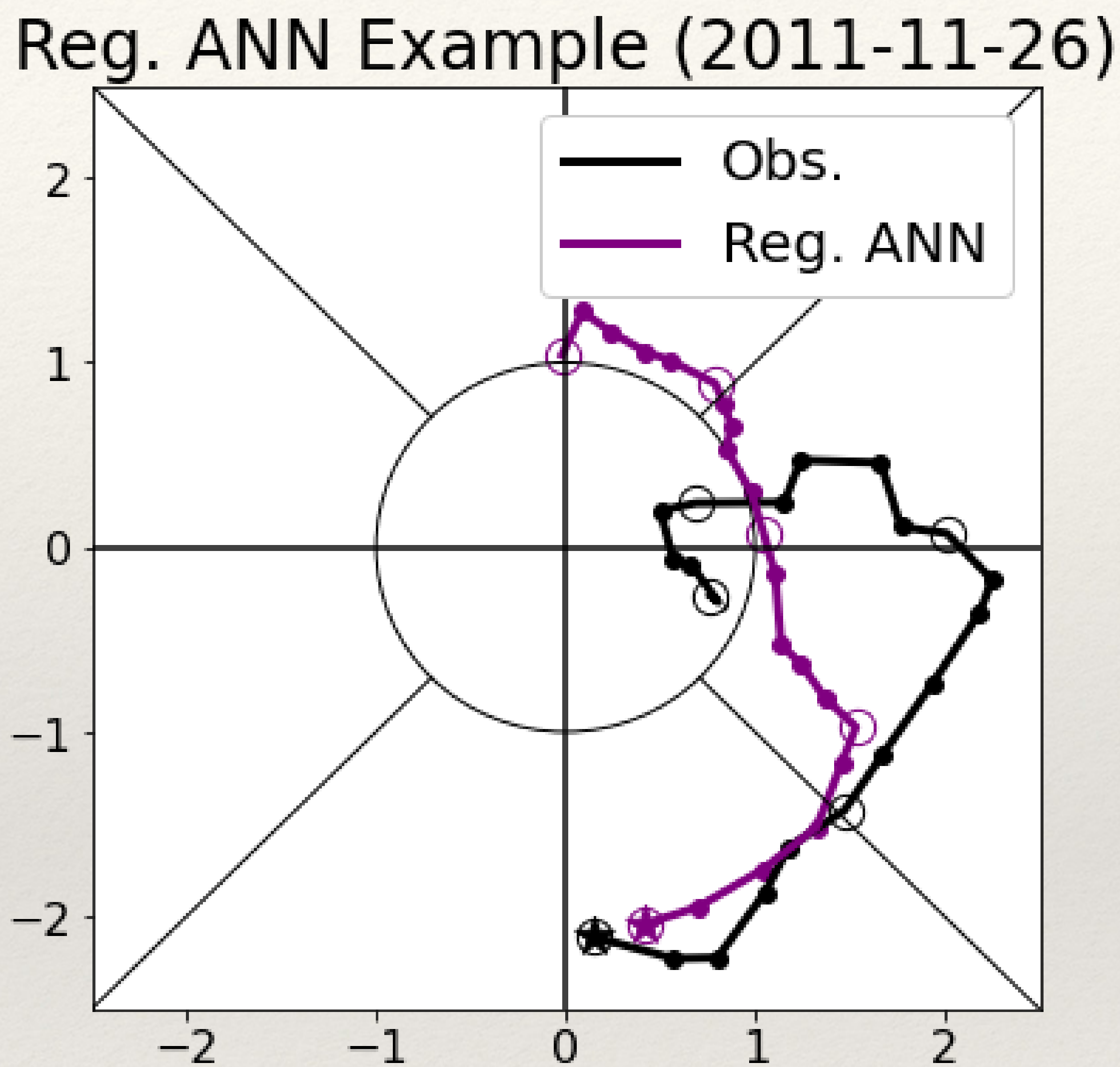


TCW + t200 + u200 Model



Martin et al. (2021; in prep)

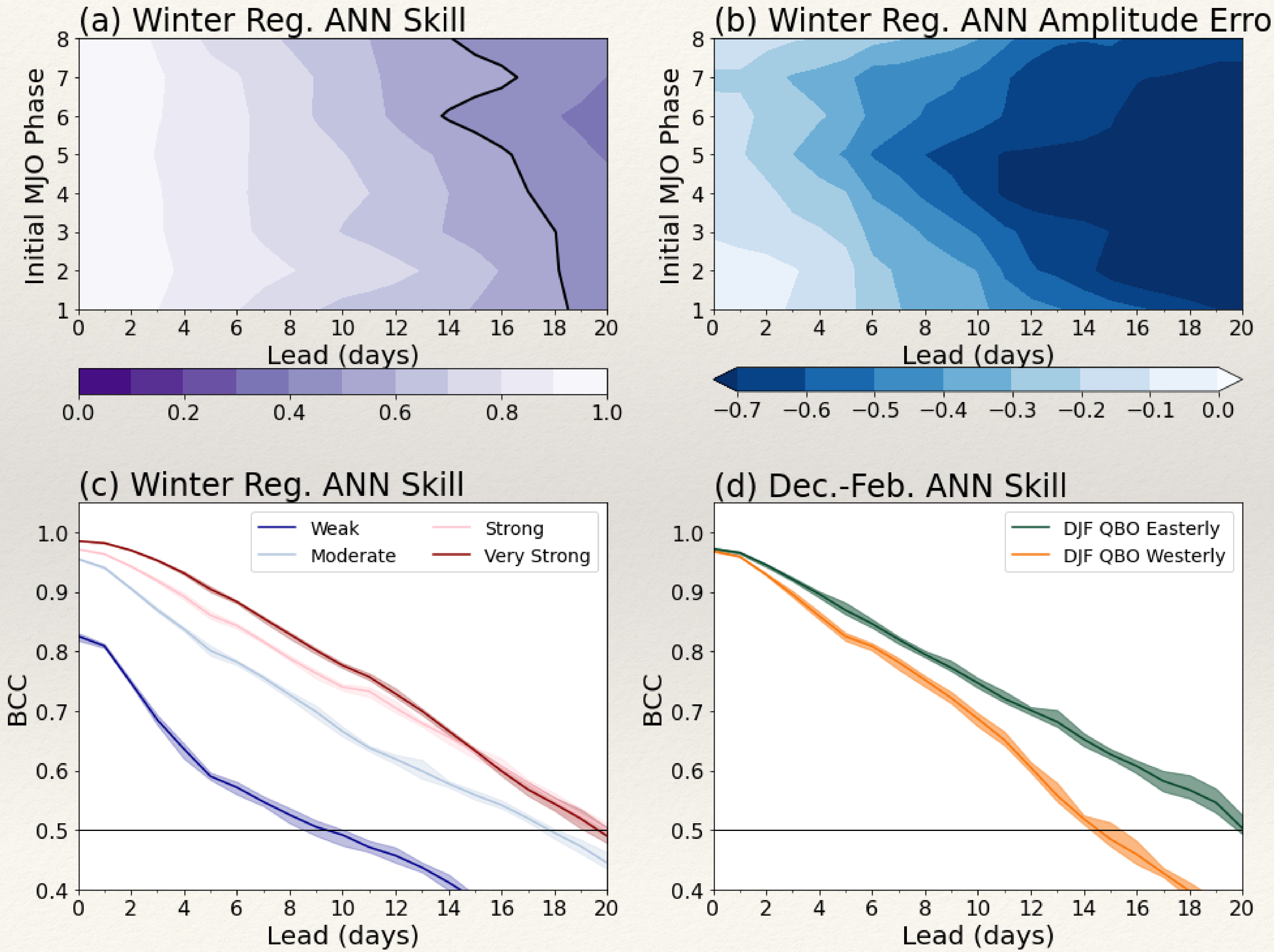
Machine Learning & the MJO

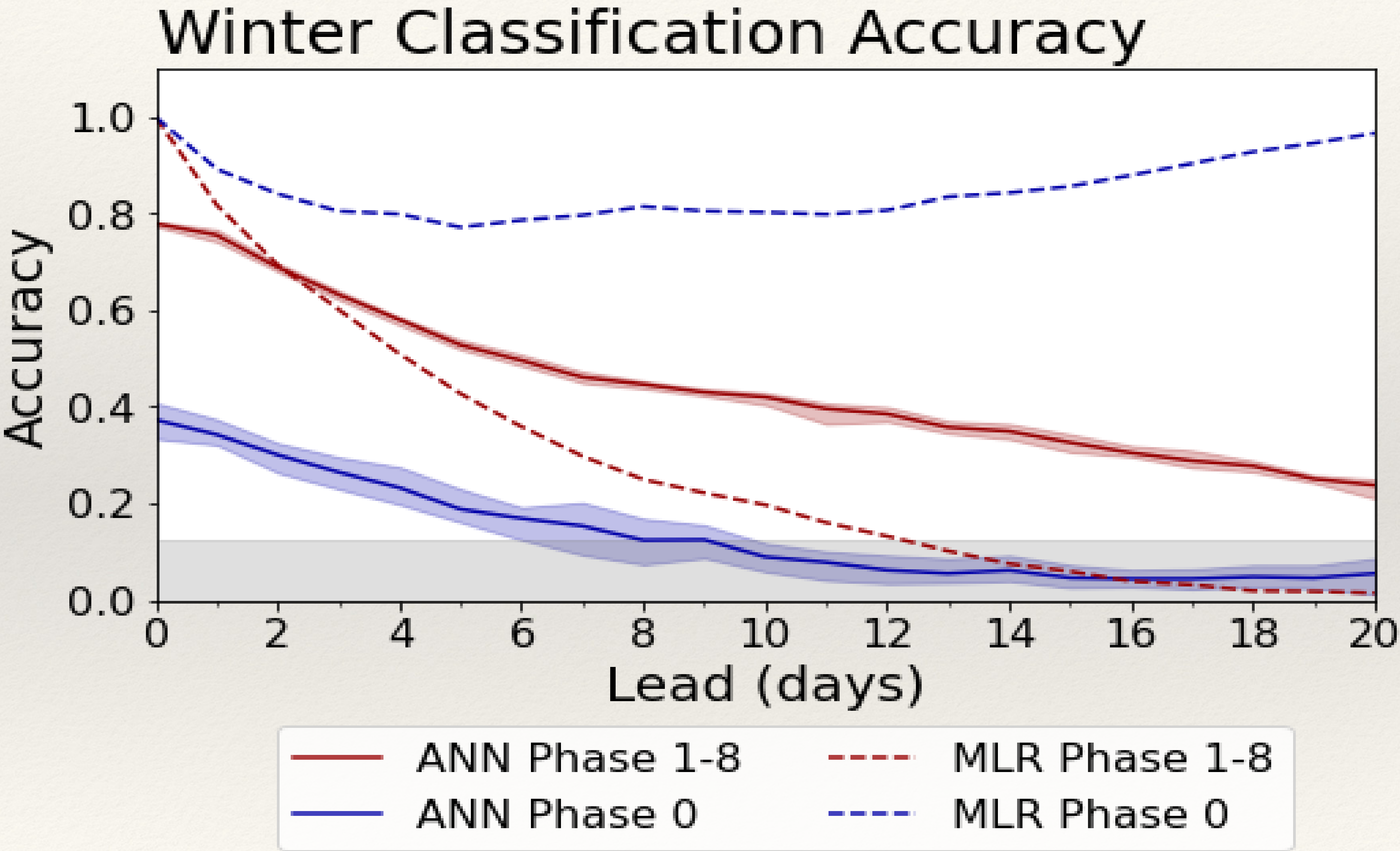


Regression Model

- A model which outputs *numerical values*

Martin et al. (2021; in prep)


(a) Winter Reg. ANN Skill
Initial MJO Phase
Lead (days)
0.0
0.2
0.4
0.6
0.8
1.0
(b) Winter Reg. ANN Amplitude Error
Initial MJO Phase
Lead (days)
−0.7
−0.6
−0.5
−0.4
−0.3
−0.2
−0.1
0.0
(c) Winter Reg. ANN Skill
Weak
Moderate
Strong
Very Strong
BCC
Lead (days)
(d) Dec.-Feb. ANN Skill
DJF QBO Easterly
DJF QBO Westerly
BCC
Lead (days)


Winter Classification Accuracy
Accuracy
1.0
0.8
0.6
0.4
0.2
0.0
0
2
4
6
8
10
12
14
16
18
20
Lead (days)
ANN Phase 1-8
ANN Phase 0
MLR Phase 1-8
MLR Phase 0

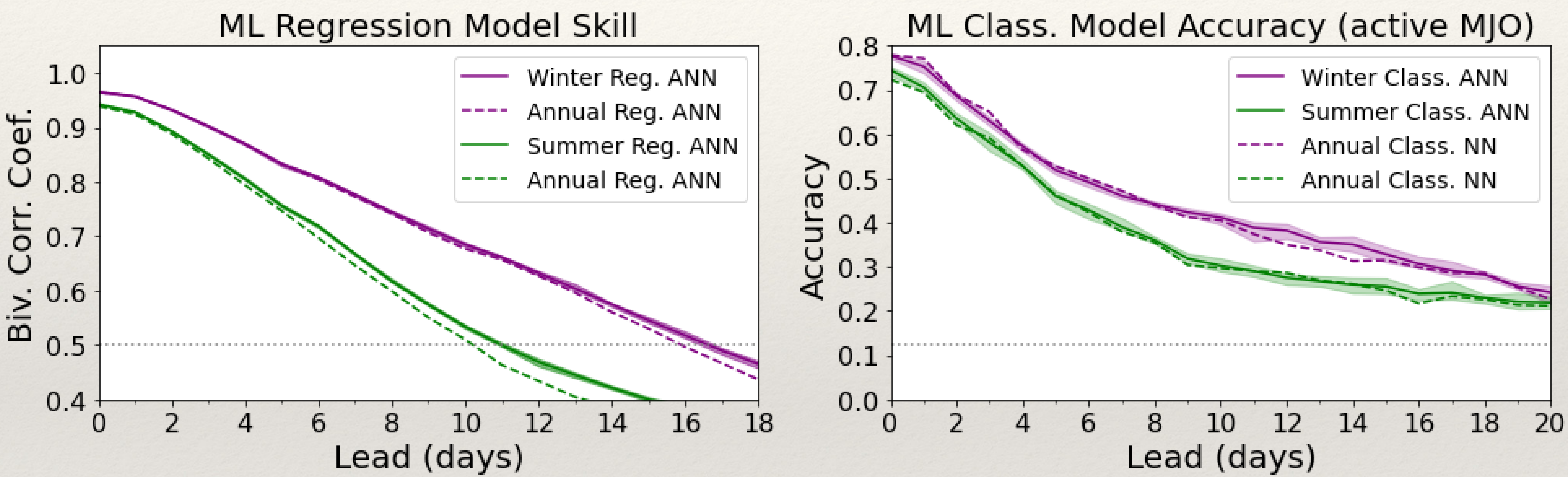

ML Regression Model Skill
Biv. Corr. Coef.
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0
2
4
6
8
10
12
14
16
18
Lead (days)
Winter Reg. ANN
Annual Reg. ANN
Summer Reg. ANN
Annual Reg. ANN
ML Class. Model Accuracy (active MJO)
Accuracy
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0
2
4
6
8
10
12
14
16
18
20
Lead (days)
Winter Class. ANN
Summer Class. ANN
Annual Class. NN
Annual Class. NN

Figure S3

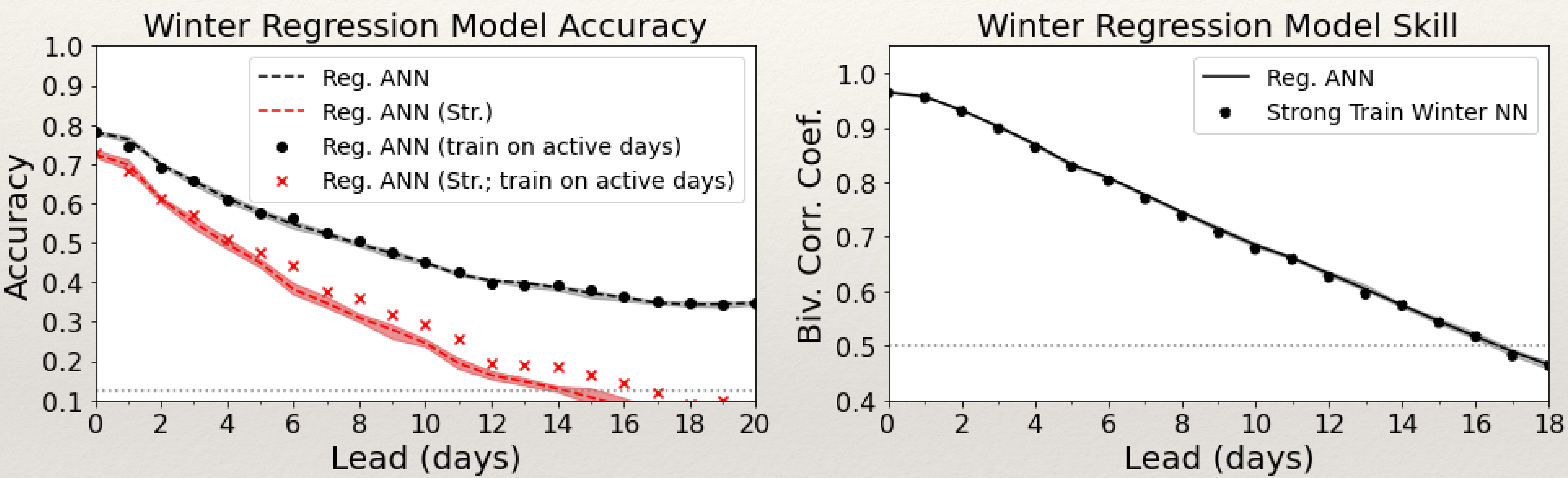
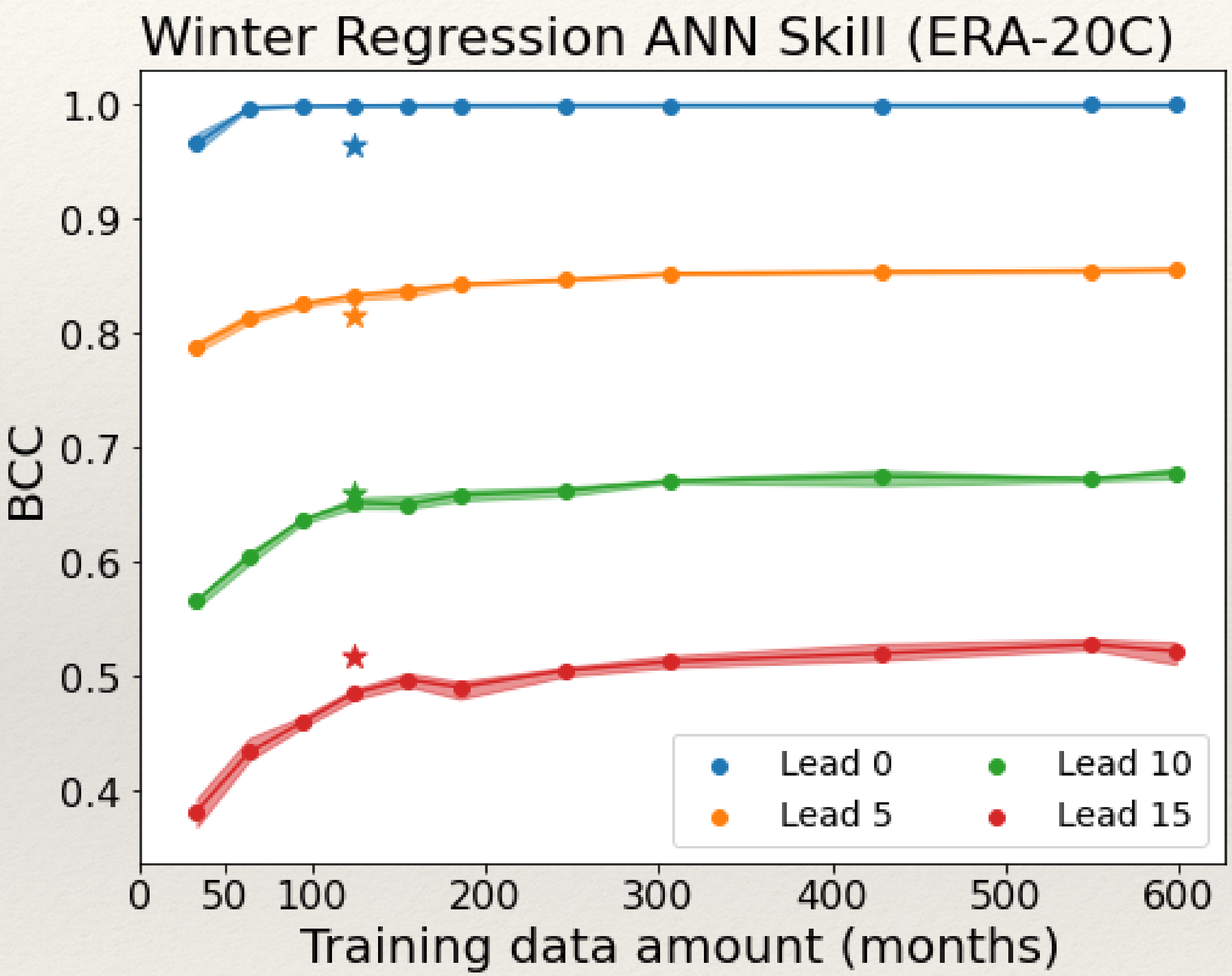


Figure S6: Strong training


Winter Regression ANN Skill (ERA-20C)
BCC
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0
50
100
200
300
400
500
600
Training data amount (months)
Lead 0
Lead 5
Lead 10
Lead 15

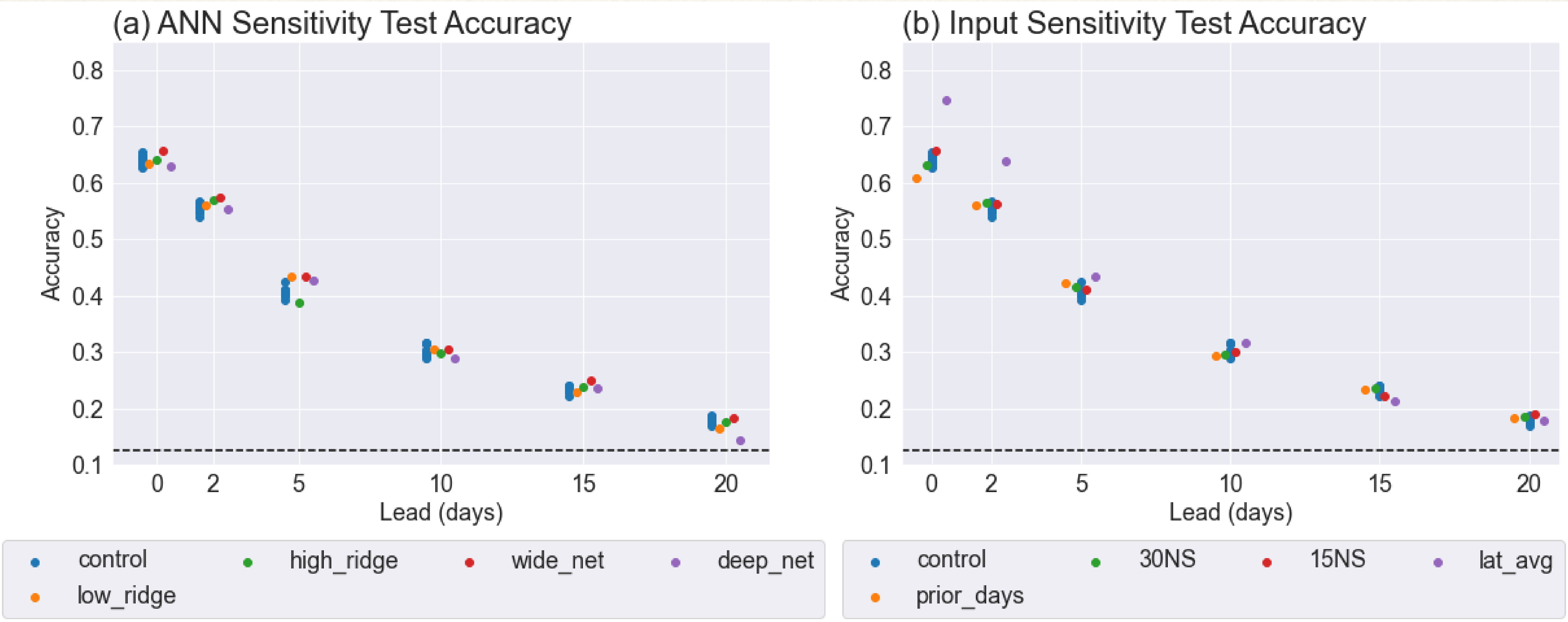


Figure S7: sensitivity tests

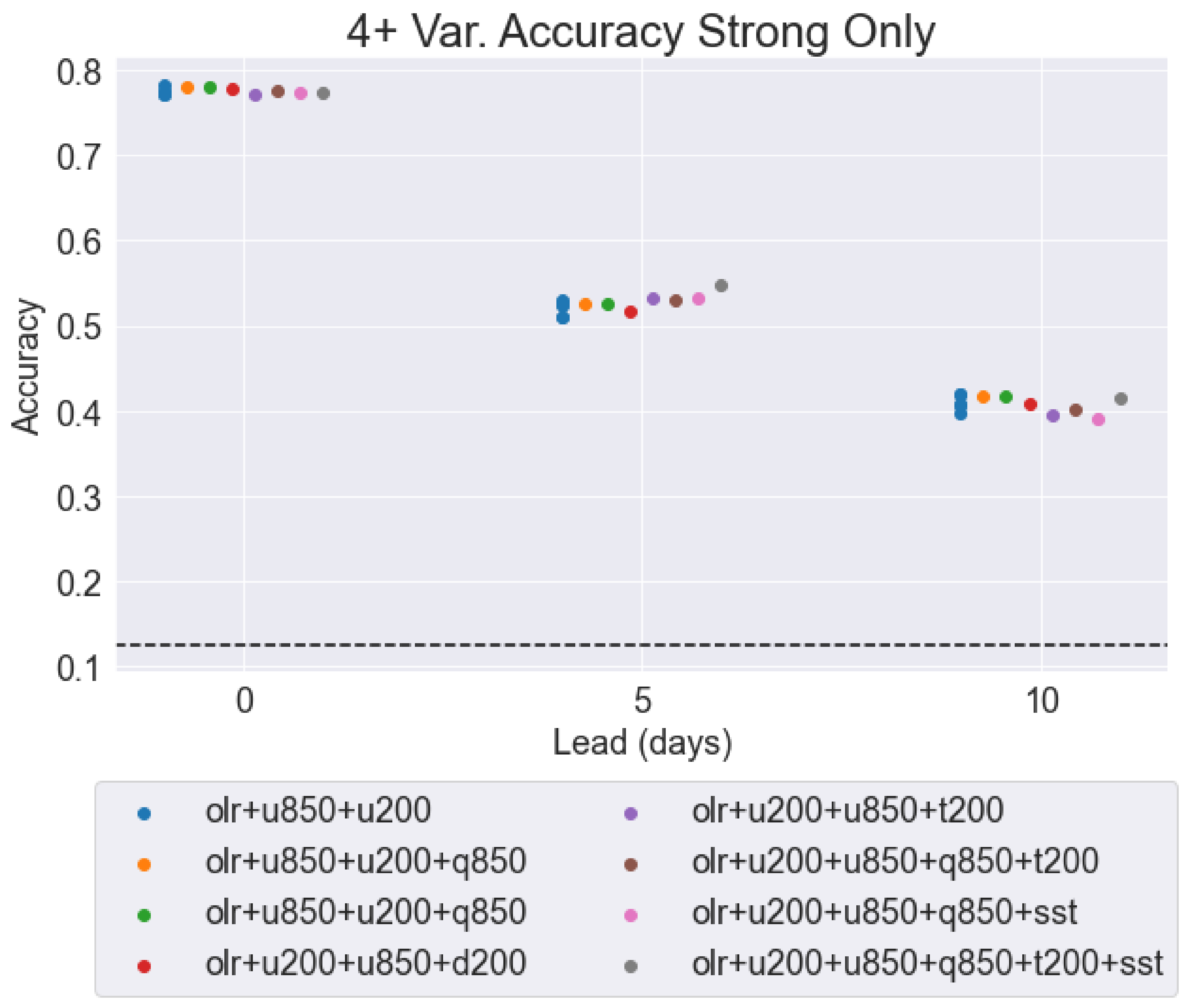


Fig. S11: Additional variable tests of combinations of 4, 5, or 6 inputs

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

$$RMM1(t_0 + \tau) = RMM1(t_0)$$
$$RMM2(t_0 + \tau) = RMM2(t_0)$$

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)

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

MLR used to calculate **L** in each season

Marshall et al. 2016:

$$\mathrm{RMM1}_t = 0.9616\ (\mathrm{RMM1}_{t-1}) - 0.1135\ (\mathrm{RMM2}_{t-1})$$

$$\mathrm{RMM2}_t = 0.1257\ (\mathrm{RMM1}_{t-1}) + 0.9875\ (\mathrm{RMM2}_{t-1})$$

M21 "**L**":

```
LR.coef_
```

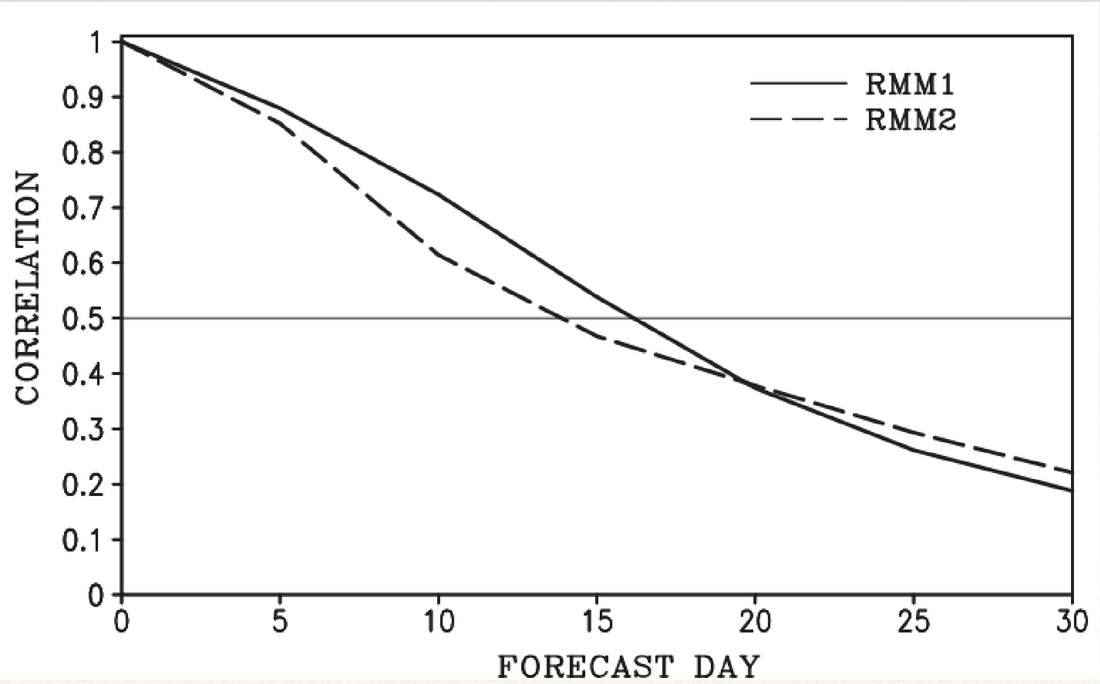
```
array([[ 0.96745844, -0.11490354],
       [ 0.12136748,  0.98466266]])
```

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 τ 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).

$$\begin{bmatrix} RMM1(t_0+\tau) \\ RMM2(t_0+\tau) \end{bmatrix} = \boldsymbol{L}_\tau \quad \Sigma_{j=1} \begin{bmatrix} RMM1(t_0-j+1) \\ RMM2(t_0-j+1) \end{bmatrix}$$

Kang & Kim 2010



Present MLR model (different train/validation period