Subseasonal to Seasonal (S2S) Forecasting at Colorado State University: Leveraging the QBO and MJO

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Brandon Wolding
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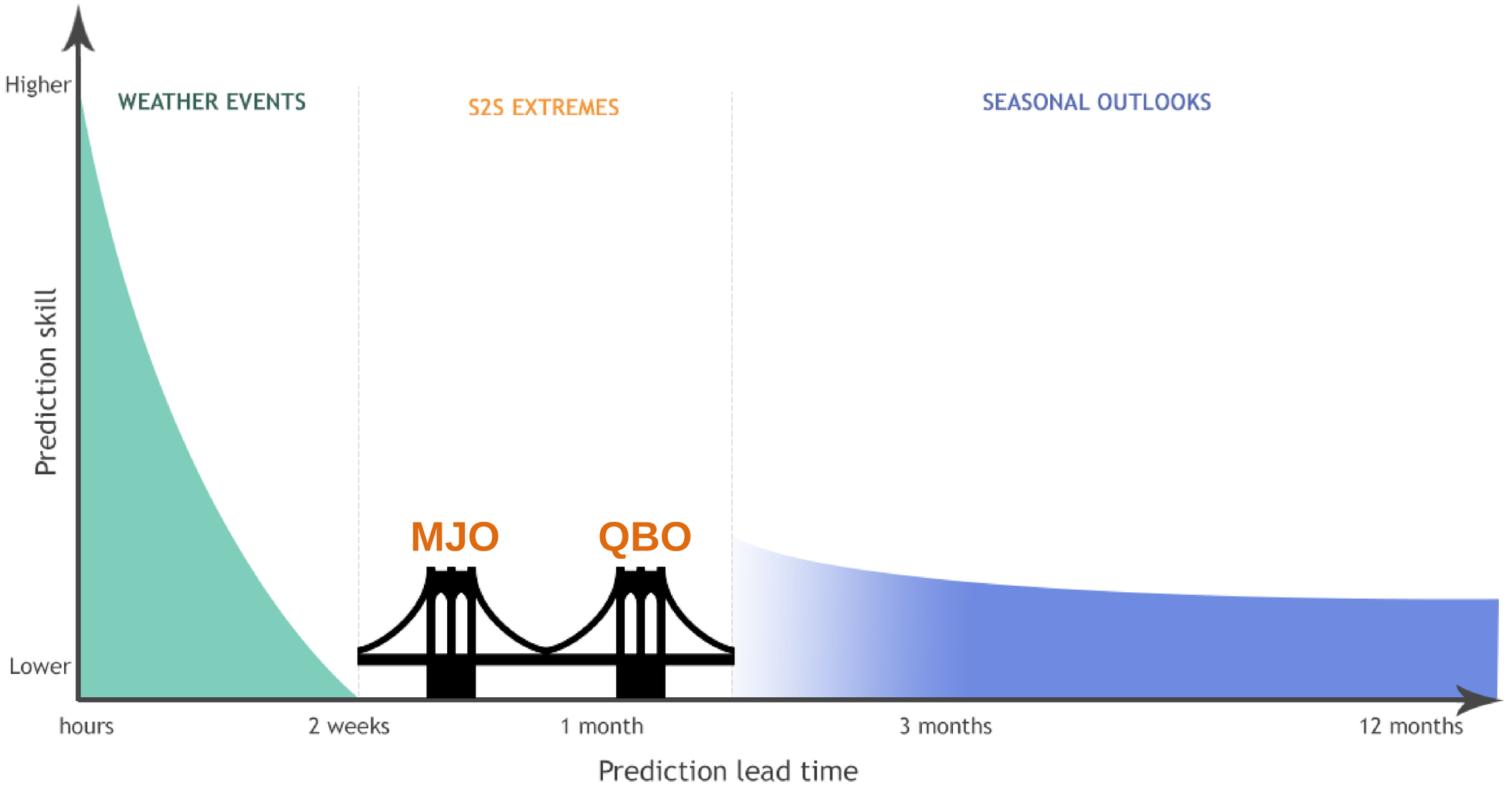
Forecast Gap at Weeks-to-Months

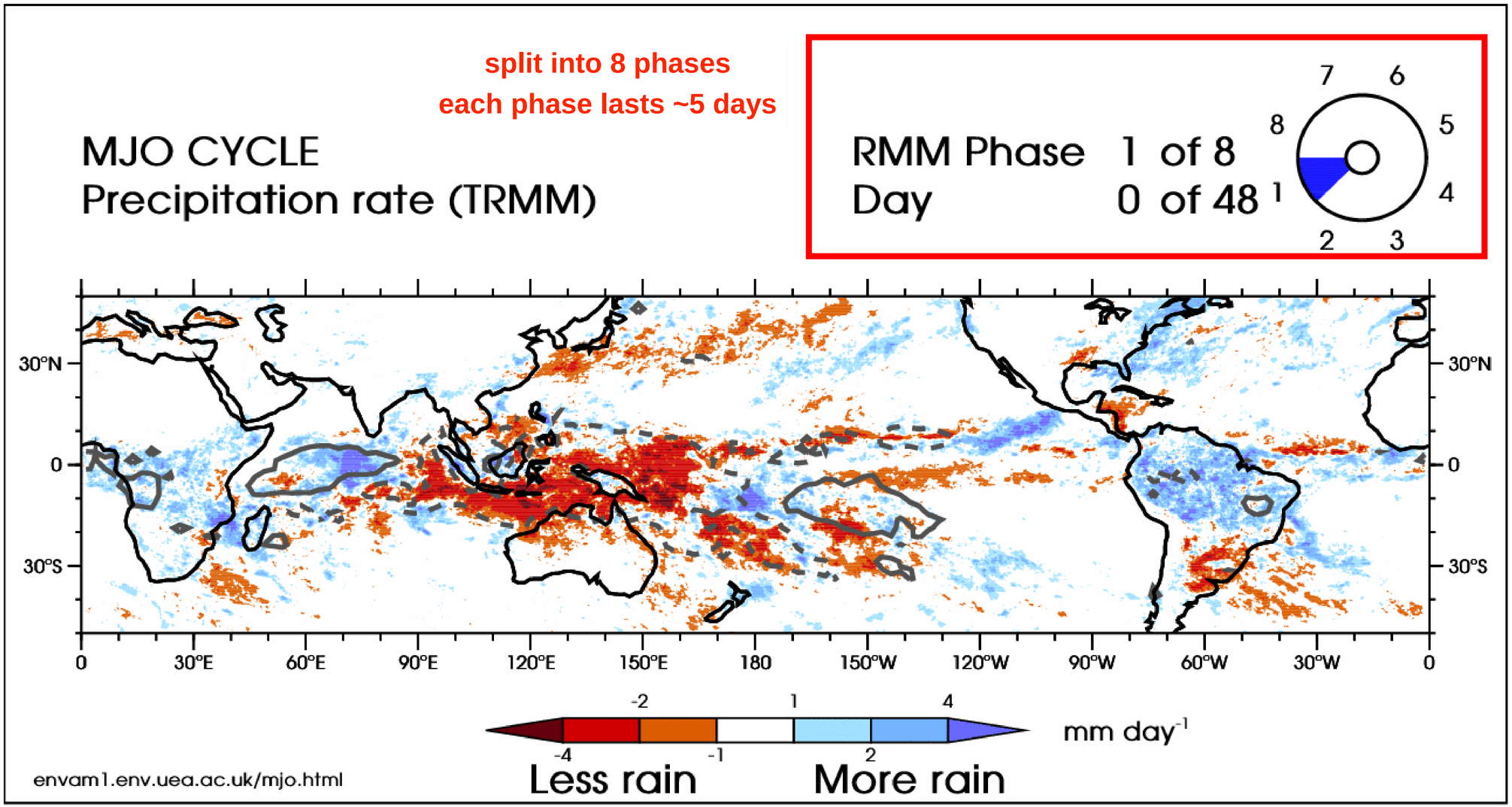


NOAA CPO image
text from Earth System Prediction Capability Office and National Academy Report

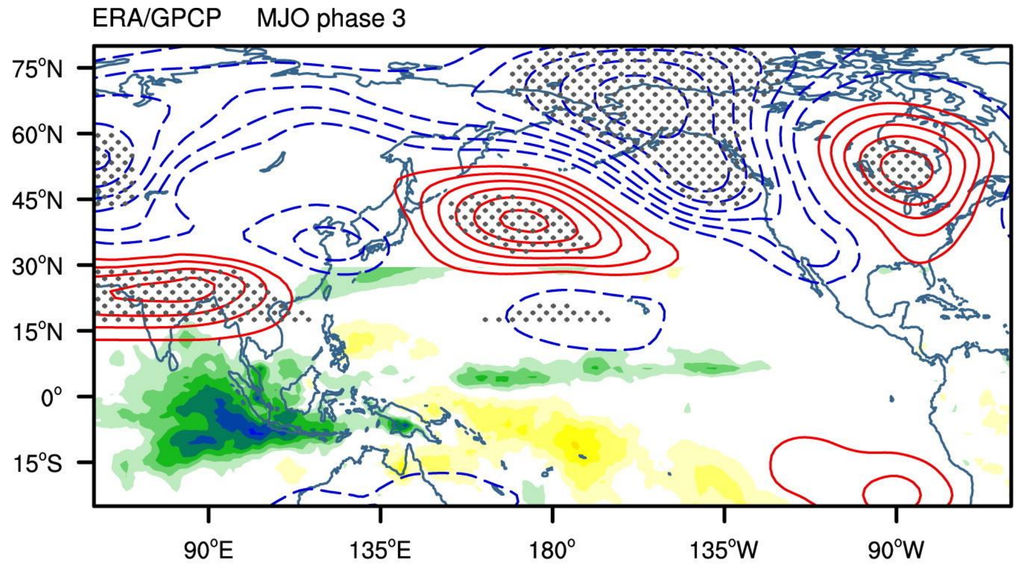
Adapted from: iri.columbia.edu/news/qa-subseasonal-prediction-project

The Madden Julian Oscillation (MJO) as a source of predictability

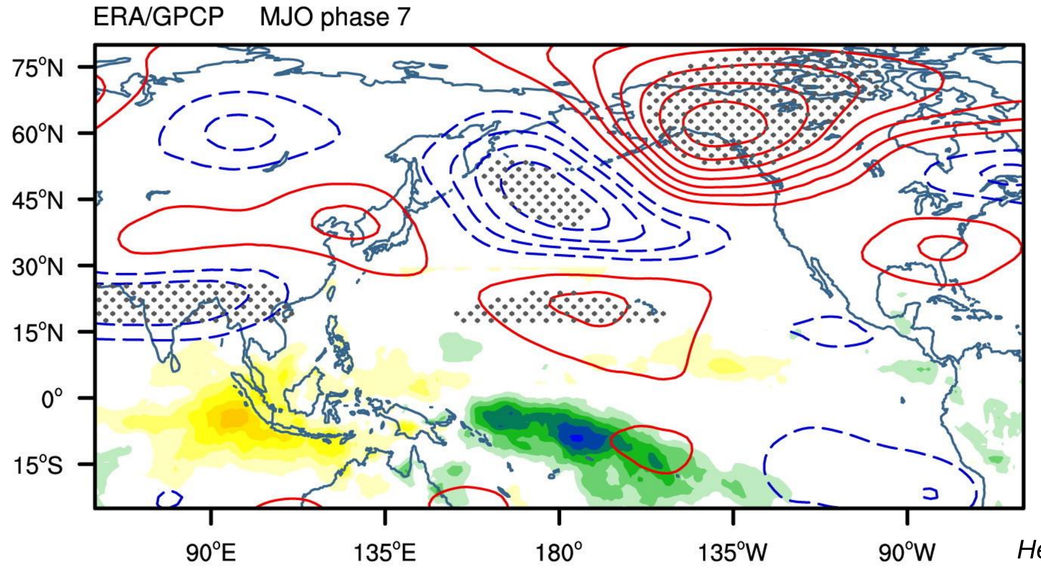
We can look to the tropics for sources of predictability of *anomalous AR activity*.



The MJO Forces Pacific/North American Pressure Fluctuations



MJO “Phase 3”

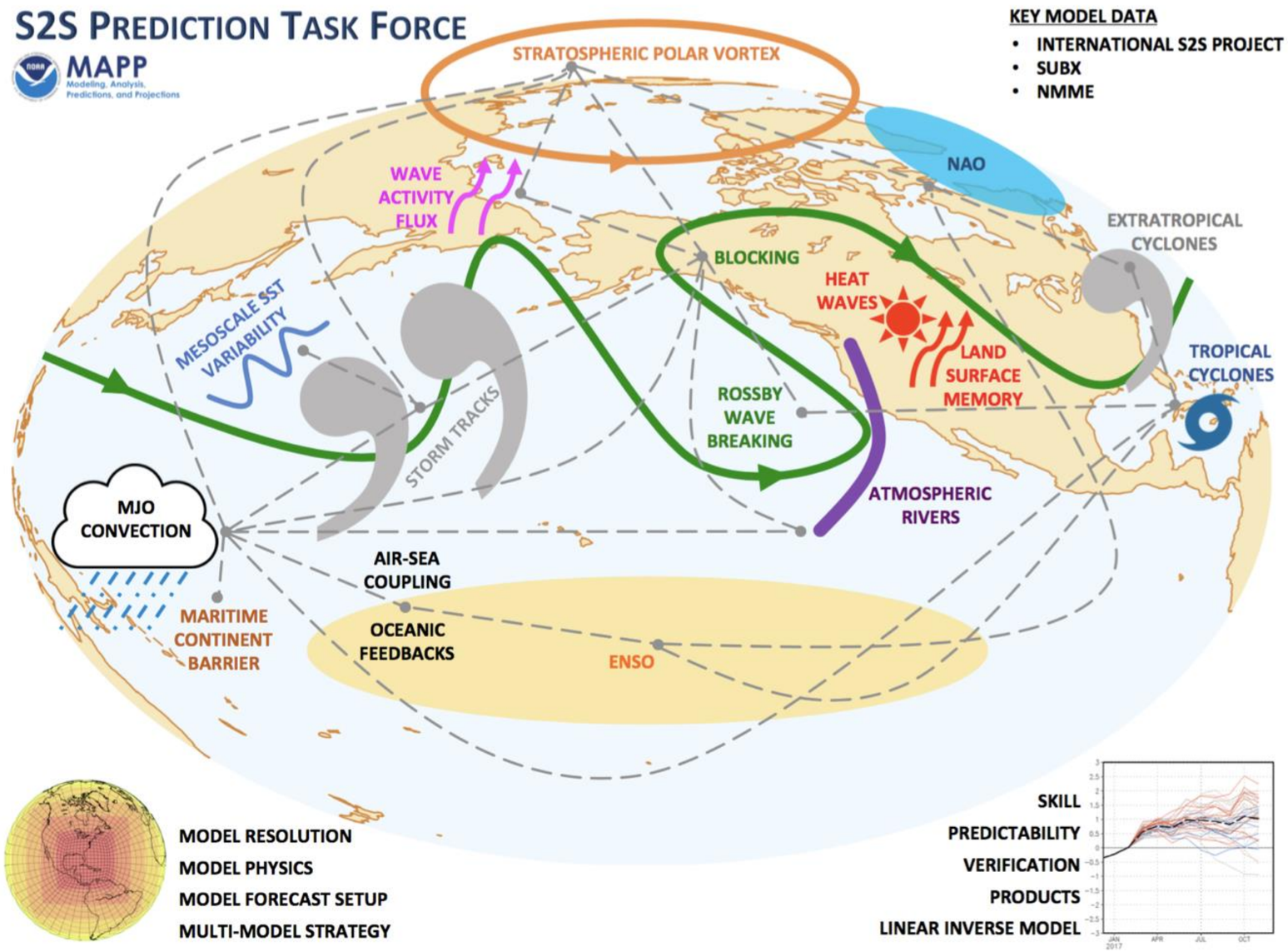


MJO “Phase 7”

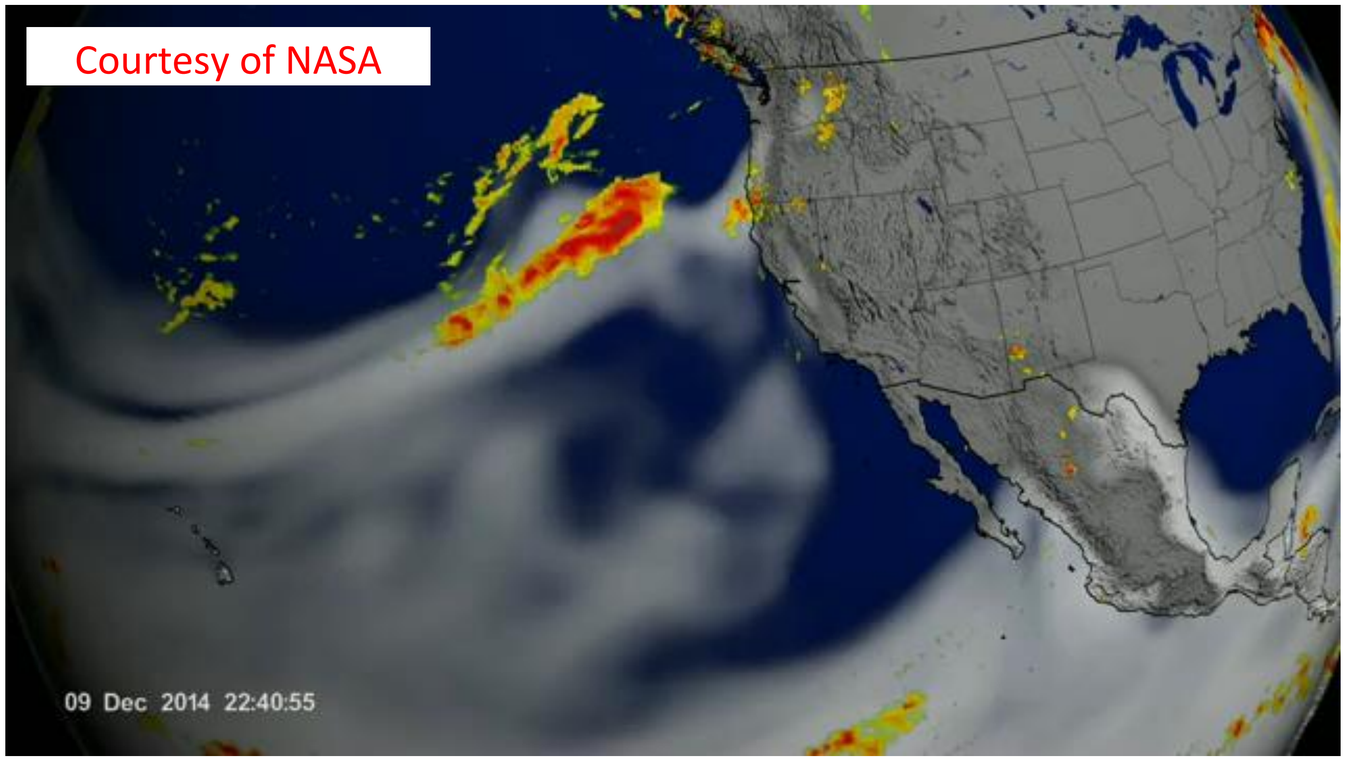
Henderson et al. (J. Climate 2017)

December-February
500 hPa geopotential height anomalies and tropical precipitation anomalies

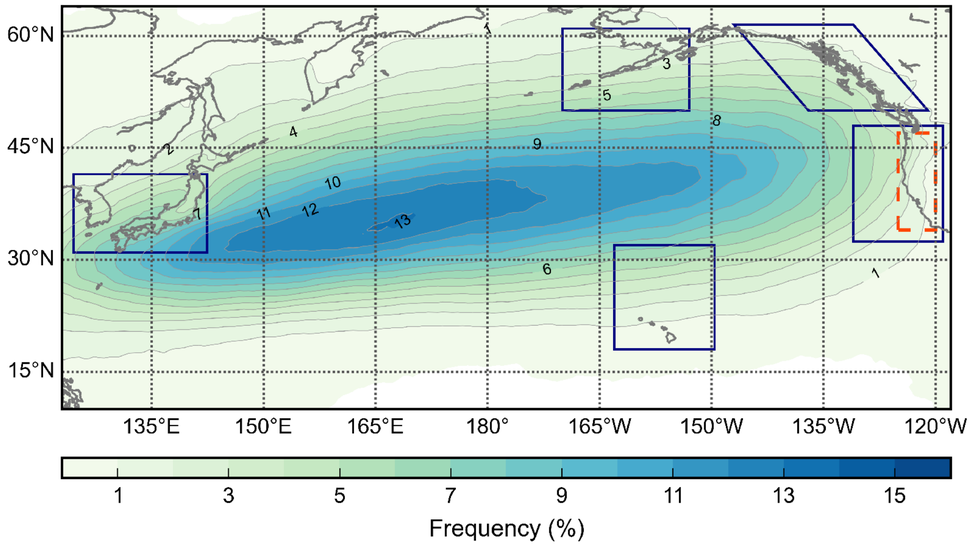
Myriad of Weather Impacts Due to the MJO



Initial Focus on Atmospheric Rivers (e.g. Zhu and Newell 1994; Ralph et al. 2004; Dettinger et al. 2011, etc)



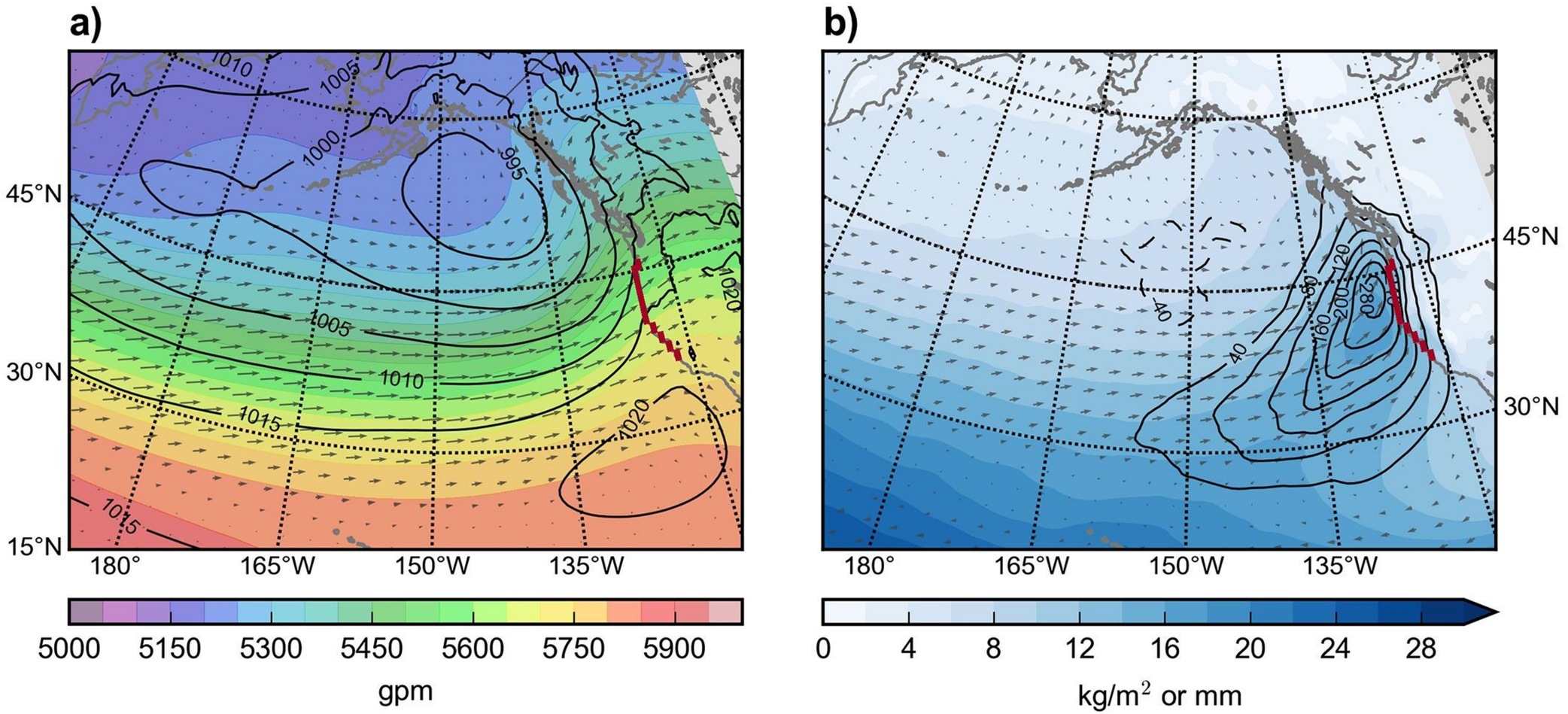
All-Season AR Climatology



Detection algorithm for ARs developed by Mundhenk et al. (2016) used here

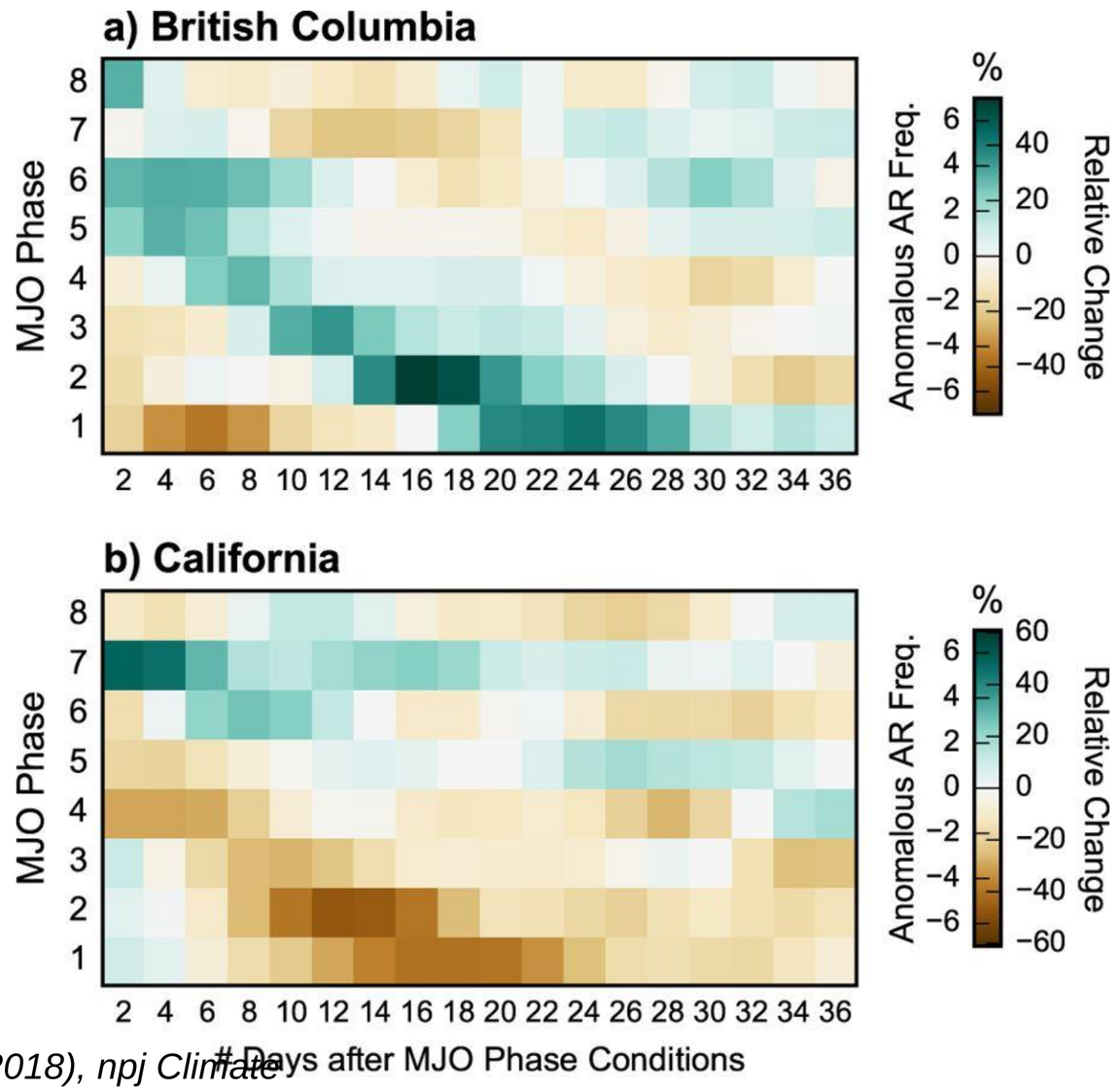
Mundhenk et al. (2016), J. Climate

Pressure Pattern That Favors West Coast Atmosphere Rivers



Mundhenk et al. (2016), J. Geophys. Res

Atmospheric River Anomalies vs. MJO Phase and Time Lag

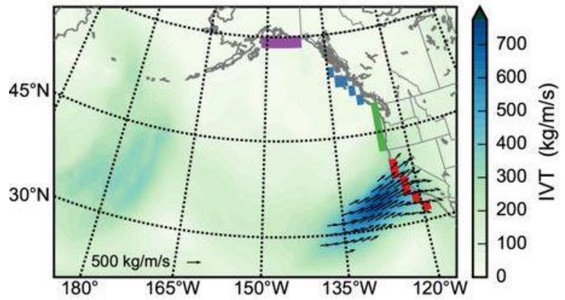


Mundhenk et al. (2018), npj Climate and Atmos. Sci.

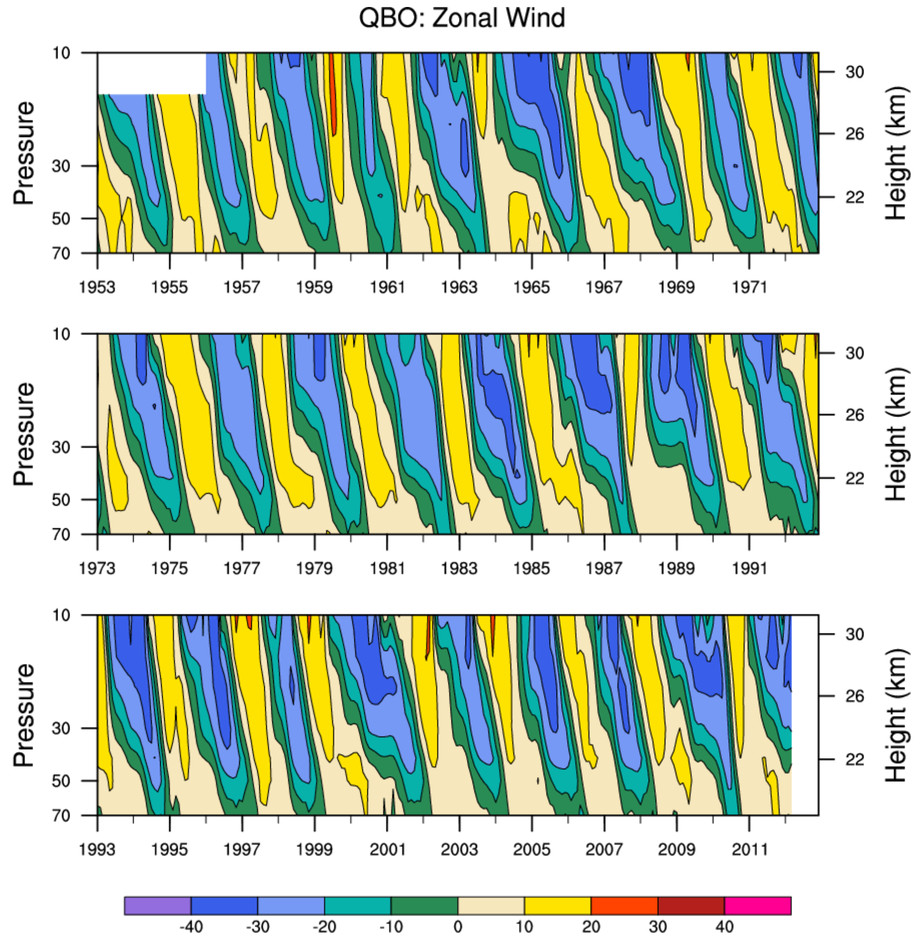
Important: Does not Consider El Niño, QBO, etc.

Boreal winter (Dec-March), 1980-2016

5-day averaged activity

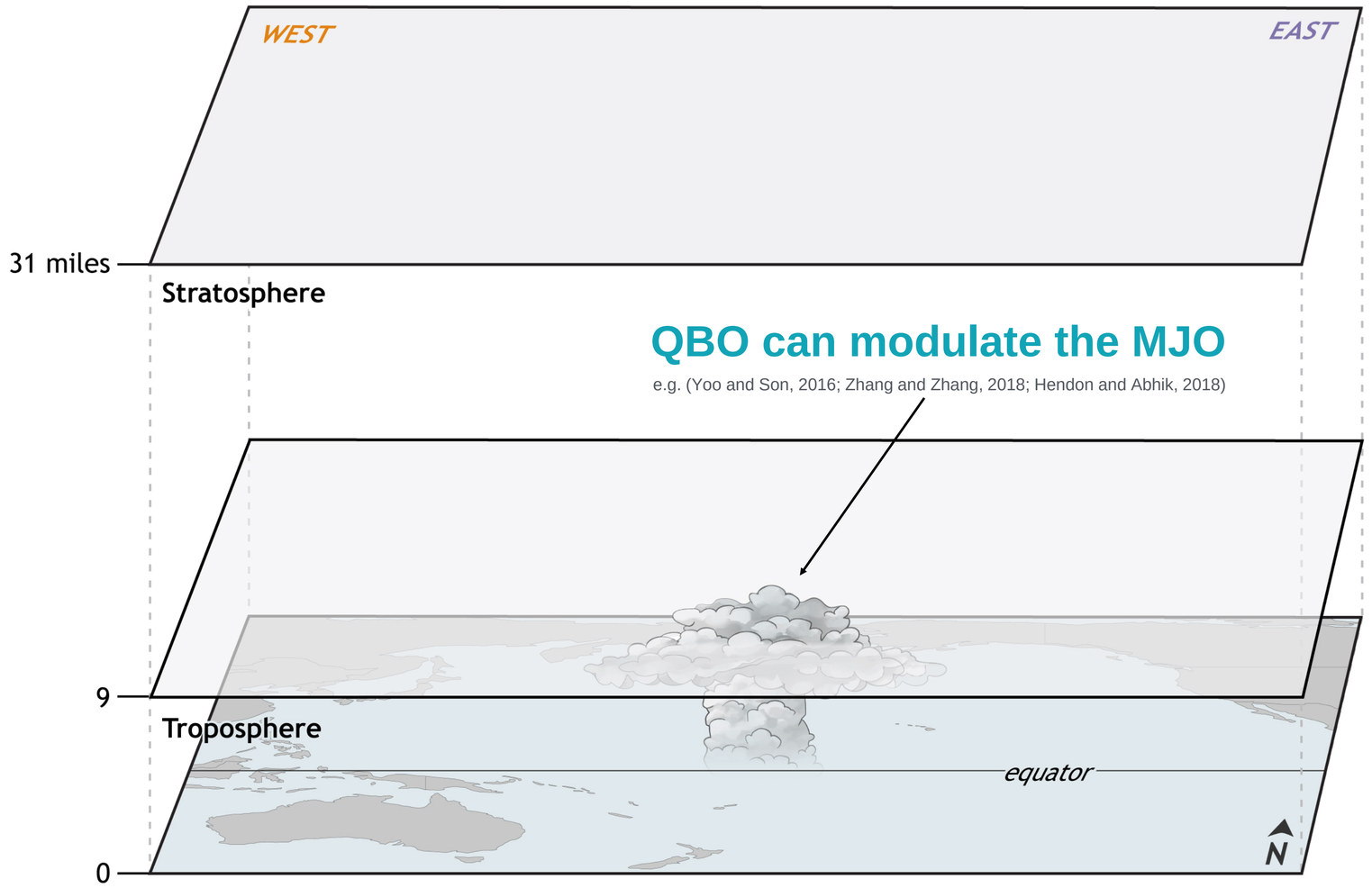


The Quasi-Biennial Oscillation (QBO) as a source of predictability



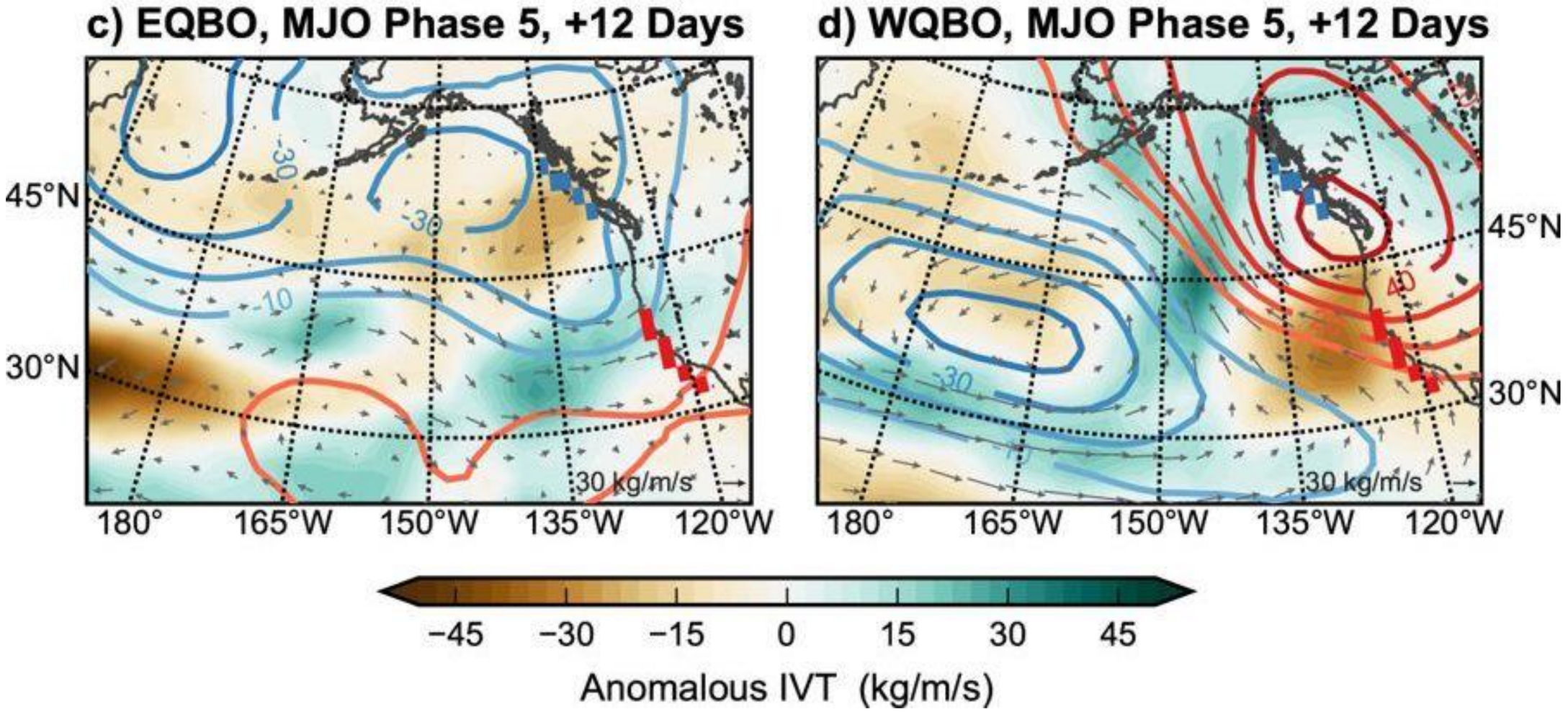
zonal winds
image from the NCAR Climate Data Guide
composed from radiosonde stations at
Canton Island (closed 1967),
Gan/Maledive Islands (closed 1975),
and Singapore; data from Freie Universitat, Berlin

Stratospheric circulation variability



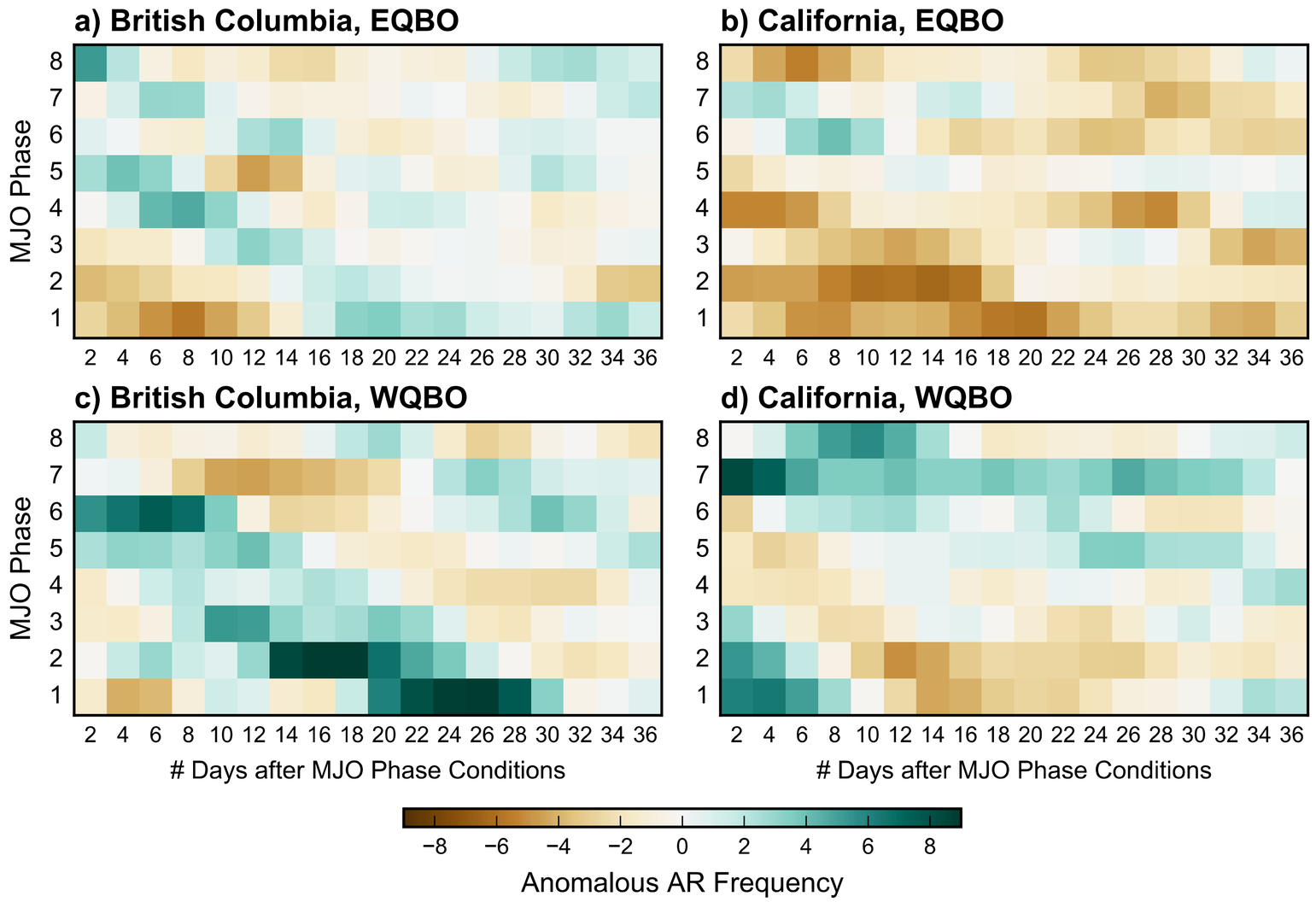
NOAA Climate.gov

The MJO’s Pressure Pattern Depends on What Phase the QBO Is In



Mundhenk et al. (2018), npj Climate and Atmos. Sci.

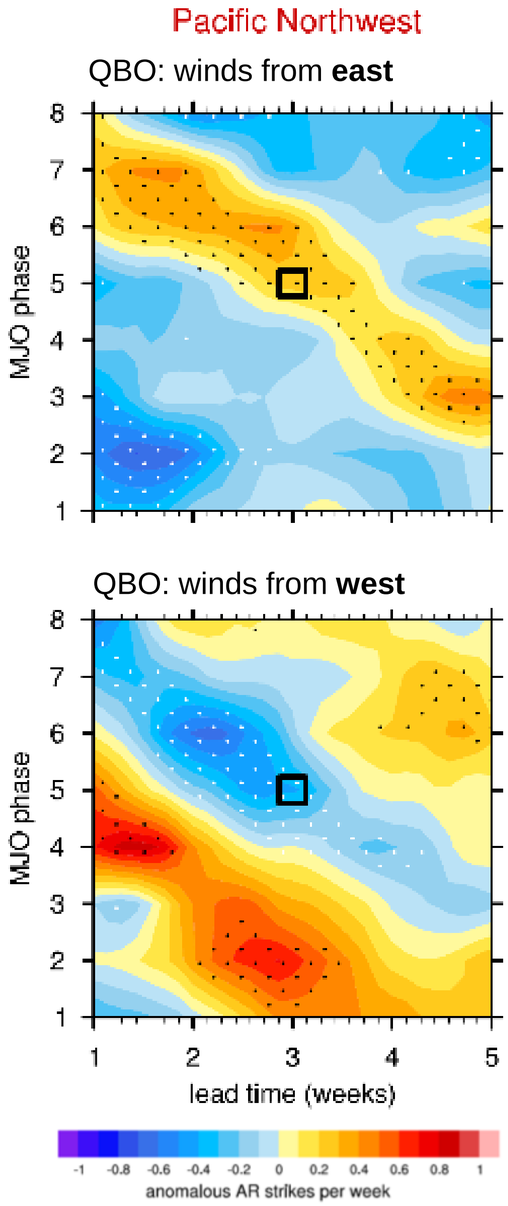
The MJO's Modulation of ARs Get Stronger When Segregating by QBO Phase



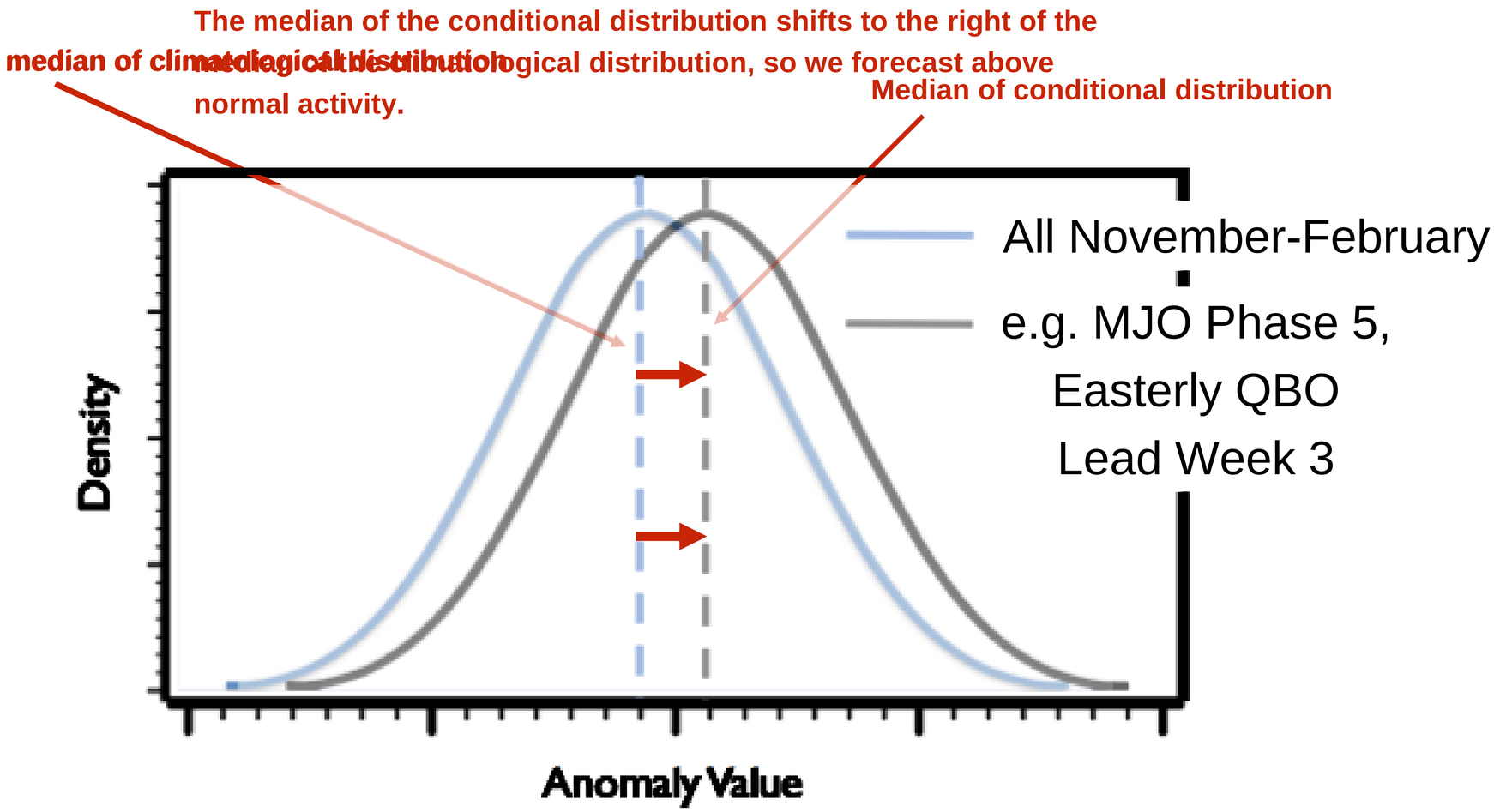
Mundhenk et al. (2018), npj Clin and Atmos. Sci.

Empirical Prediction Model for West Coast ARs

Skillful empirical forecasts of Pacific Northwest ARs



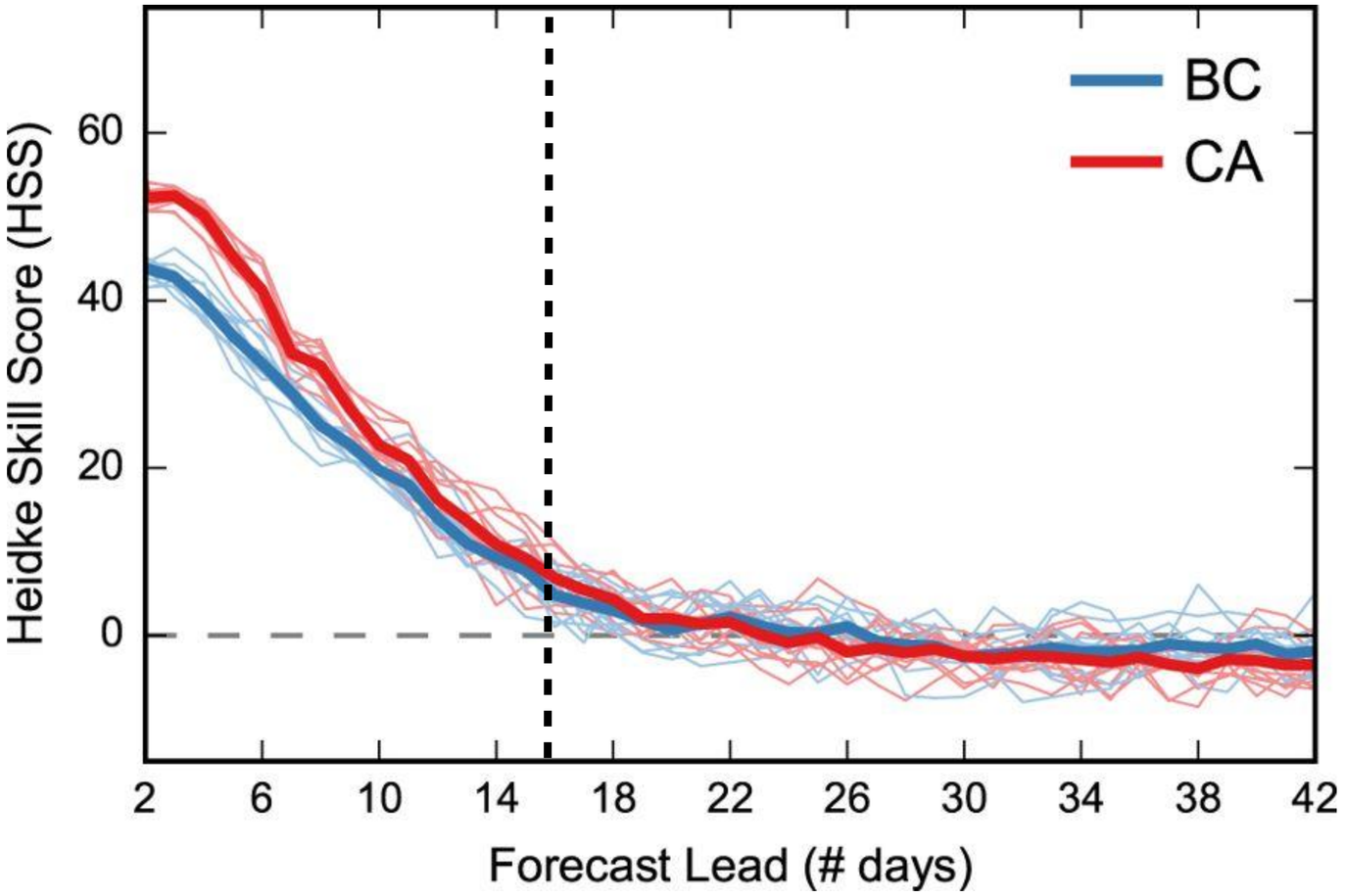
Composites of 7-day average activity
ERA-Interim



Baggett et al. (GRL, 2017)

AR Prediction Capability with ECMWF Model

5-day average anomalous AR activity



Heidke Skill Score

# of correct forecasts

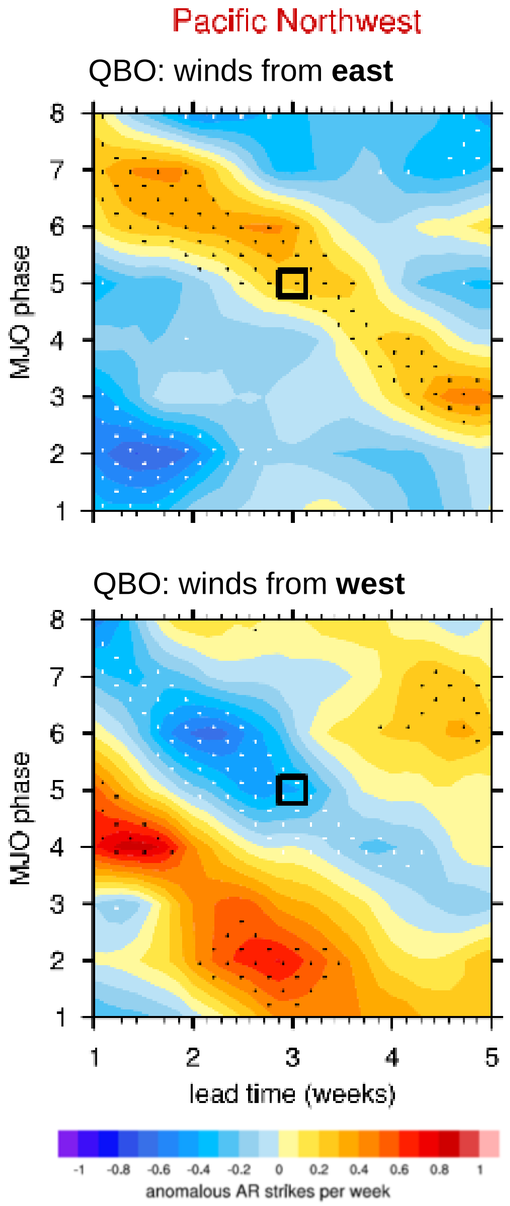
$$HSS = \frac{(H - E)}{(T - E)} \times 100,$$

# of total forecasts

# of correct by chance = T/2

Mundhenk et al. (2018), npj Climate and Atmos. Sci.

Skillful empirical forecasts of Pacific Northwest ARs



Composites of 7-day average activity
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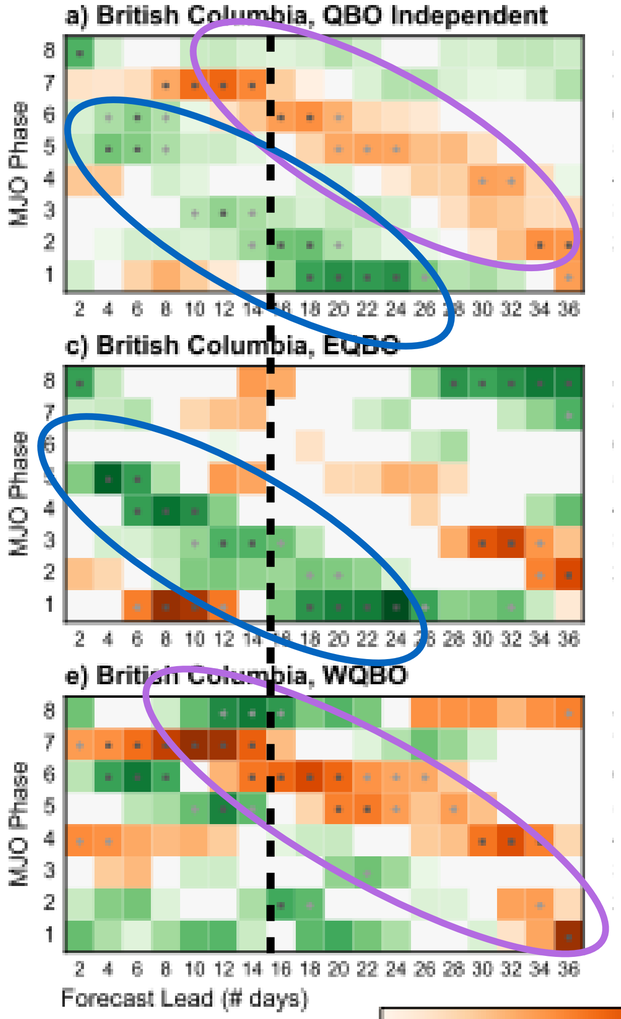


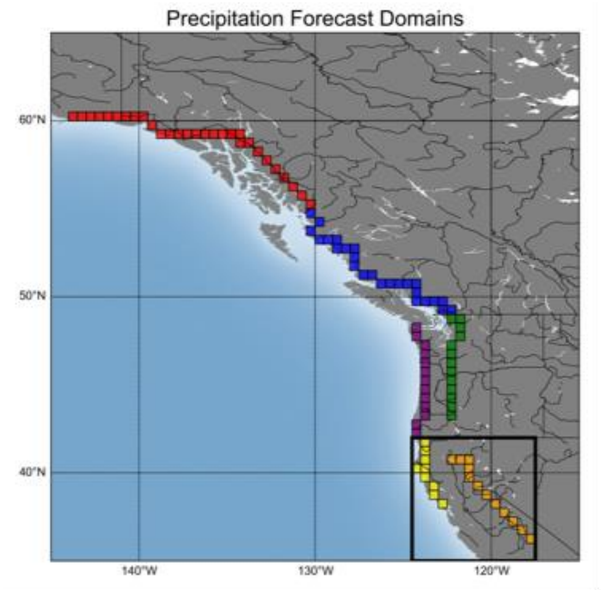
forecasts for 5-day average activity
MERRA-2

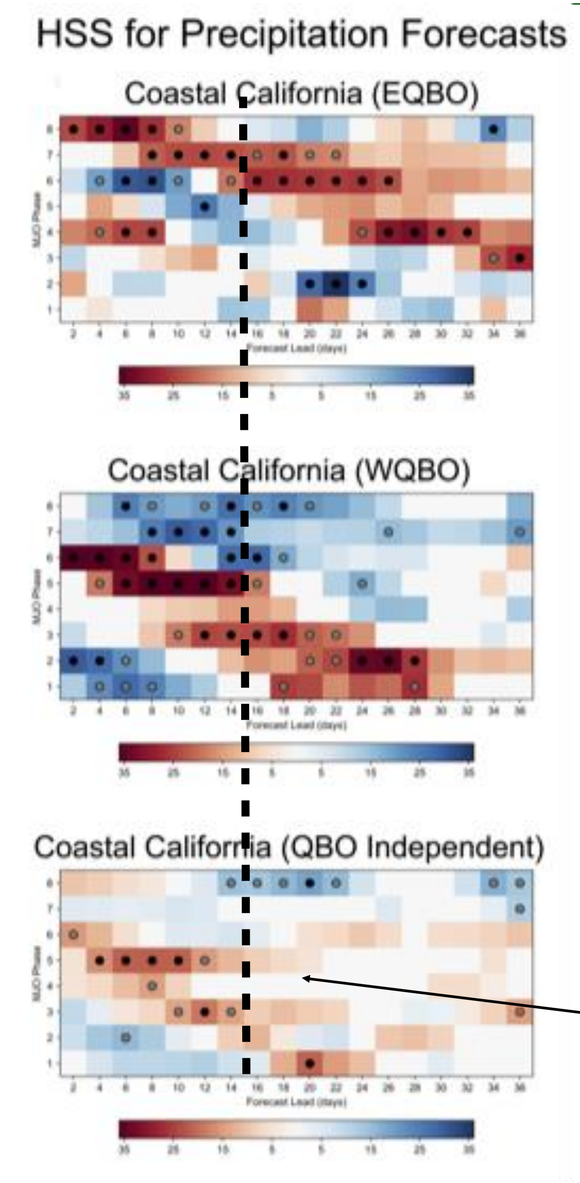
Heidke Skill Score

prediction skill 30+ days ahead of time using a statistical model based solely on the MJO & QBO

Baggett et al. (GRL, 2017)
Mundhenk et al. (NPJ Climate, 2018)

Skillful empirical forecasts of California Precipitation





empirical model also shows skill in CA rainfall

the signal is weak if the QBO is not considered

thesis work by Kyle Nardi

NOAA Climate Testbed Project (collaboration with CPC)

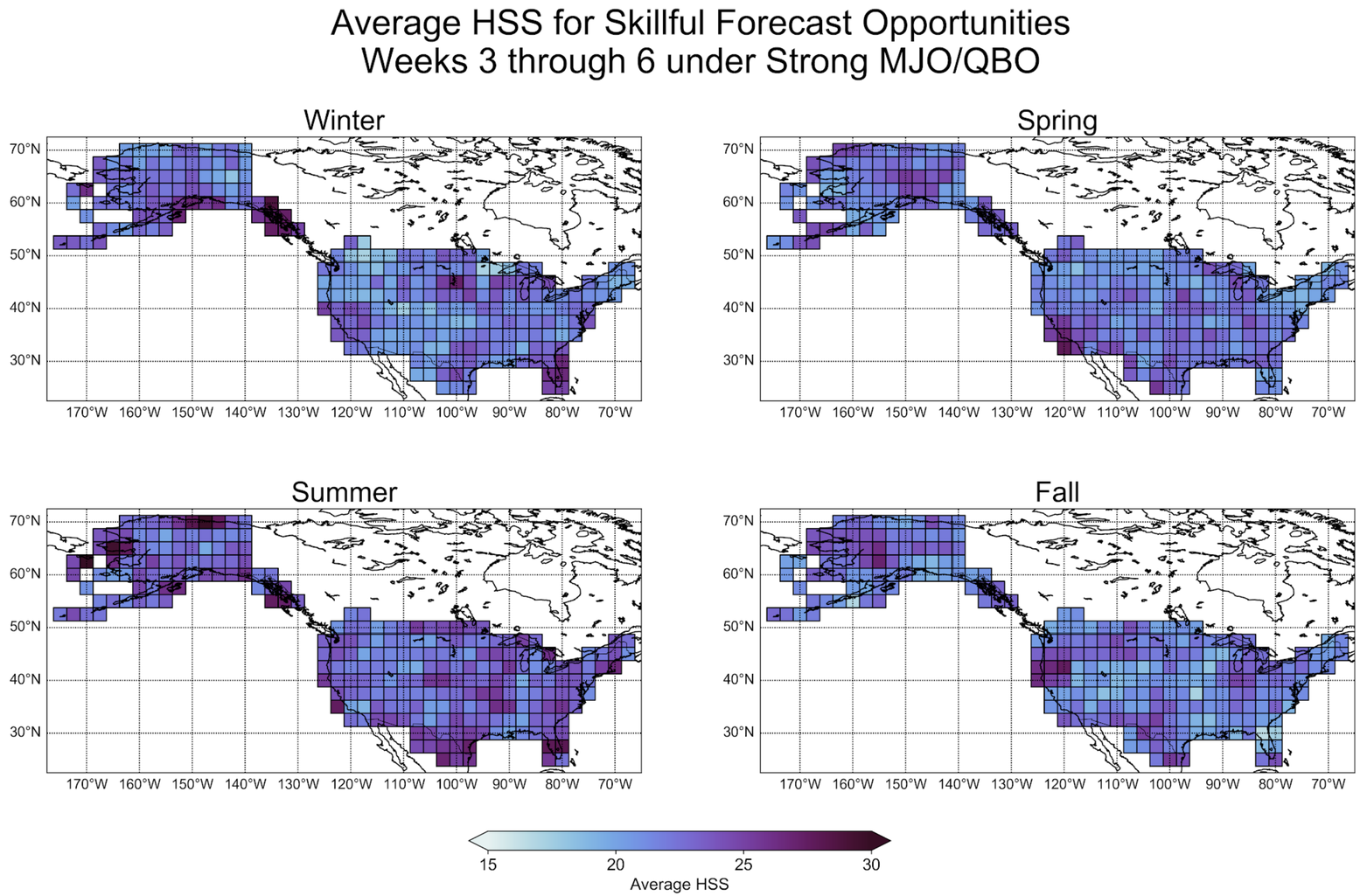
Translation the forecast tool to operations at CPC

Dan Harnos

Laura Ciasto

- **Goal 1:** Successfully transition the anomalous AR frequency forecast tool to operations.
- **Goal 2:** Refine and extend the methodology of Mundhenk et al. (2018) to maximize skill of AR activity and AR-related variables.
- **Goal 3:** Leverage additional predictors, including dynamical model MJO forecasts, to extend the skillful forecasts beyond Week 5.

3-6 Week Precipitation Skill as a Function of Season (Strong MJO/QBO)



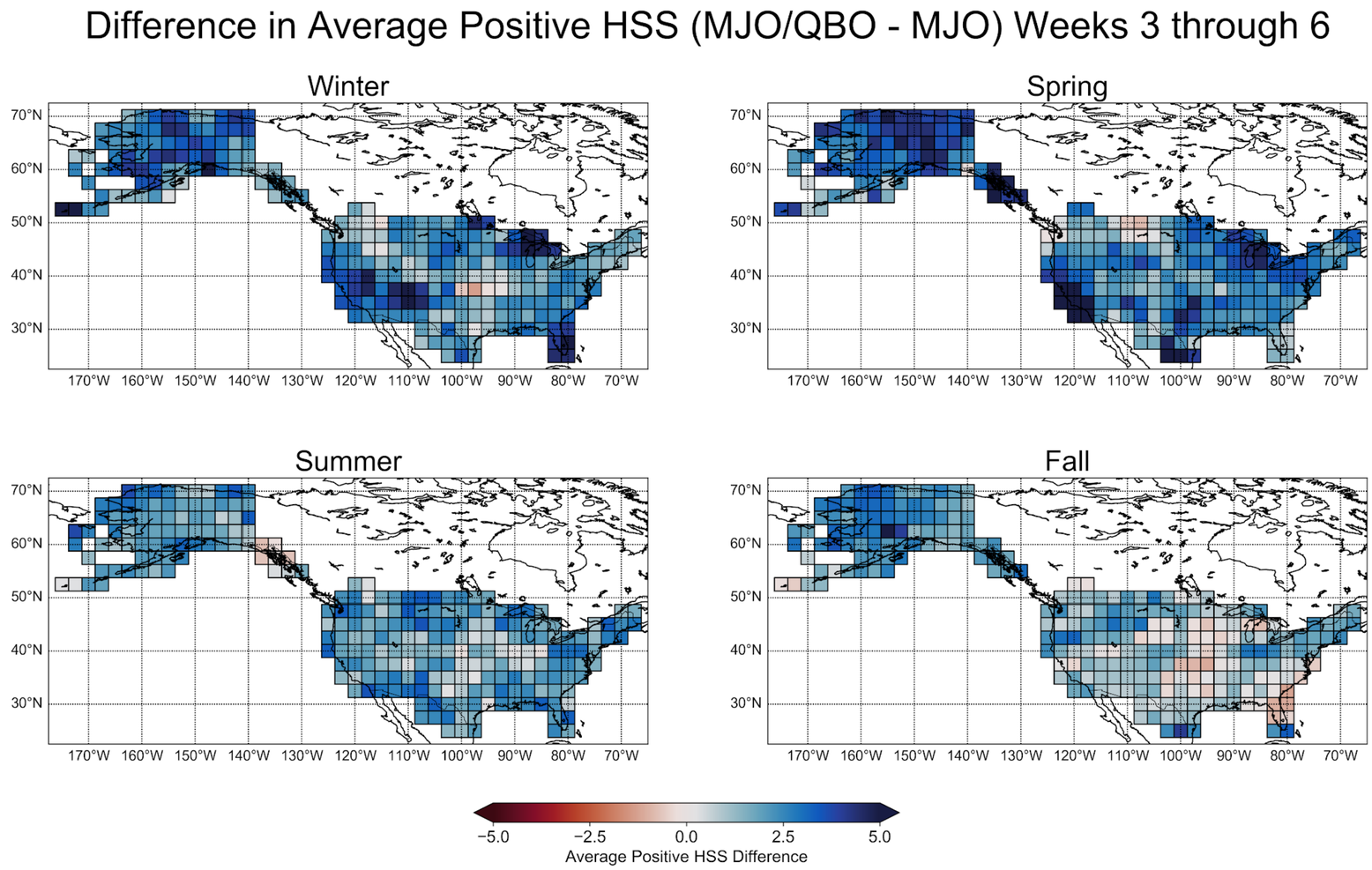
Averaged across all MJO phases

HSS of 33= 2x more correct forecasts than incorrect.

HSS of 0=as many correct as incorrect forecast

Kyle Nardi, Elizabeth Barnes, Cory Baggett, Eric Maloney , 2019

How Much Does the QBO Help our Forecasts?

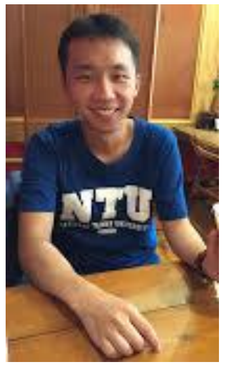


Averaged across all MJO phases

Large benefits in Spring and Winter along west coast

Kyle Nardi, Elizabeth Barnes, Cory Baggett, Eric Maloney , 2019

Machine Learning Results for West Coast ARs



Kai-Chih Tseng, 2019

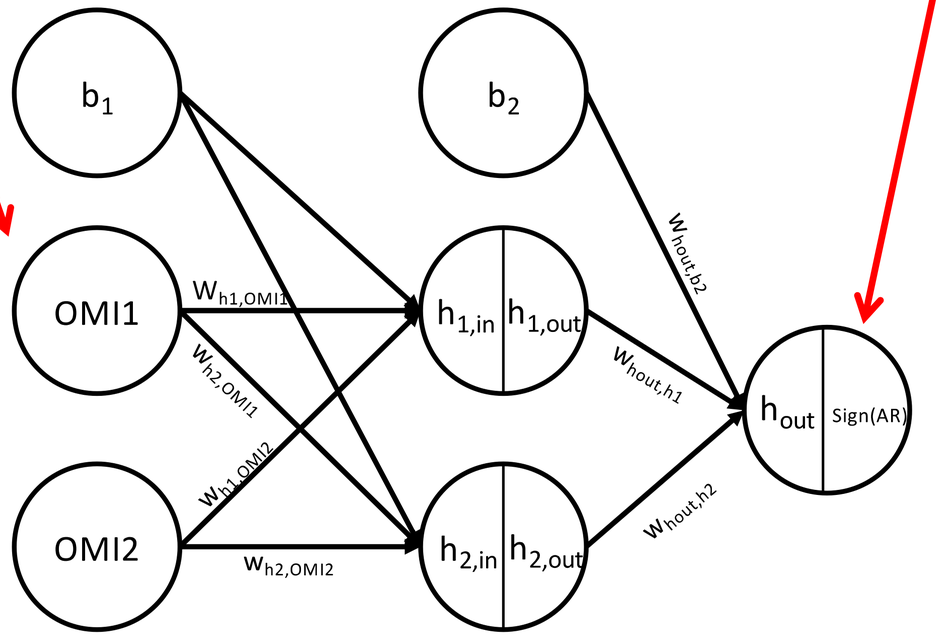
Simple Neural Network

Input:

MJO state

Output:

Predicted sign of AR anomaly



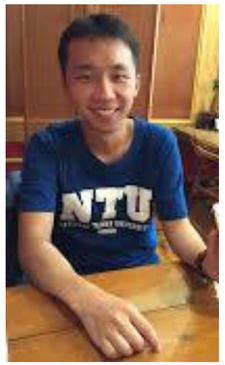
Input Layer to Hidden Layer

$$h_{1,in} = w_{h1,OMI1} OMI_1 + w_{h1,OMI2} OMI_2 + b_1$$
$$h_{1,out} = \frac{1}{1 + e^{-h_{1,in}}}$$

$$h_{2,in} = w_{h2,OMI1} OMI_1 + w_{h2,OMI2} OMI_2 + b_1$$
$$h_{2,out} = \frac{1}{1 + e^{-h_{2,in}}}$$

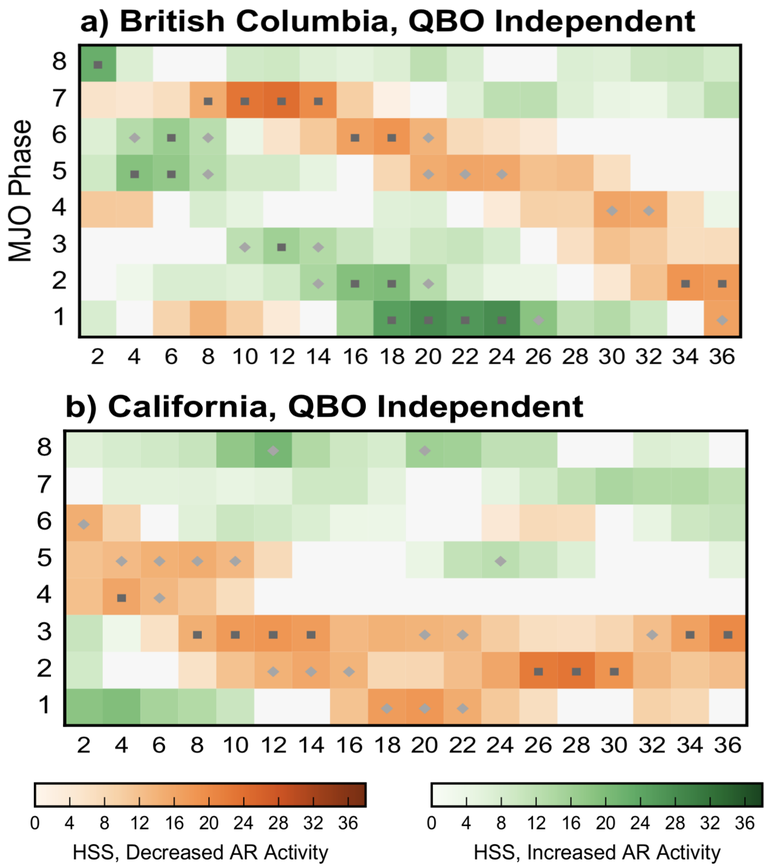
Hidden Layer to Output Layer

$$h_{out} = w_{hout,h1} h_1 + w_{hout,h2}\, h_2 + b_2$$
$$Sign(AR) = \frac{1}{1 + e^{-h_{out}}}$$

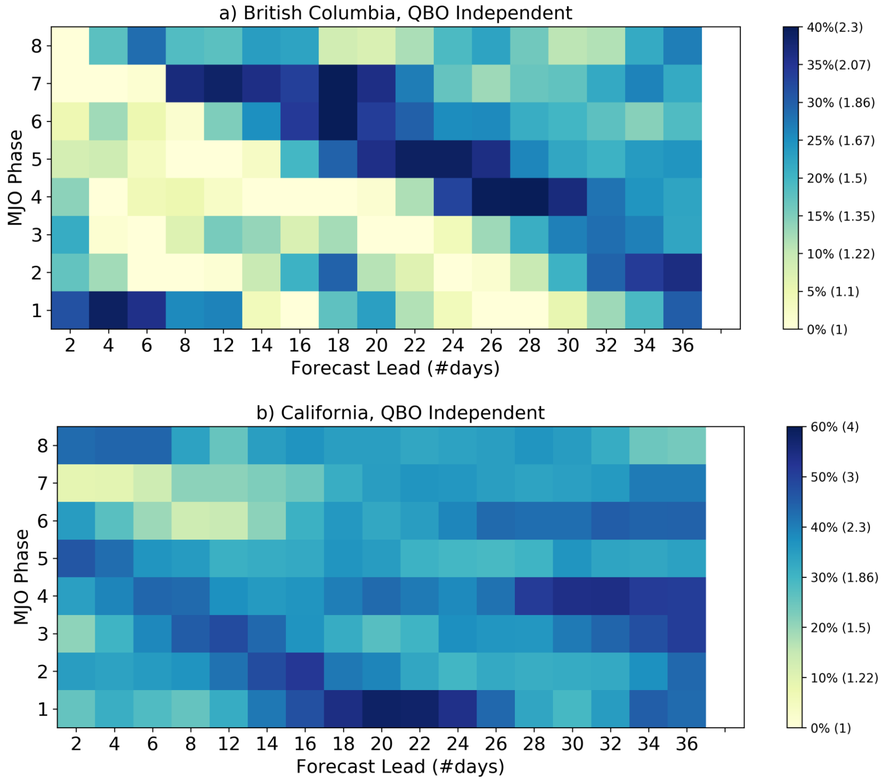


Kai-Chih Tseng, 2019

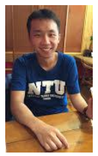
AR Prediction Skill Increases using Machine Learning



Based on Composite Approach



Based on Neural Network



Kai-Chih Tseng, 2019

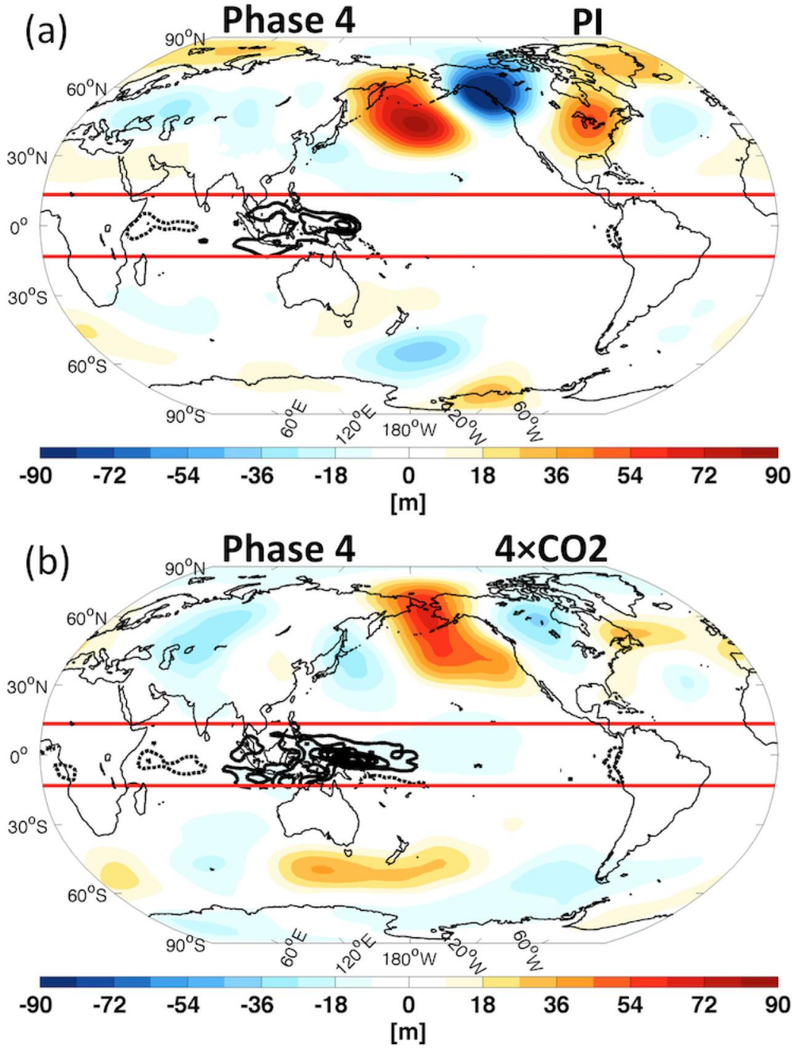
The MJO May Weaken As a Prediction Source in Warming Climate?

”Current climate”

MJO Pressure Anomalies in the Sp-CESM climate model

$4xCO_2$

Wolding et al. (2017, JAMES)



Conclusions and Next Steps

- A statistical model with knowledge of the MJO and QBO provides skill at predicting wintertime West Coast AR activity at 5 week leads during
- Provides substantially higher skill than using only knowledge of the MJO alone
- Skill is provided at longer lead times than that provided by dynamical forecast systems
- Analysis extended to other seasons and regions for precipitation
- Initial exciting machine learning results suggests substantial increases in skill over statistical model derived from composites.

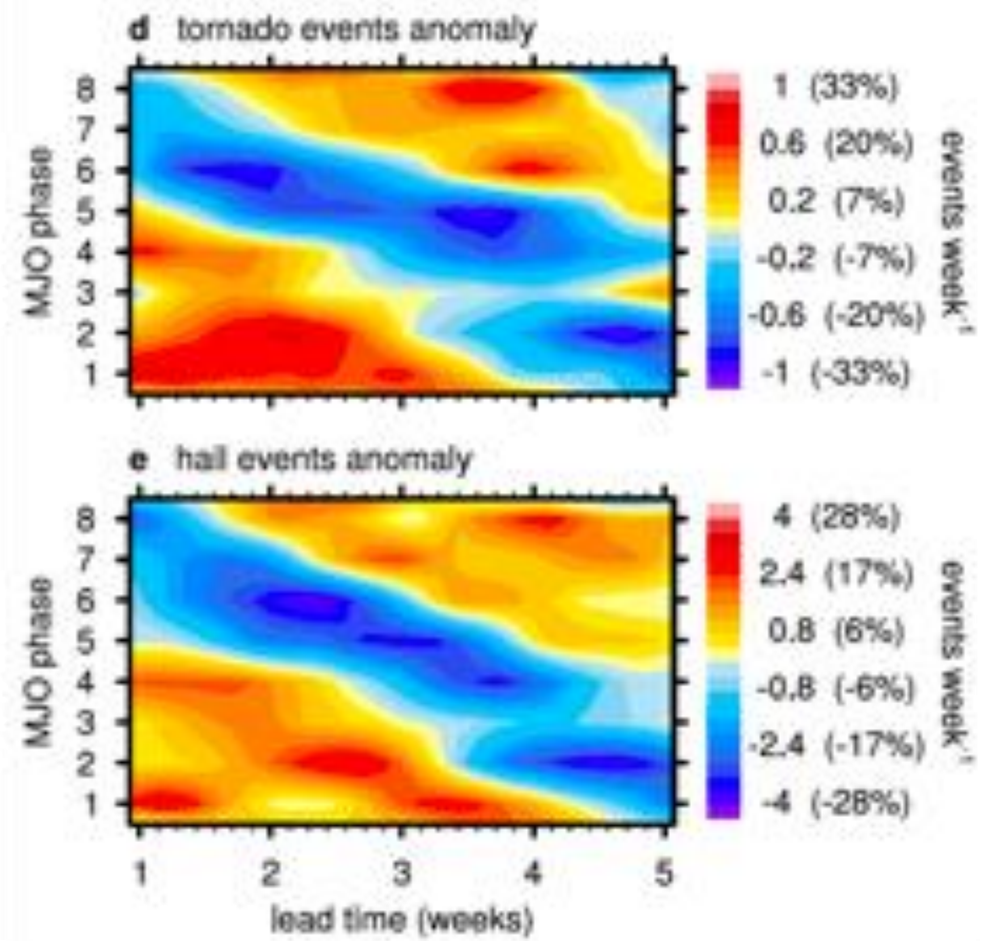
Next steps

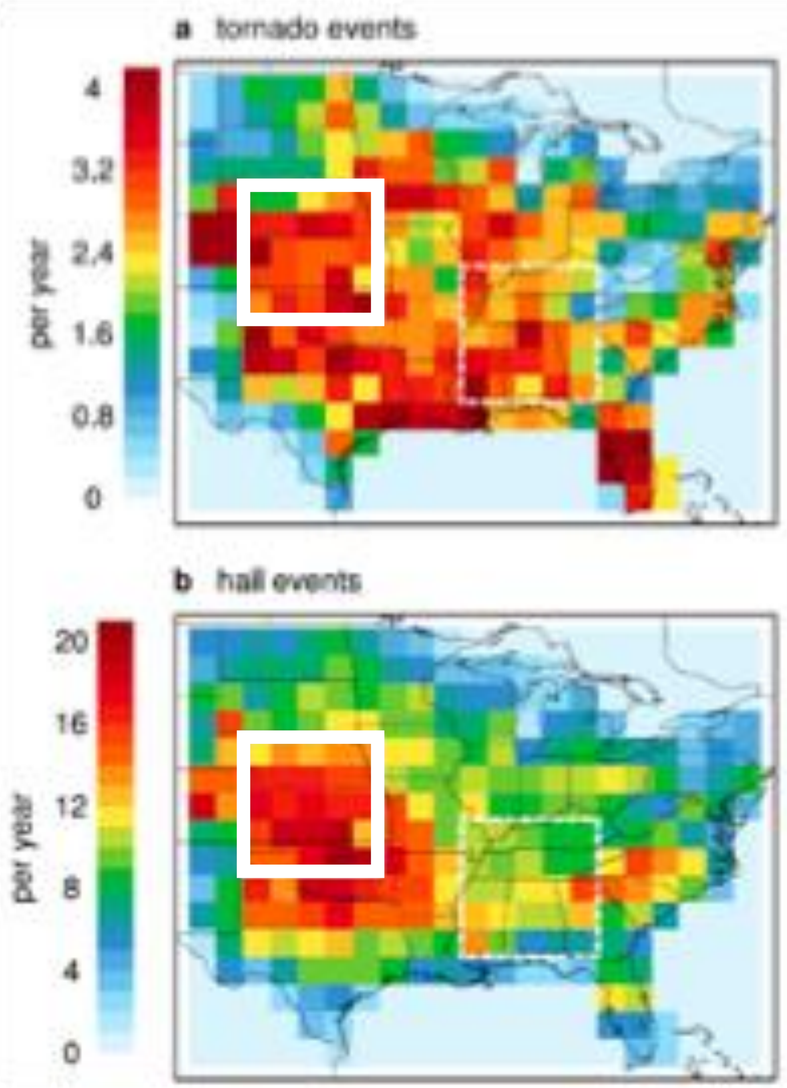
- Do more with ENSO
- Expand machine learning model (include QBO, other regions, variables, seasons)
- Expand focus on other regions and seasons
- Understand implications of climate change for our prediction models
- Dig into the dynamics

Thanks

Lake Tahoe, December 2018

- Skillful empirical forecasts of U.S. Plains Severe Weather **ANOMALIES**



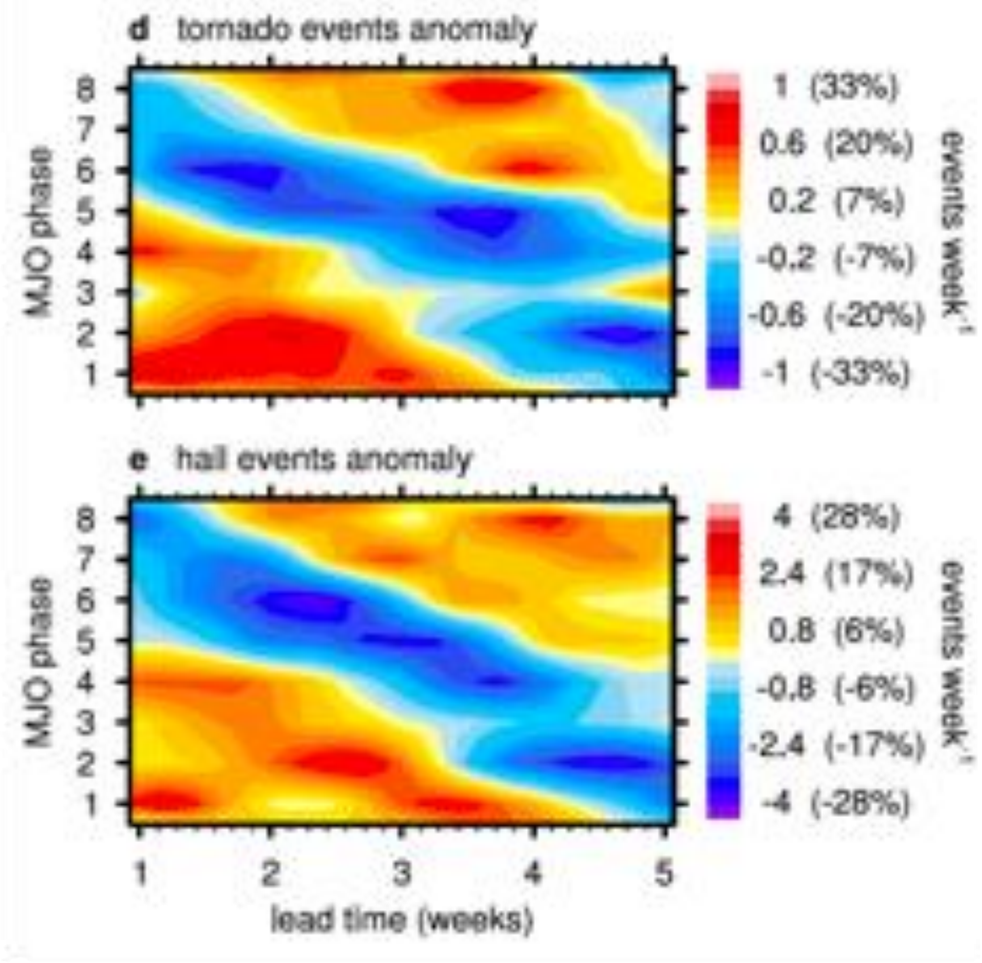


Baggett et al. (2018; under review)

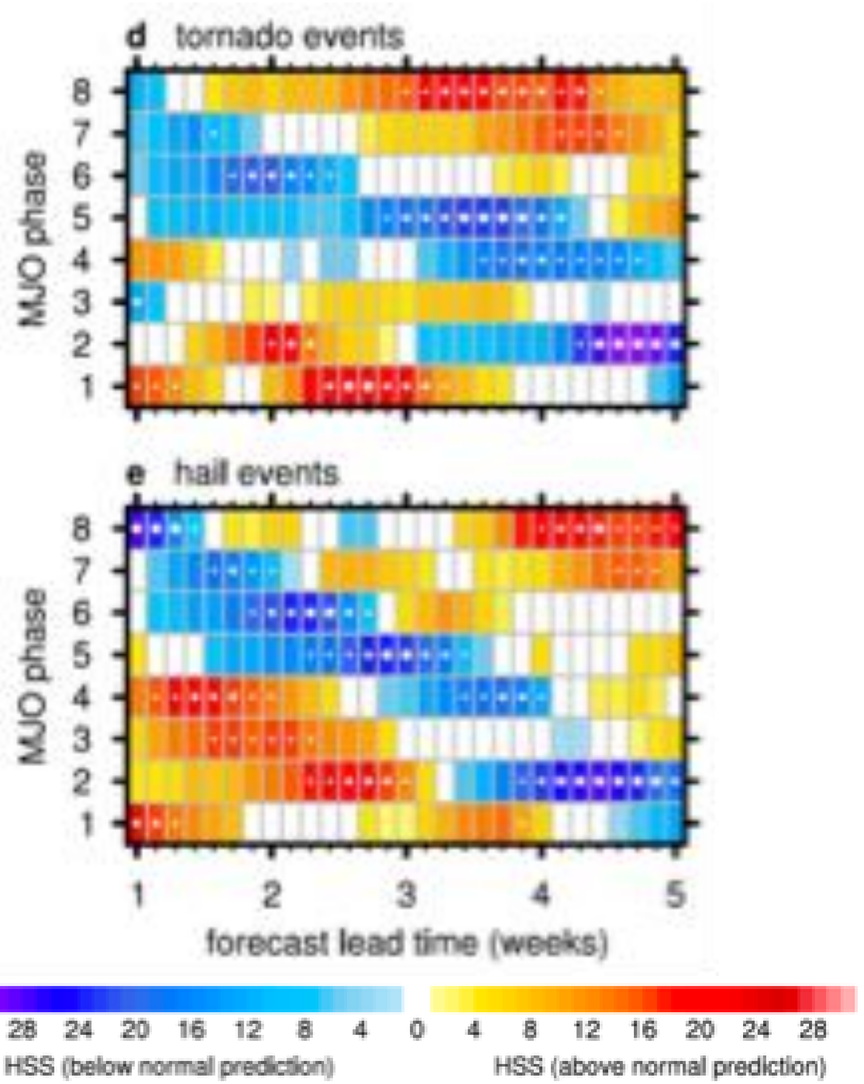
all results for March-July

- Skillful empirical forecasts of U.S. Plains Severe Weather

ANOMALIES



HEIDKE SKILL SCORES



Baggett et al. (2018; under review)

- Linking the QBO and MJO

The MJO…“is more **active** and **propagates eastward farther** into the western Pacific during the **easterly** phase” of the QBO.

Hendon and Abhik (2018; GRL)

“…MJO activity during the **easterly** QBO phase translates to **improved prediction of the MJO**…”

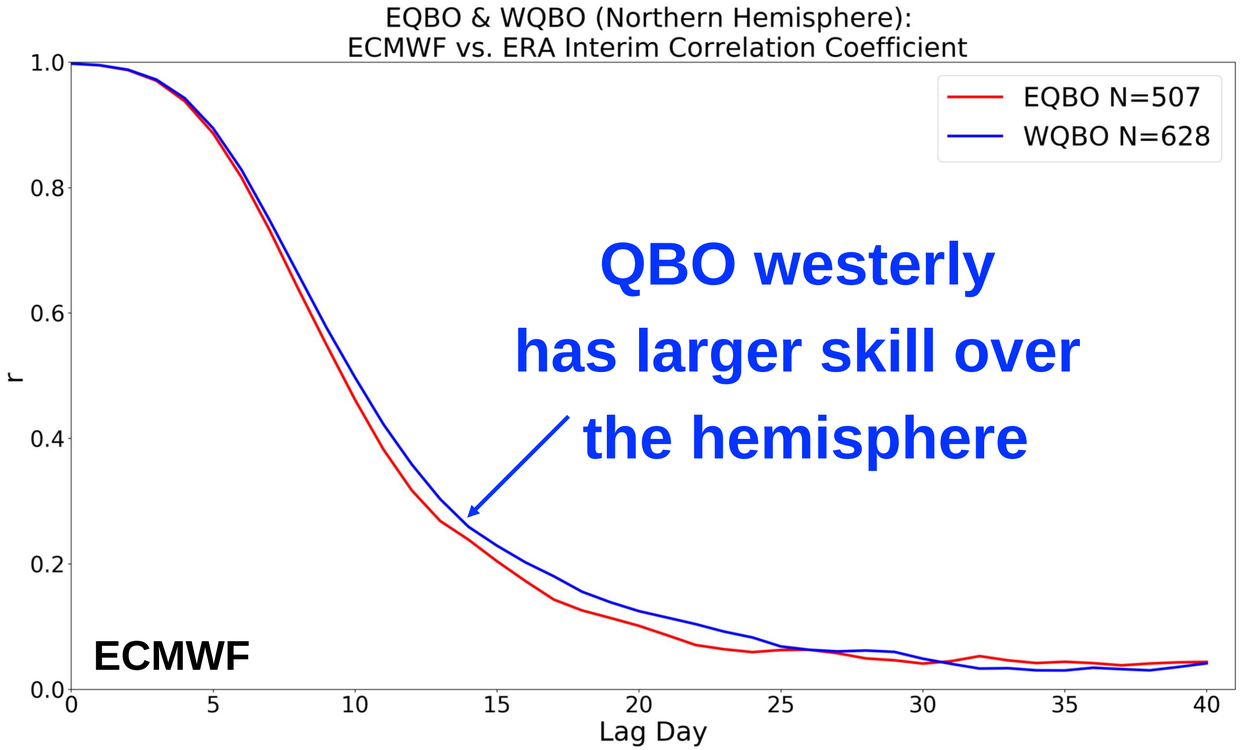
in the POAMA coupled model forecast system
Marshall et al. (2017; CDYN)

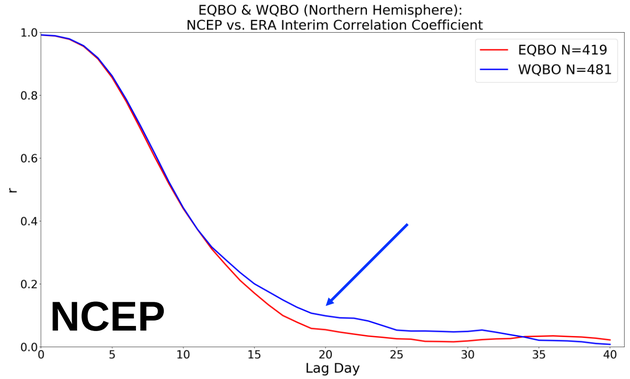
So…are MJO teleconnections stronger and better predicted during easterly QBO??

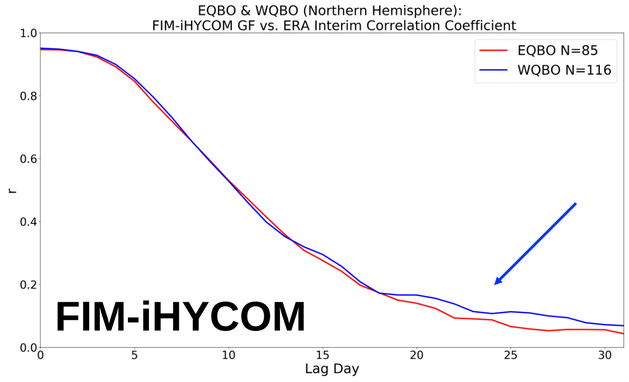
Forecast skill during QBO+ and QBO-: **Northern Hemisphere**

Are dynamical model forecasts of midlatitude Z500 more skillful during easterly QBO compared to westerly QBO?

- DJF reforecasts of Z500 from the S2S Database and SubX
- Split reforecasts into QBO+ and QBO- (based on 0.5 sigma)
- Use spatial correlations of Z500 anomalies to quantify skill (30N-75N)







preliminary work by Kirsten Mayer

WORK IN PROGRESS - still need to rule out other players, e.g. ENSO

Forecast skill during QBO+ and QBO-: **North Atlantic**

Are dynamical model forecasts of midlatitude Z500 more skillful during easterly QBO compared to westerly QBO?

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- Split reforecasts into QBO+ and QBO- (based on 0.5 sigma)
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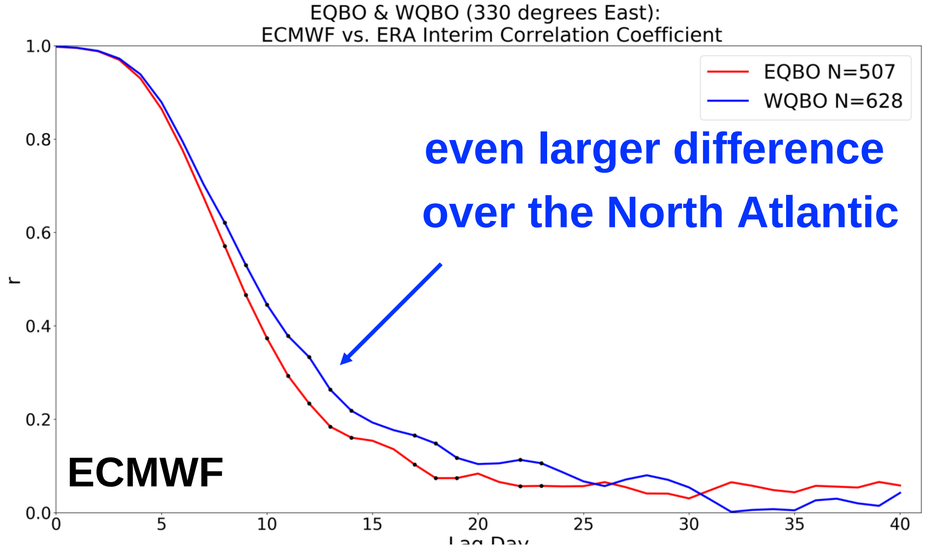
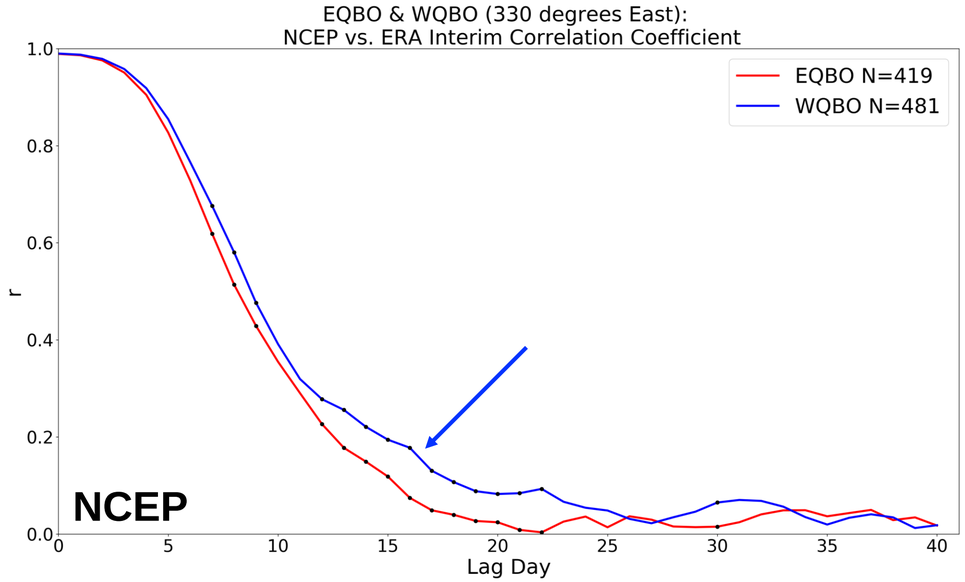
WHY

stratospheric vortex?

ENSO?

MJO teleconnections?





preliminary work by Kirsten Mayer

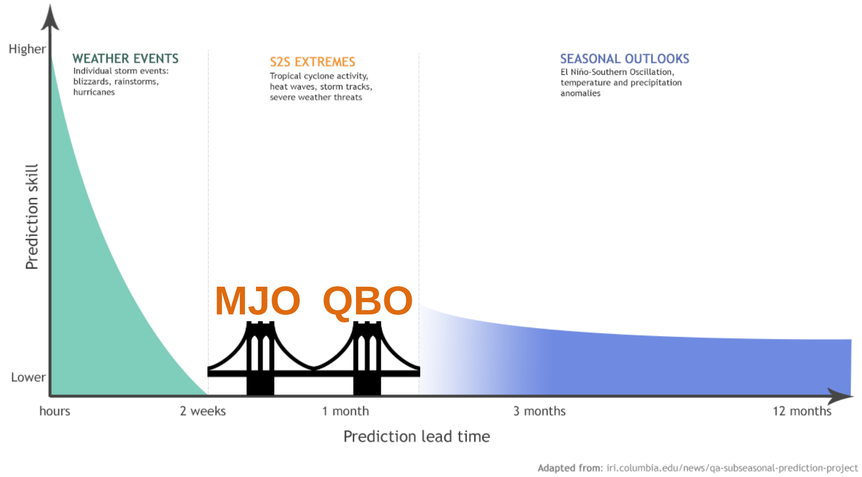
WORK IN PROGRESS - still need to rule out other players, e.g. ENSO

Overview

1. Anomalous extreme weather (e.g. ARs, precipitation, tornadoes, hail) can be skillfully forecast up to 4+ weeks in advance using the MJO and QBO as predictors

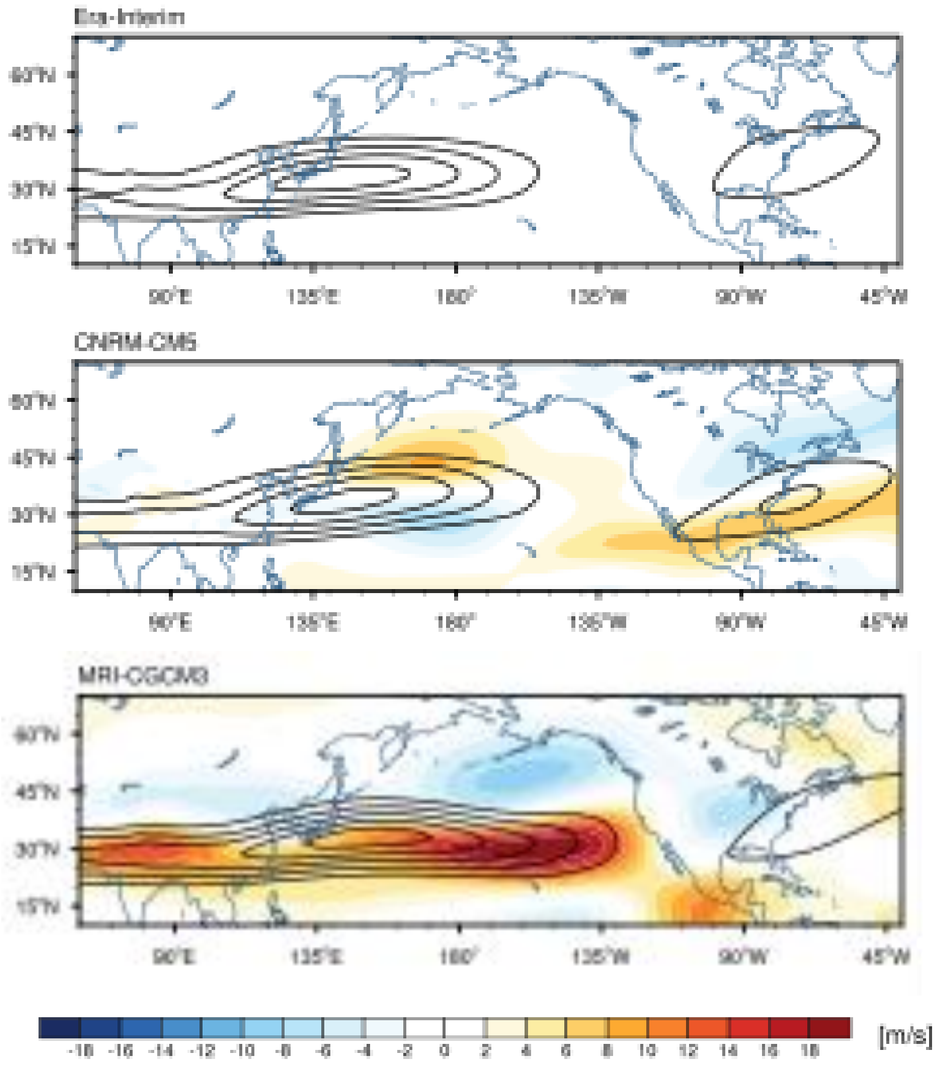
2. The STRIPES index can be used to explore other variables and regions where the MJO and QBO may provide skill at S2S timescales

3. Dynamical models appear more skillful during QBO westerly compared to easterly for midlatitude Z500, and MJO teleconnections appear stronger (but more work needs to be done)

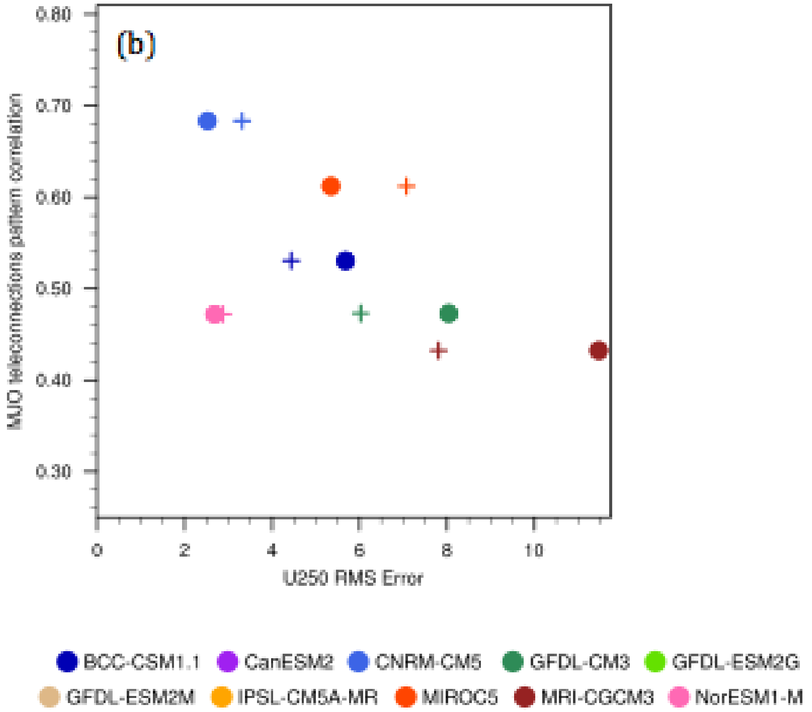


- Jenney, Andrea., D. Randall, E. Barnes: Quantifying regional sensitivities to periodic events: Application to the MJO. *Journal of Geophysical Research: Atmospheres*, submitted 08/2018.
- Baggett, Cory F. , Kyle M. Nardi, Samuel J. Childs, Samantha N. Zito, Elizabeth A. Barnes, Eric D. Maloney: Skillful 5 Week Forecasts of Tornado and Hail Activity. *Journal of Geophysical Research: Atmospheres*, submitted 05/2018.
- Nardi, Kyle M., Elizabeth A. Barnes, and F. Martin Ralph: Assessment of Numerical Weather Prediction Model Re-Forecasts of the Occurrence, Intensity, and Location of Atmospheric Rivers along the West Coast of North America. *Monthly Weather Review*, *https://doi.org/10.1175/MWR-D-18-0060.1*.
- Mundhenk, Bryan, Elizabeth A. Barnes, Eric Maloney and Cory F. Baggett: Skillful Empirical Subseasonal Prediction of Landfalling Atmospheric River Activity using the Madden-Julian Oscillation and the Quasi-biennial Oscillation. *npj Climate and Atmospheric Science*, doi: 10.1038/s41612-017-0008-2
- Baggett, Cory, Elizabeth A. Barnes, Eric Maloney and Bryan Mundhenk, 2017: Advancing Atmospheric River Forecasts into Subseasonal Timescales. *Geophysical*

MJO Teleconnections in GCMs

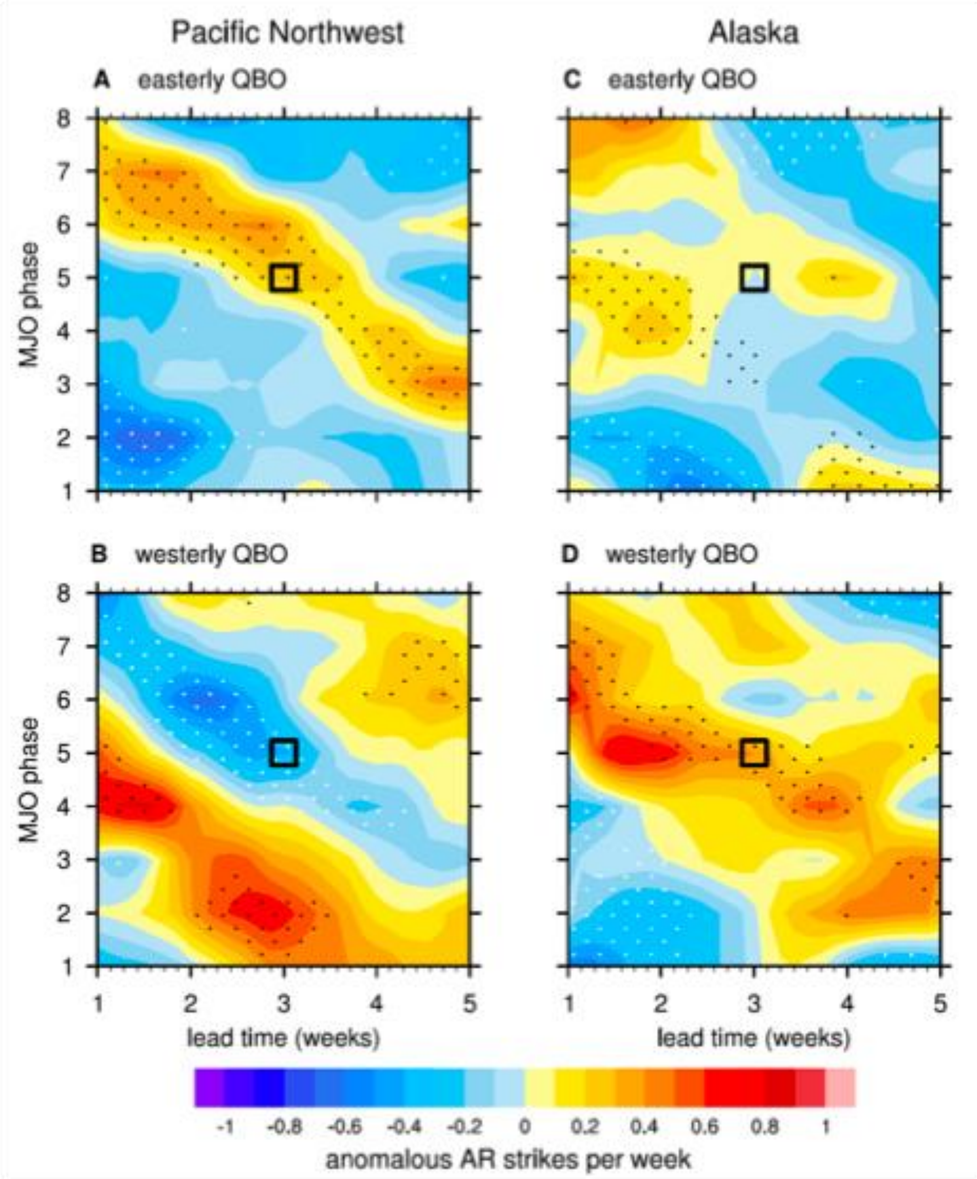


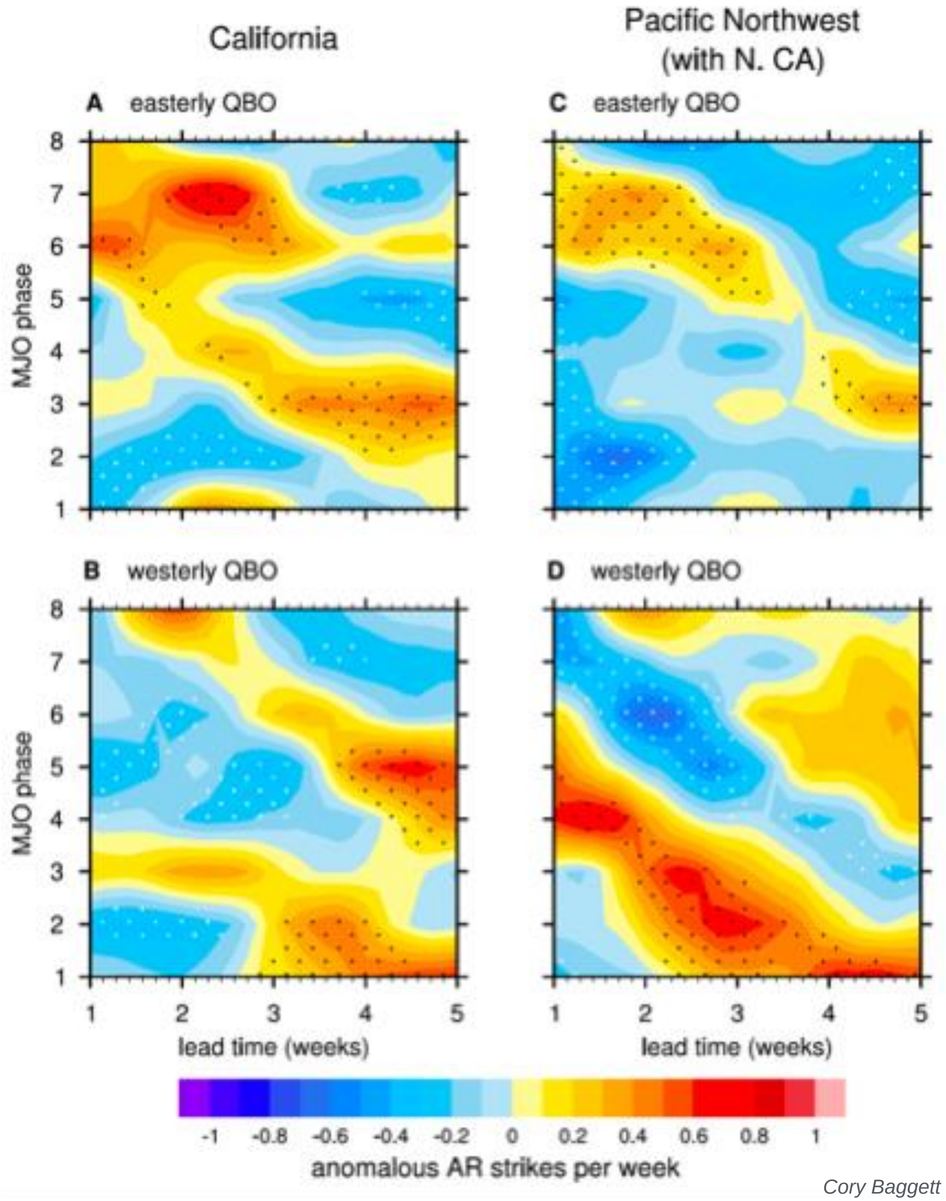
GCMs with good MJOs but poor basic states can have the same teleconnection errors as those with poor MJOs



Stephanie Henderson et al. (2017; JCLI)

Other Regions (ERA-Interim)





Cory Baggett et al. (submitted)

Logarithmic Skill Score (Tippett et al. 2017)

$$p_i = \frac{n_i + C^{-1}}{N + 1}$$

$$\mathrm{LS} = \log p_i$$

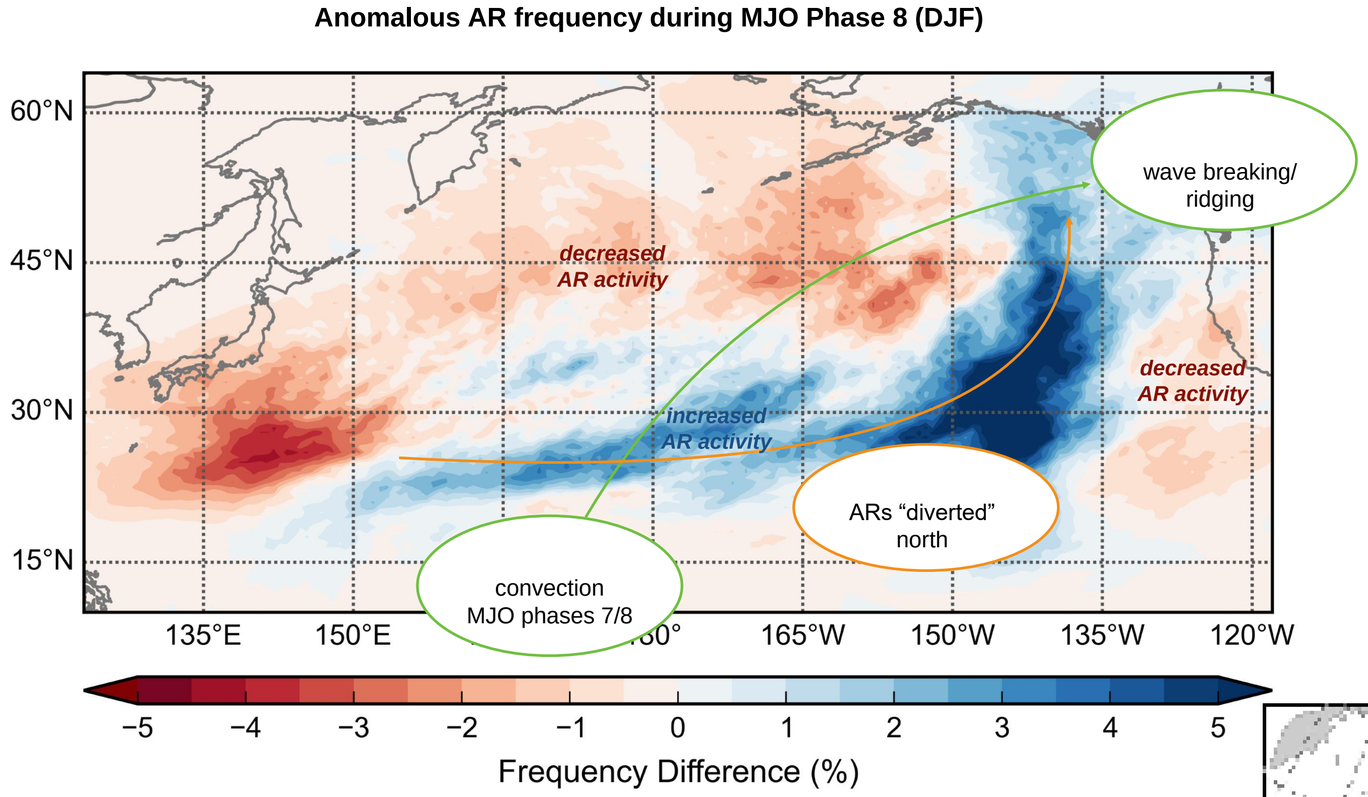
$$\mathrm{LSS} = \overline{\mathrm{LS}} - \overline{\mathrm{LS}_{\mathrm{ref}}}$$

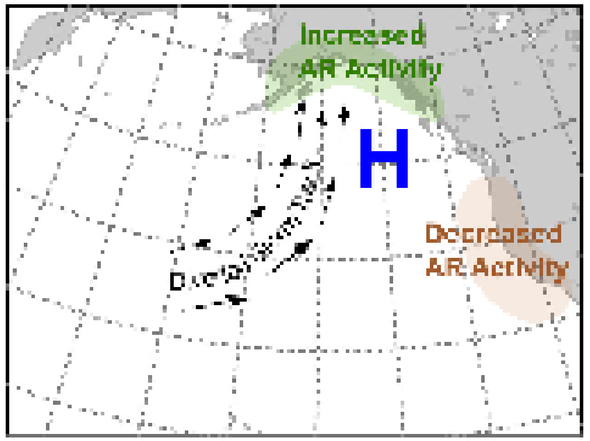
N = # of ensemble members

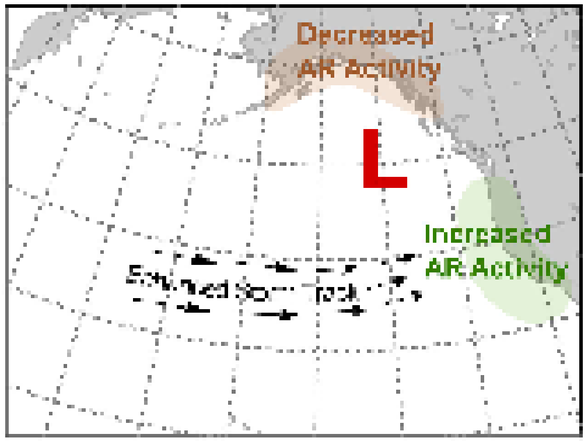
n_i = # of members forecasting c_i

C = # of categories

Connections between blocking and ARs







Bryan Mundhenk et al. 2016; JCLI
MERRA