A State-Dependent Model-Error Representation for Online Climate Model Bias Correction

Will Chapman, Judith Berner

Thanks: Jim Edwards, Jack Atkinson, Jesse Nusbaumer

https://m2lines.github.io/

Funded by SCHMIDT FUTURES

Background / Context

Sources for uncertainty and model error:

1.

Initial Condition Uncertainty

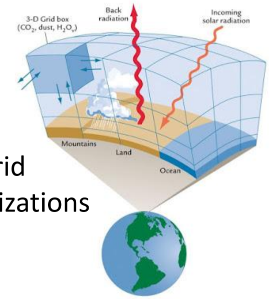
Climate Modeling

the discretized equations of motion

Initial Condition State Variables (U,V,T,Q) → Dynamic Core + Physics Package →

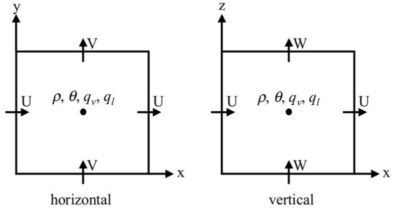
subgrid processes

2.



Subgrid parameterizations

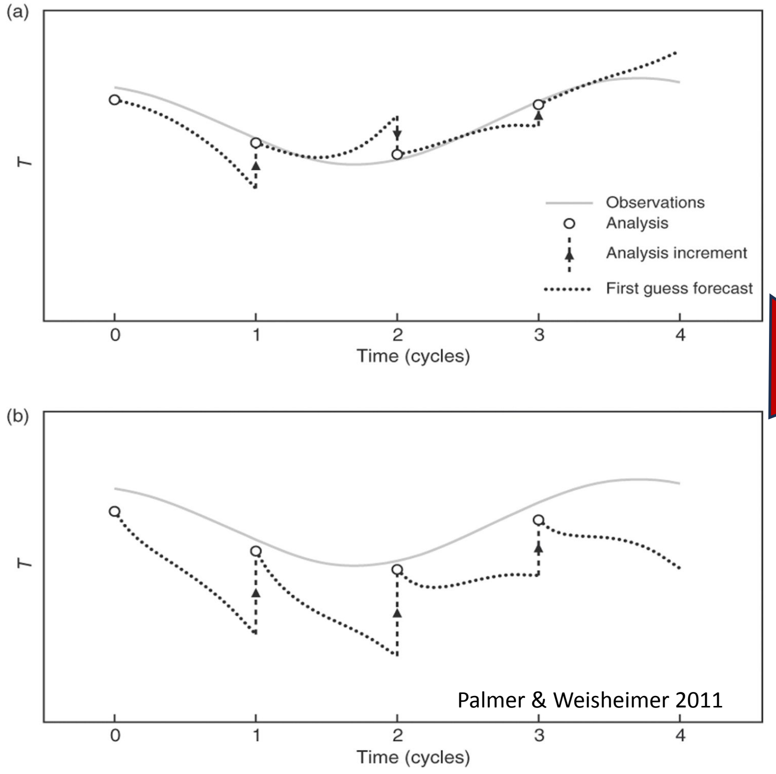
Numerical Approx.



Model Deficiency

How can we help address these errors directly with machine learning?

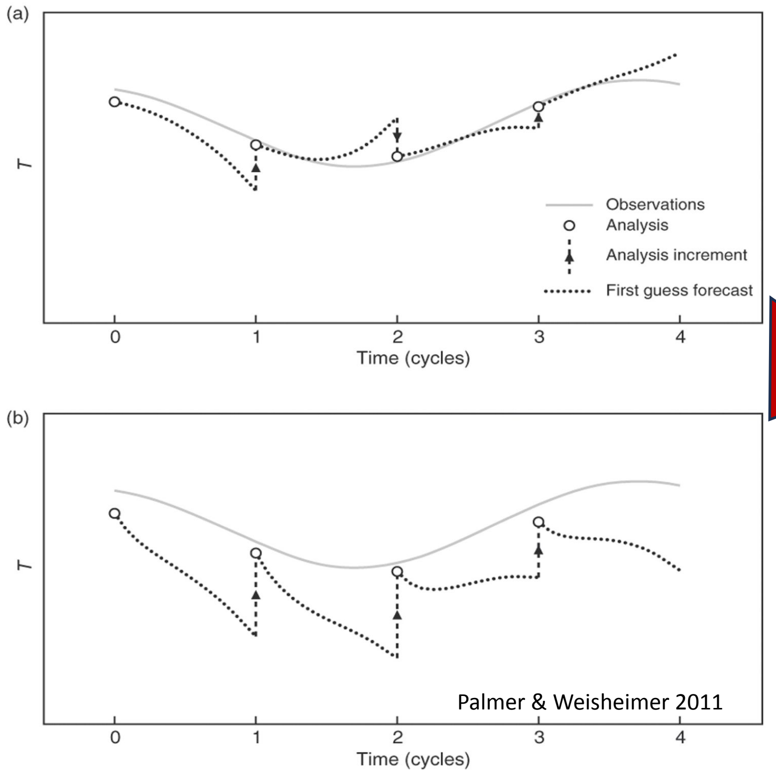
Using Data Assimilation to Identify Structural Model Error



- **Schematic**: *The analysis increment is correcting the model trajectory systematically to a warmer state.*
- *This is evidence of a systematic model error (assuming unbiased obs)*

Although the amplification of the effect of [INSERT FORCING] on [INSERT BIASED PROCESS] will occur on ***timescales of decades***, the intrinsic timescale associated with [INSERT BIASED PROCESS] itself is typically on the order of hours. Hence it should in principle be possible to assess whether the anomalously small values of [INSERT PROCESS] are realistic or not, by studying the performance of such models in short-range weather prediction mode.

Using Data Assimilation to Identify Structural Model Error



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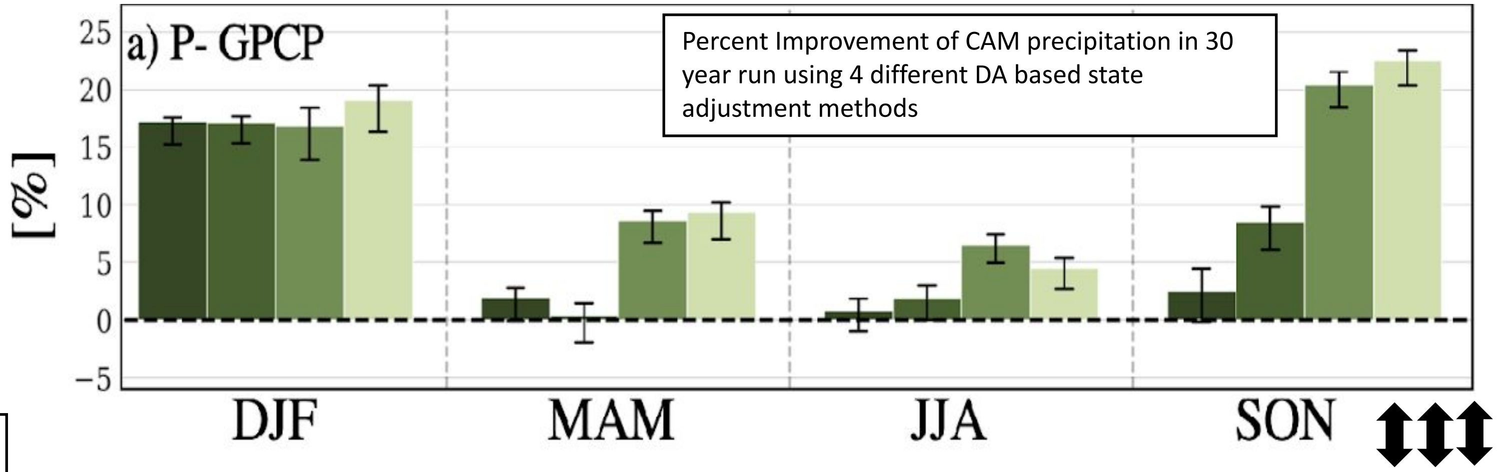
Comparing Nudging and DA:



Can we do this in a *more* state-dependent way?

Quarterly Journal of the Royal Meteorological Society
RMetS

RESEARCH ARTICLE

Deterministic and Stochastic Tendency Adjustments Derived from Data Assimilation and Nudging

William E. Chapman PhD, Judith Berner PhD

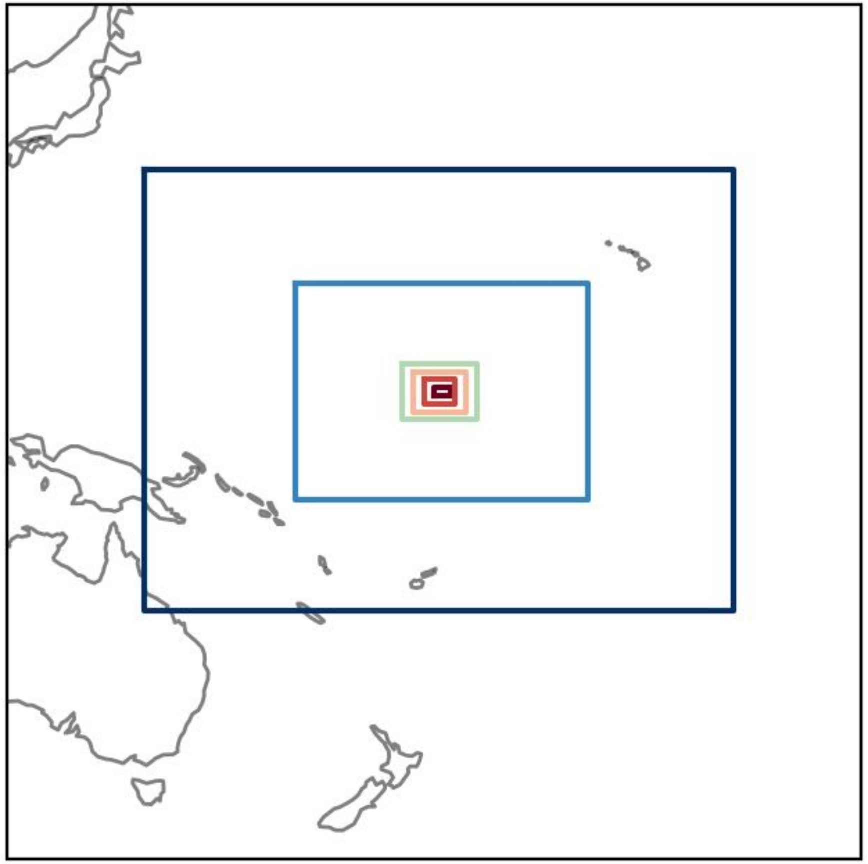
Our Process for A State-Dependent Model-Error Representation for Online CAM6 Bias Correction:

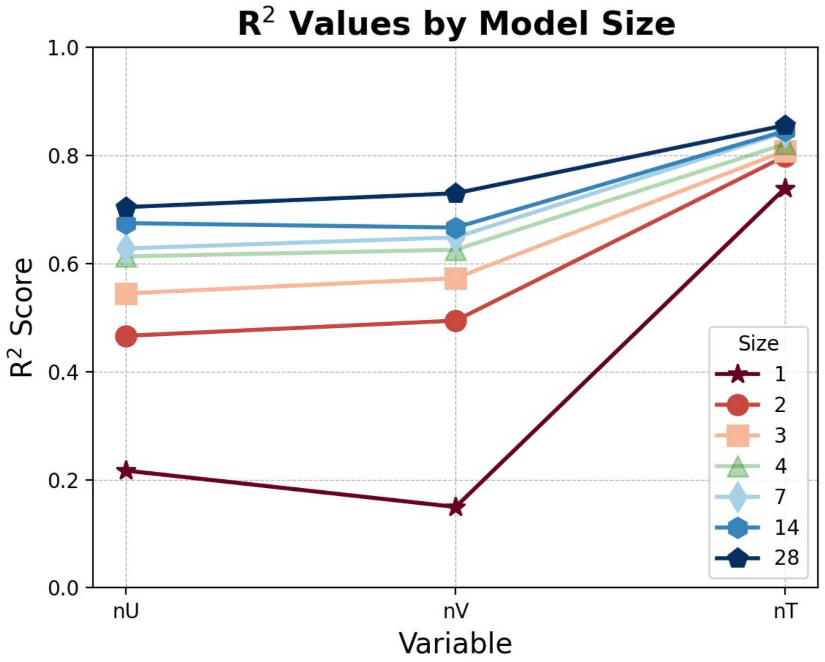
- Run ***CAM6*** for 9 years linearly relaxing to ERA5 (OBS every hour) ***[2000-2008]***
    - U,V winds only (*nudging T/Q also proved problematic for the model climo*)
- Collect Model Increments
    - Form diurnal cycle + annual cycle (H.O.D.; 31-day running mean).
    - Calculate the Increment Anomaly [**I.A.**] at every timestep
    - 2-day rolling mean the I.A. (eliminates high frequency nudging tendencies)
        - Shown in a "perfect model" nudging experiment not to be model error.
- Train a ***CNN*** at every model level to predict the anomaly increment

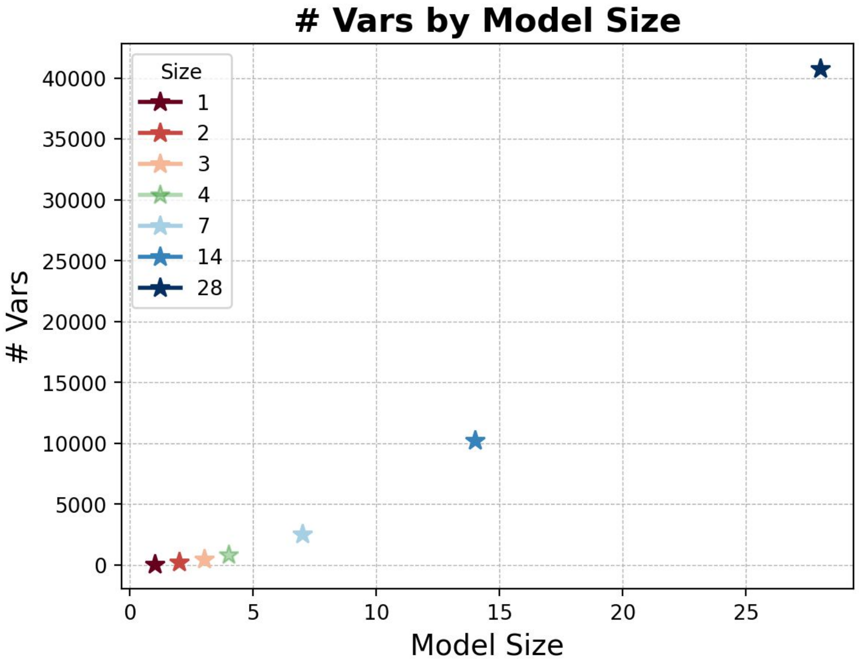
Why not a single column parameterization?

CNN

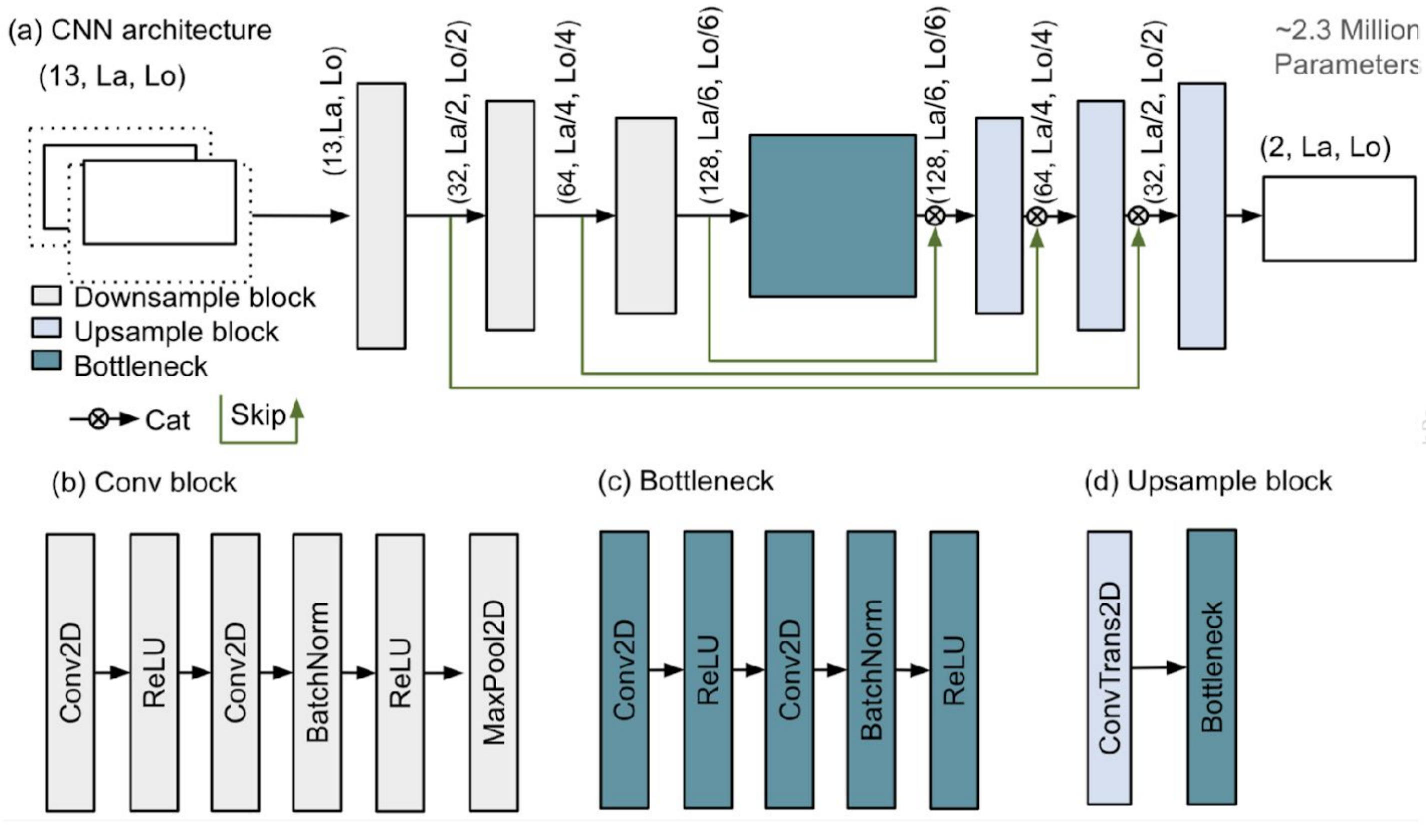
Spatial Extent







Model Architecture and Skill



Predictor Variables:

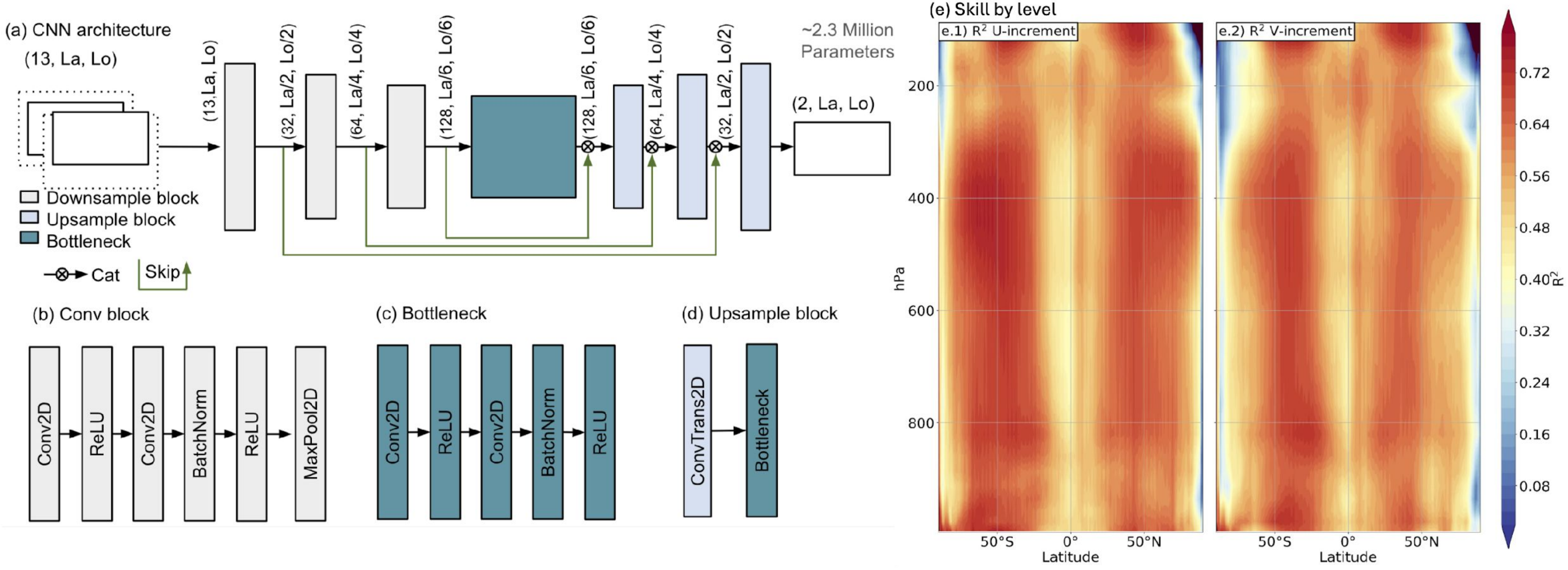
Suite of input variables, which were learned via model input ablation / shuffling

Table 1. Input Variables for a Single CNN[a]

Input Variable	Extent	Common Name
U [m/s]	[Lat / Lon / @ Target Level]	Zonal Wind
V [m/s]	[Lat / Lon / @ Target Level]	Meridional Wind
T [K]	[Lat / Lon / @ Target Level]	Temperature
Q [kg/kg]	[Lat / Lon / @ Target Level]	Specific Humidity
Omega [Pa/s]	[Lat / Lon / @ Target Level]	Vertical Velocity
U'W' [m^2/s^2]	[Lat / Lon / @ Target Mid-Level]	Zonal Momentum Flux
TauX [N/s]	[Lat / Lon / Surface]	Zonal Surface Stress
TauY [N/s]	[Lat / Lon / Surface]	Meridional Surface Stress
USTAR [m/s]	[Lat / Lon / Surface]	Surface Friction Velocity
TBOT [K]	[Lat / Lon / Surface]	Lowest Model Level Temperature
PBLH [m]	[Lat / Lon / Surface]	Boundary Layer Height
sin(DOY)	-	Sine of the Day of Year
sin(HOD)	-	Sine of the Hour of Day
Target Variable	**Extent**	**Common Name**
Nudge$U$ [m/s/s]	[Lat / Lon / @ Target Level]	Zonal Wind Nudge Anomaly Increment Tendency
Nudge$V$ [m/s/s]	[Lat / Lon / @ Target Level]	Meridional Wind Nudge Anomaly Increment Tendency

[a] A new CNN is trained for every model level

Model Architecture and Skill



FTORCH [with help from *Jack Atkinson ICCS*]

FTorch

A library for coupling (Py)Torch machine learning models to Fortran

license MIT

This repository contains code, utilities, and examples for directly calling PyTorch ML models from Fortran.

For full API and user documentation please see the online documentation which is significantly more detailed than this README.

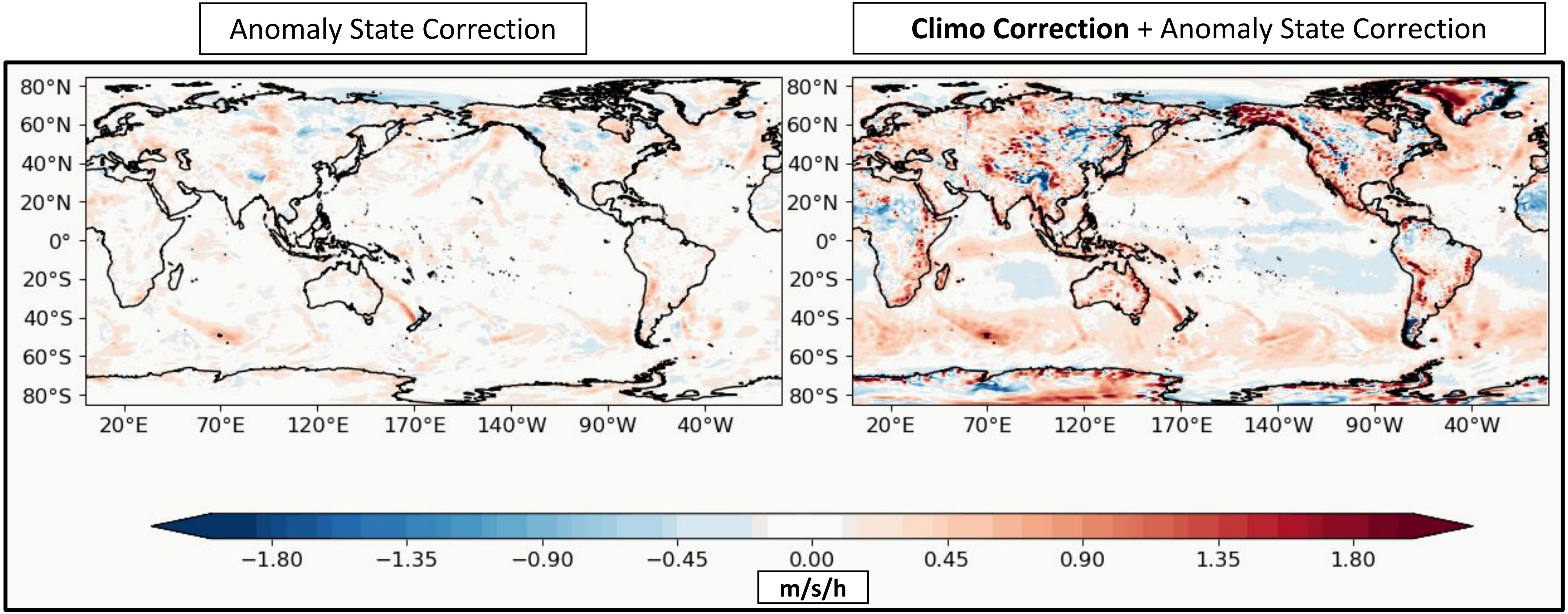
PROS:

- Easy to link the libraries
- Fast
  - You don't need to load the ML model after init

CONS

- This is ONLY for pytorch implementation

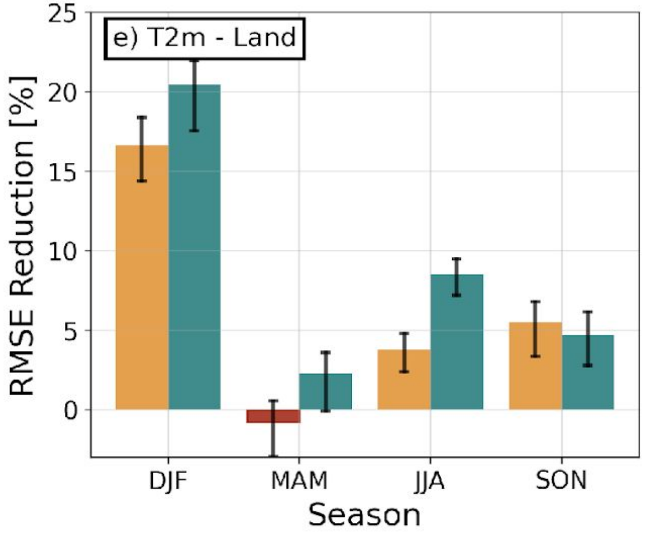
What does this look like in a run?



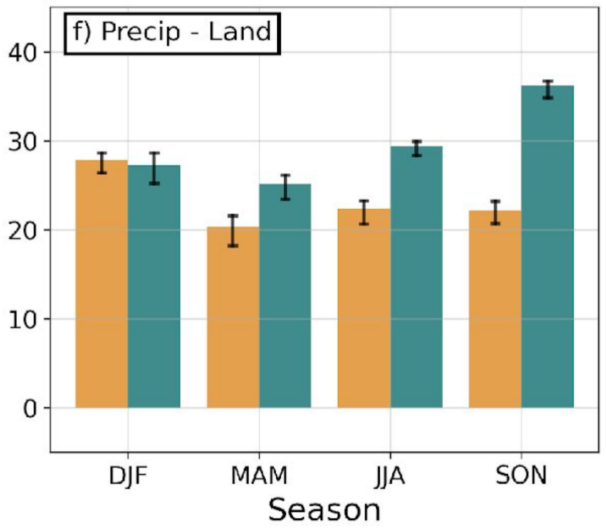
Zonal wind (U) at lowest model level

RMSE improvement:

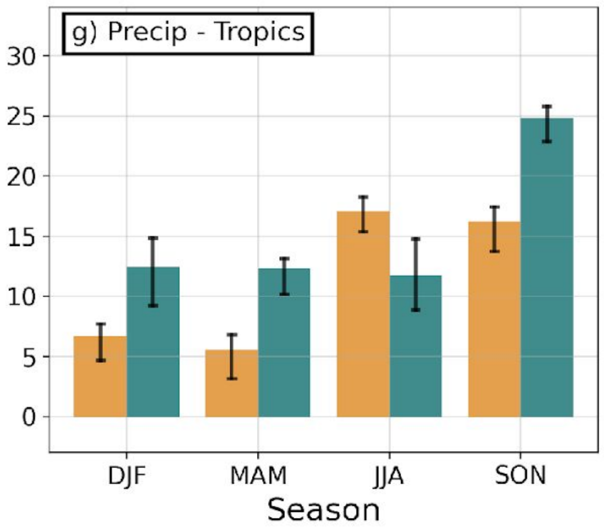
T2m



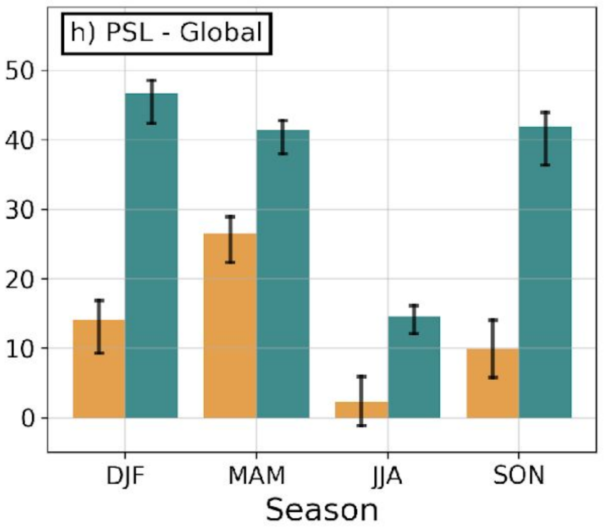
GPCP – Precip.



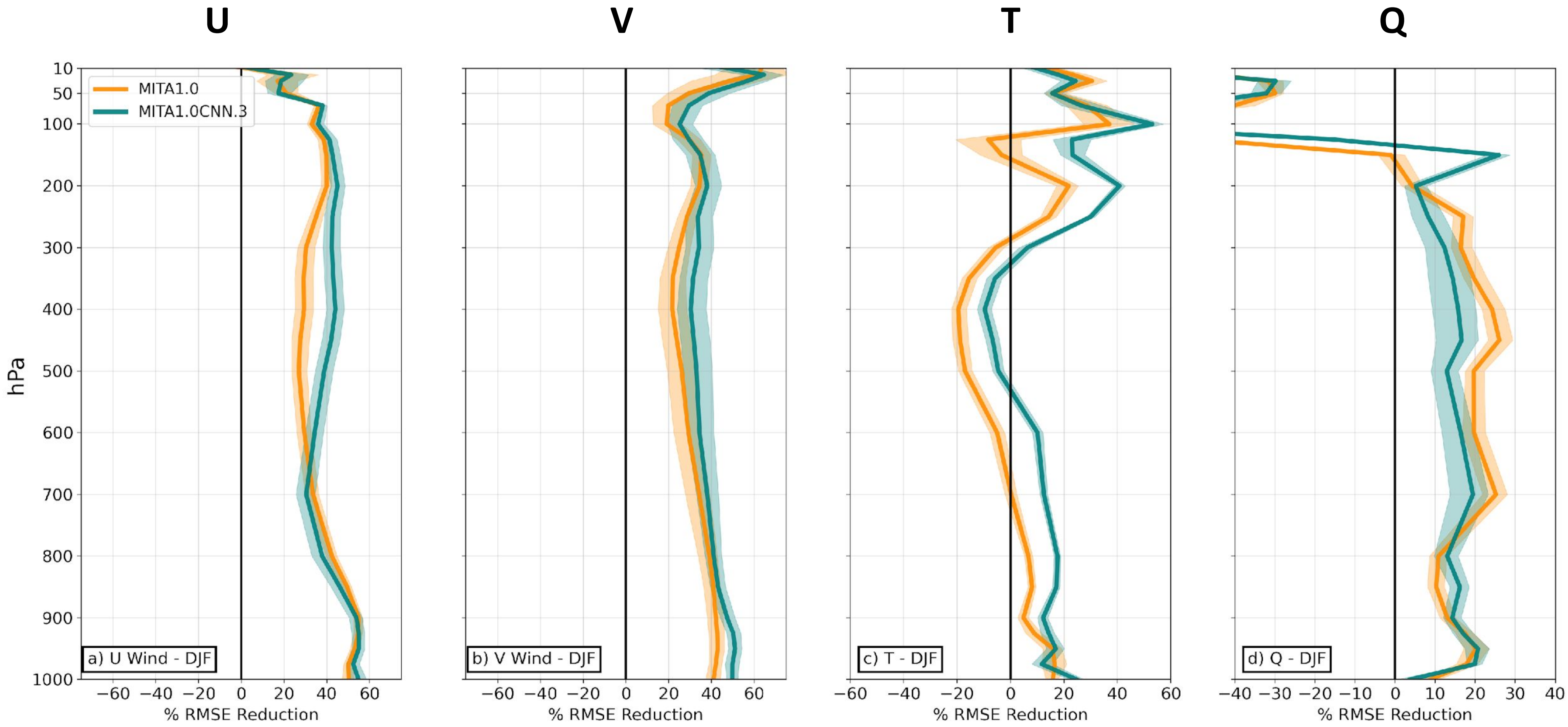
GPCP Precip. Tropics



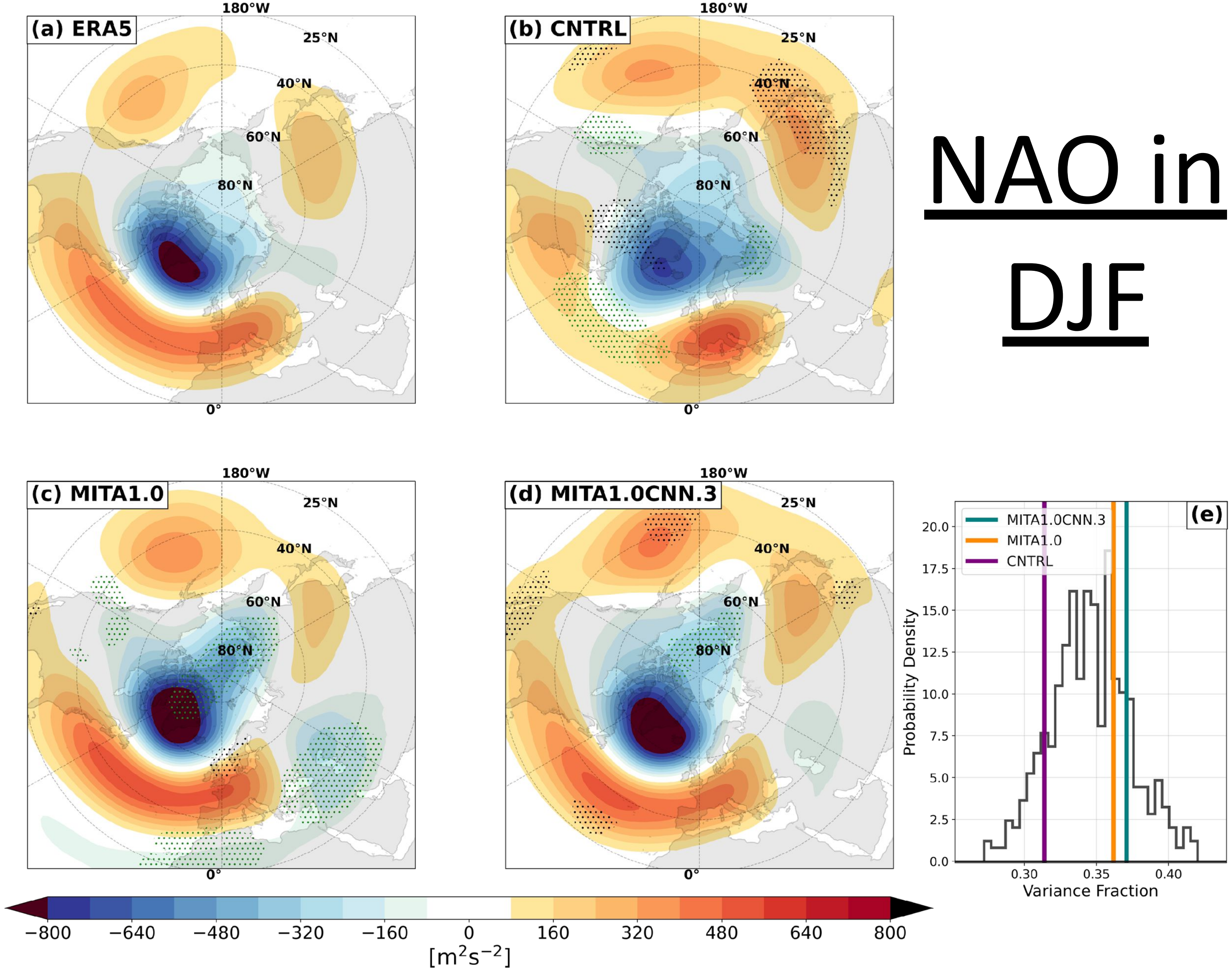
Sea Level Pressure



RMSE improvement:



Modes of Variability:



NAO in DJF

Why?:

$$\xi_3 = \nabla^{-2}(-\mathbf{V}_r^H \cdot \nabla\zeta^H)^L + \nabla^{-2}\{-\nabla\cdot(-\mathbf{V}_d^H \zeta^H)\}^L$$

$$\xi_4 = \nabla^{-2}(-\mathbf{V}_r^L \cdot \nabla\zeta^L)^L + \nabla^{-2}\{-\nabla\cdot(-\mathbf{V}_d^L \zeta^L)\}^L$$

Because the schemes improve:

ζ_3: The interaction among all the low-frequency transient eddies.

ζ_4: The self-interaction among the high-frequency anomalies.

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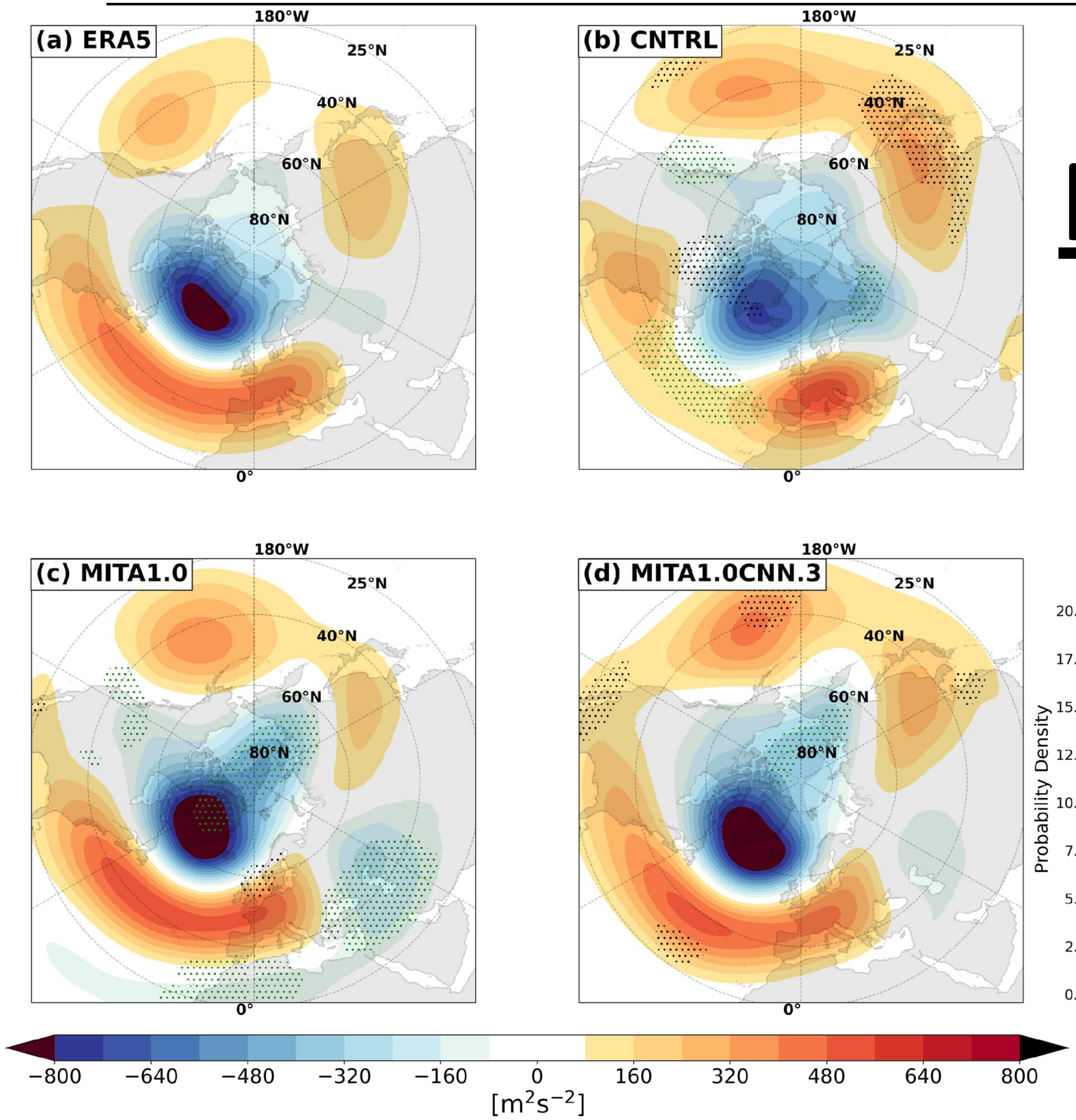

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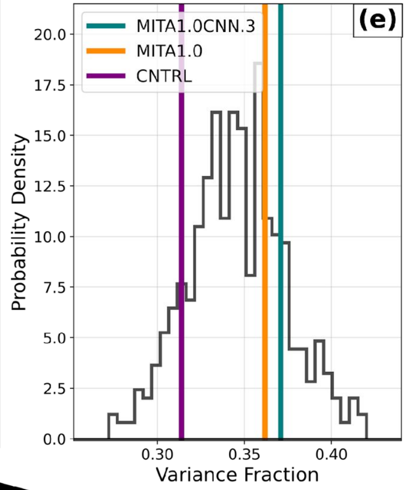

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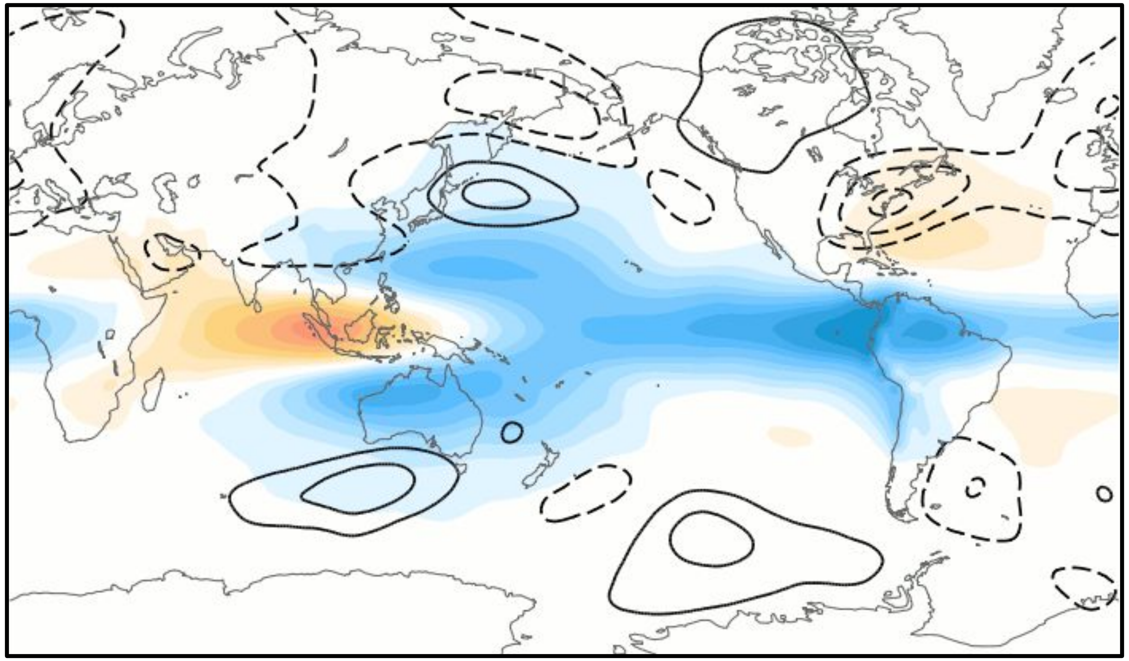
Madden Julian Oscillation



Produced by the Adames group

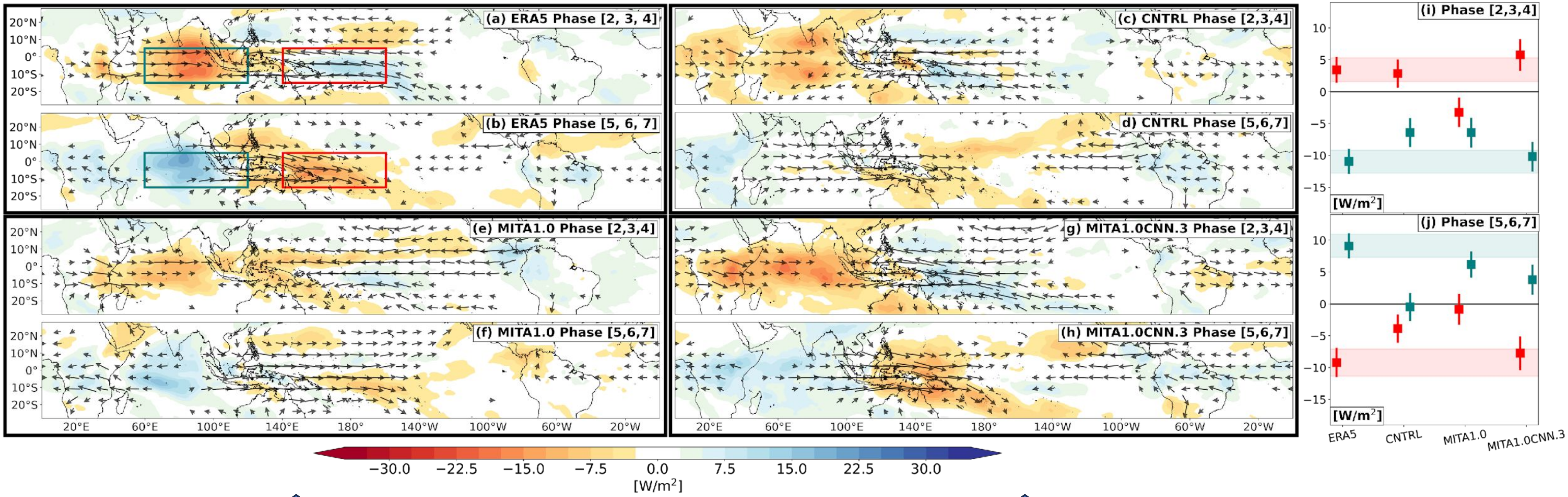
<u>MJO</u>

- Madden-Julian Oscillation (MJO) impact on North Pacific Geopotential height.
- The MJO is an eastward propagating equatorial pattern of anomalous heating that circulate the Earth typically in 30 to 60 days.
- The MJO can affect weather patterns in mid-latitudes through teleconnections. It can influence the Pacific jet stream, potentially altering weather patterns in North America, Europe, and other parts of the world
- Use two indices (wheeler and Hendon 2004) to characterize the propagation of the MJO

Madden – Julian Oscillation

Observations

CONTROL RUN

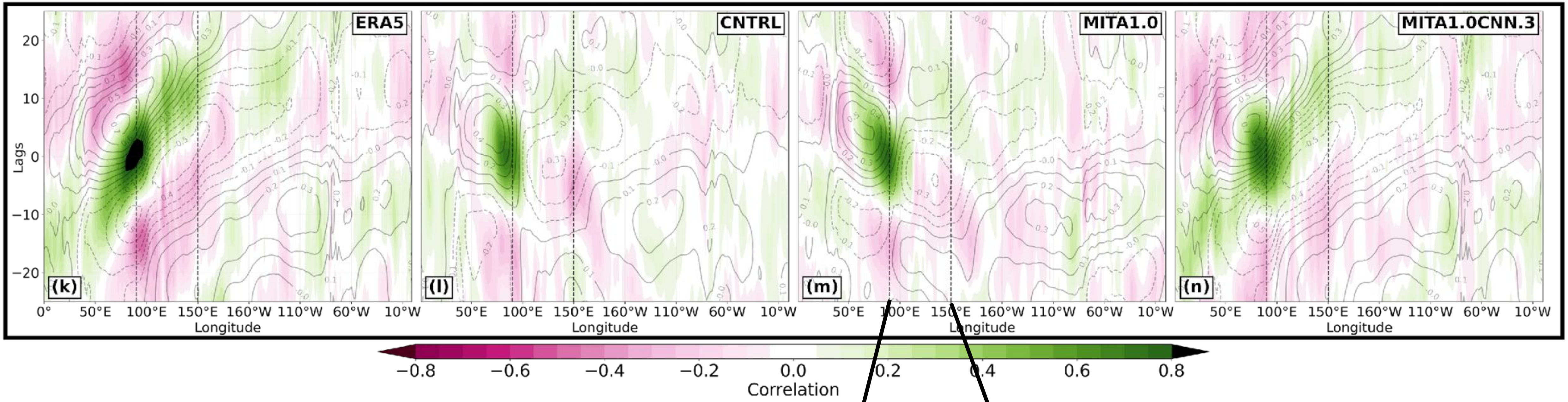


Climo Correction

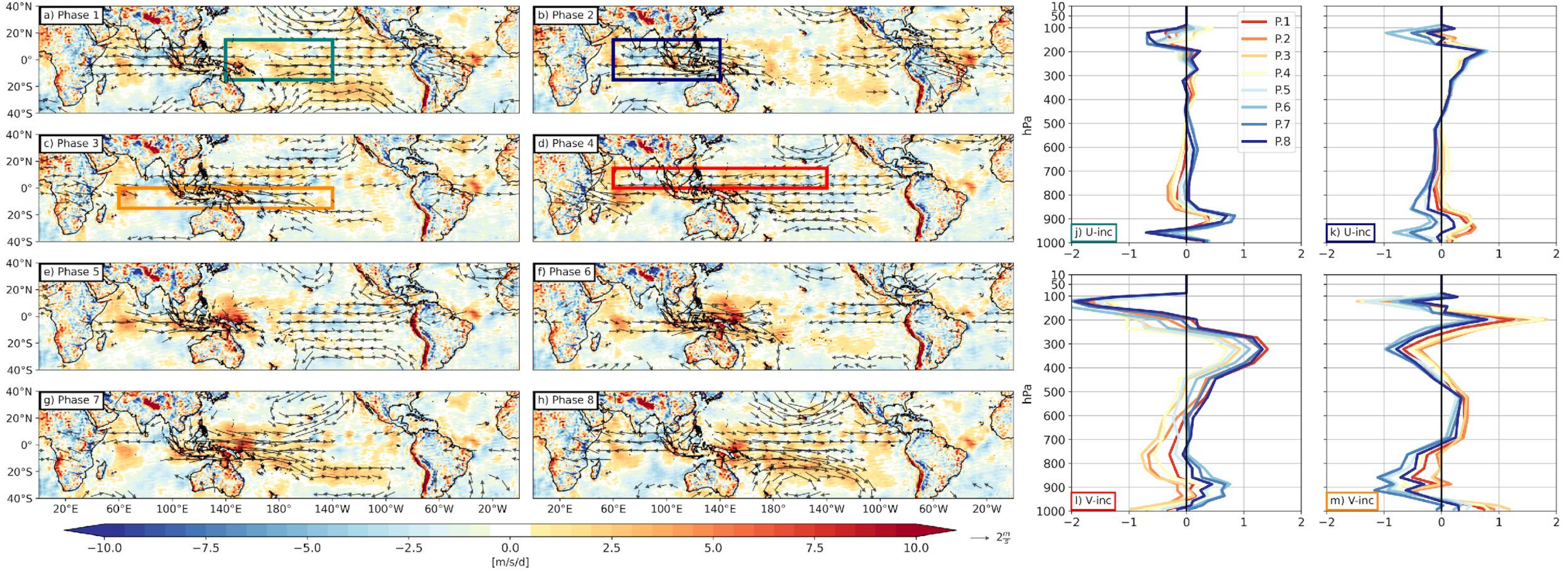
CNN

Madden – Julian Oscillation

Propagation across the Maritime Continent is tough for climate models



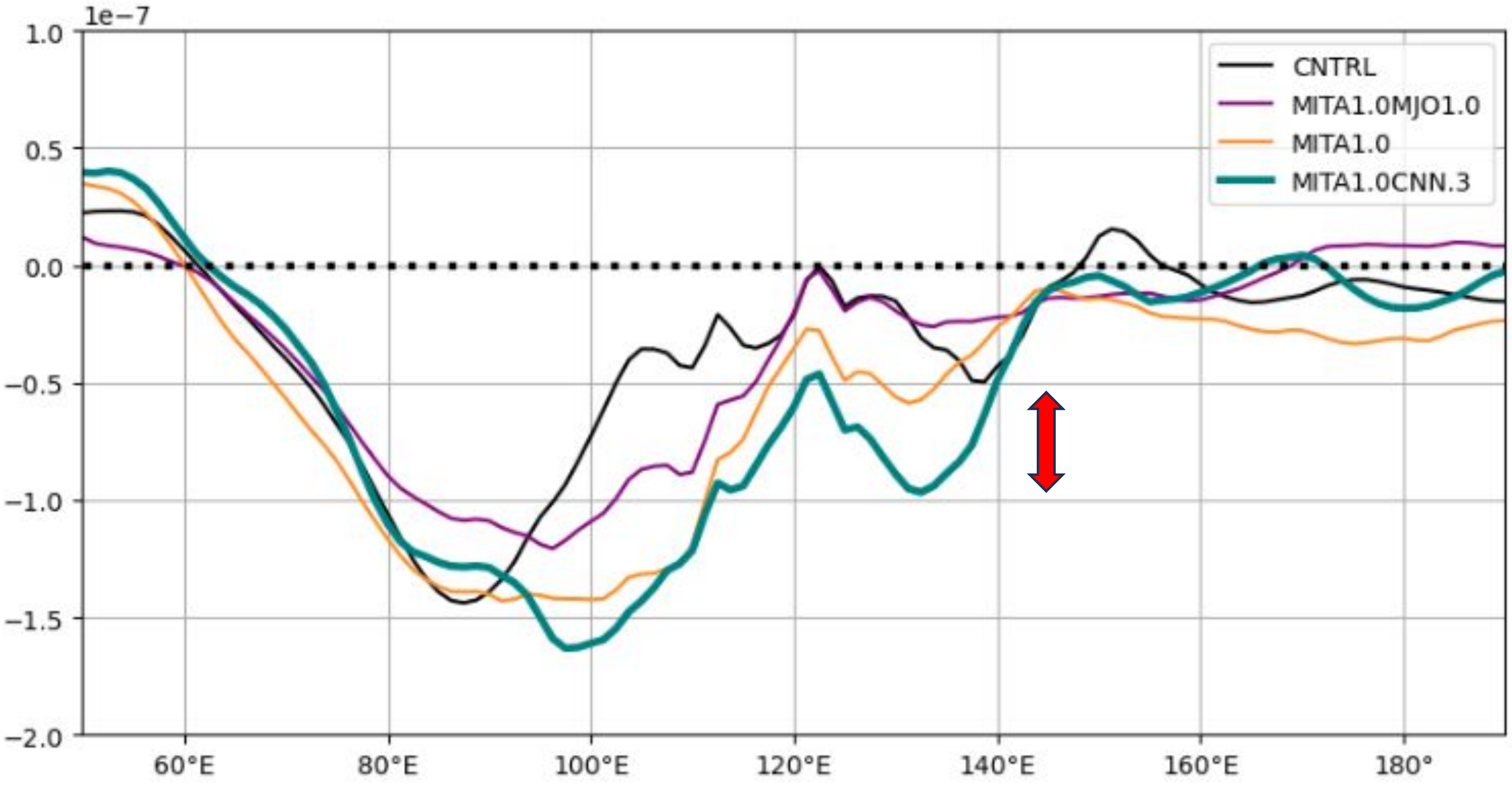
What is the CNN Doing??



Increments composited by MJO phase in the boxes on the left.

Boundary Layer Moisture Convergence:

Regressing Boundary Layer Moisture Convergence (100—850hpa) on to Indian Ocean Precipitation, then averaging [5°S-5°N].



<u>Exploring ideas in the Trio-Interaction theory for MJO propagation (Wang et al. 2016)</u>

The CNN *enhances the lower tropospheric heating to the east of the MJO major convection. When the lower tropospheric heating is increased, the induced structural change, i.e., the increased Kelvin wave easterly (lower pressure) enhances the BL moisture convergence (BLMC) to the east of the MJO center ??*

Yang, Y. M., & Wang, B. (2019).

Conclusion:

- We learn a state dependent correction to CAM via a linearly relaxation back to observations
  - (Crawford et al 2020, Watt-Meyer et al 2022, Bretherton et al 2022, Chen et al 2022, Laloyaux et al 2022, Kwa et al 2023, Watt-Meyer 2024, Gregory et al 2024).
- We have enabled CNNs in CAM/CESM via FTORCH
- We show some significant improvements (and some degradation) to the model climatology.
- We evaluate the major modes of coupled and semi-uncoupled variability and show significant improvement to the model representation of these fields.
  - We'd like to know why the MJO is so improved, progress is being made in this arena.

Questions?