# Attribution of Seasonal Climate Anomalies December-January-February 2023-24

(https://www.cpc.ncep.noaa.gov/products/people/mchen/AttributionAnalysis/)

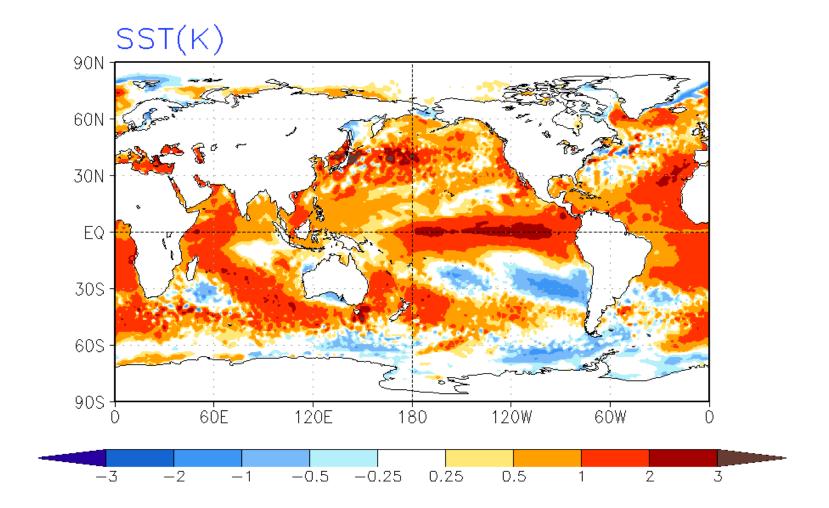
## Summary of Observed Conditions and Outlooks

- In DJF 2023/24, warm SST anomalies associated with El Niño continued in the equatorial eastern Pacific with a further reduction in warming anomalies along the coastal regions of South America. Almost over all ocean basins, specifically, over the North Pacific, central southern Pacific, Atlantic, and western and southern Indian Ocean, the SST warm anomalies persisted (slide 4). Initialized with warm SST anomalies, CFSv2 maintained the large-scale structure of the warming over the global oceans (slide 10).
- The AMIP simulations, the initialized forecasts, and other MME forecasts all captured the large-scale distribution of observed precipitation anomalies in tropical latitudes – drier (wetter) conditions in the equatorial eastern and southern Indian Ocean and Maritime Continent (equatorial western Pacific) and wetter conditions stretching along a narrow equatorial band across the entire Pacific basin (slides 11, 37-39).
- A distinctive feature in rainfall was below normal anomalies in the equatorial eastern Indian Ocean associated with the positive phase of the Indian Ocean Dipole Mode and was well reproduced in model simulations and predictions (slide 11, 37-39).
- Consistent with the notion of SSTs constraining atmospheric variability, the tendency for above normal 200-mb heights and above normal land surface temperature anomalies continued almost throughout the globe both in observations and model predictions and simulations (slide 12, 13).
- The initialized CFSv2 forecasts predicted well the tendency for above normal 200-mb height and land surface temperature over North America in general, while the z200 positive center over the high latitude North America was shifted westward resulting in a missed forecast of the observed below normal anomalies over the east Alaska and the southwest areas (slide 15, 16).
- January 2024 monthly forecast skill for 200-mb height, T2m, and precipitation over North America improved from the shortest leads (slide 33-35).

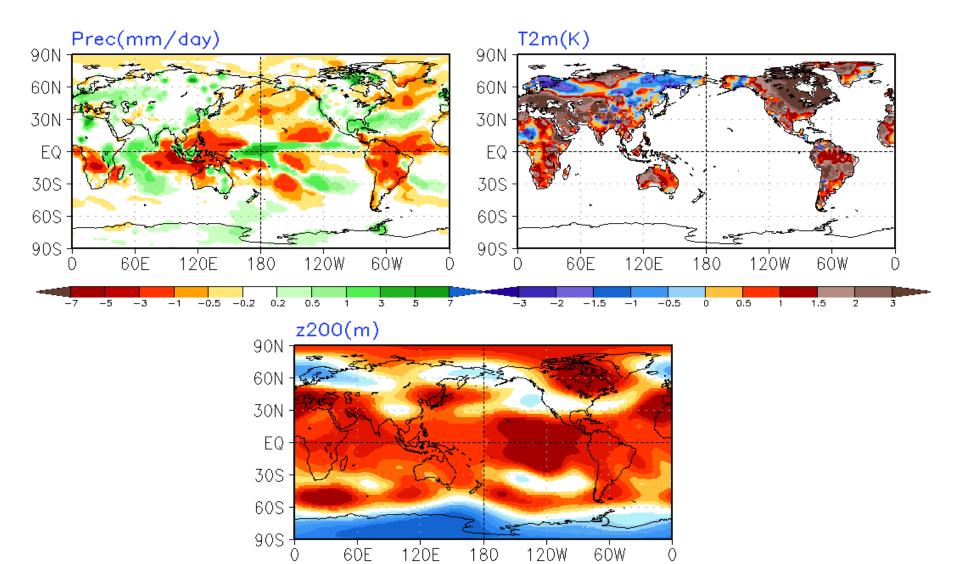
**Observed Seasonal Anomalies** 

Global and North America

# Observed Anomaly DJF2023/2024



# Observed Anomaly DJF2023/2024



180

15

-15

120W

45

30

6ÓW

60

75

90

-30

6ÔE

-60

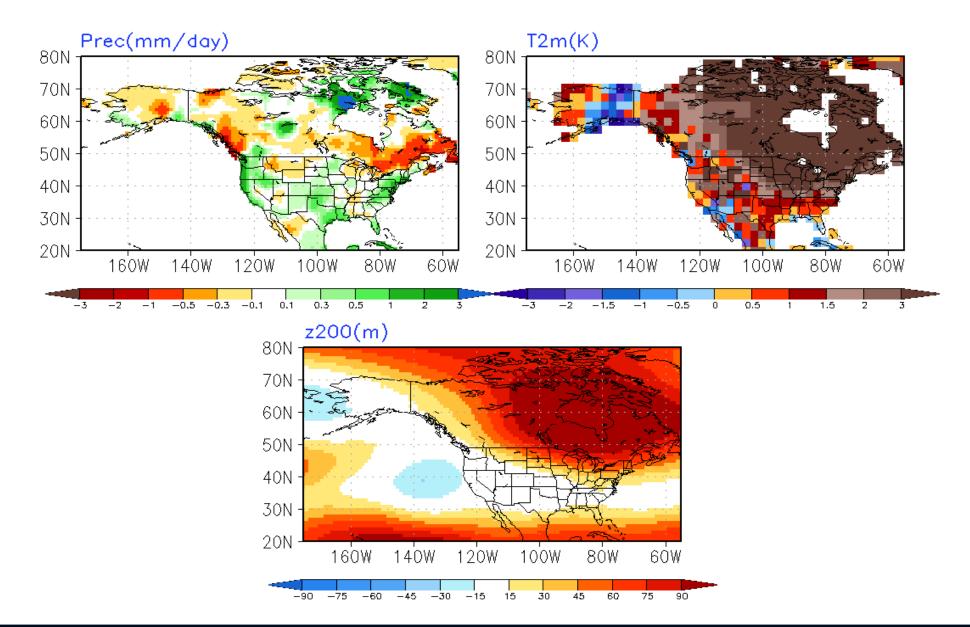
-45

Δ

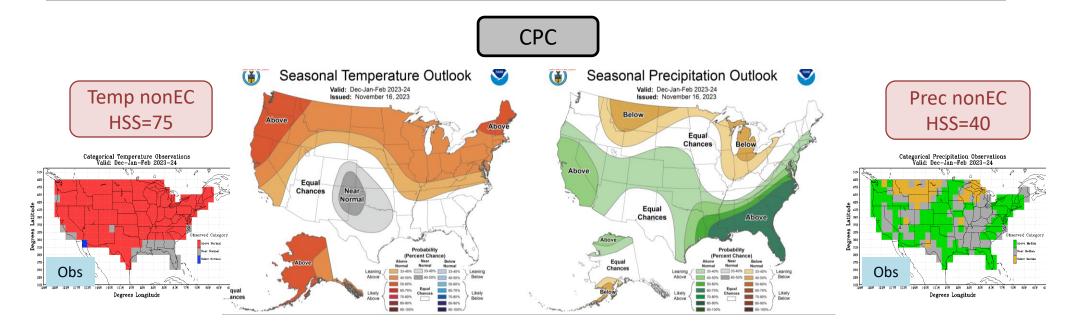
-90

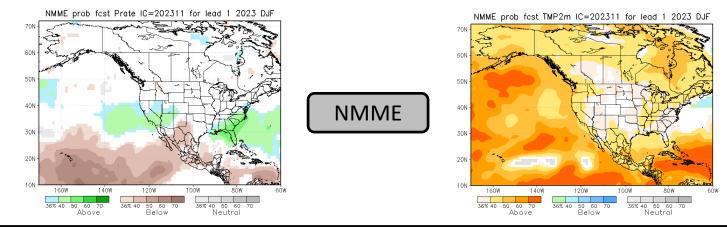
-75

# Observed Anomaly DJF2023/2024



### CPC Seasonal Outlooks and NMME Forecasts





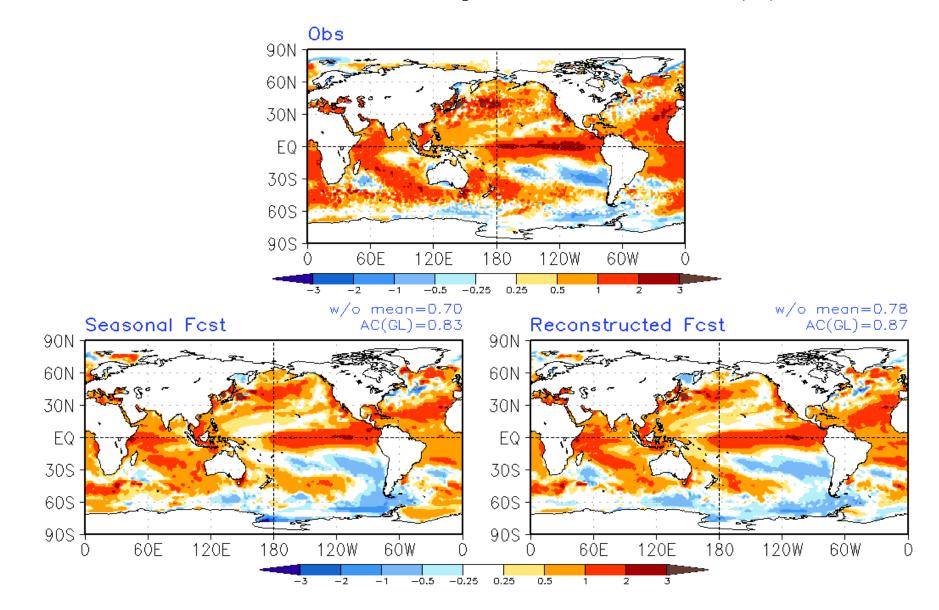
For the rationale behind CPC outlooks see https://www.cpc.ncep.noaa.gov/products/archives/long lead/PMD/2023/202311 PMD90D

Model Simulated/Forecast Ensemble Mean Anomalies

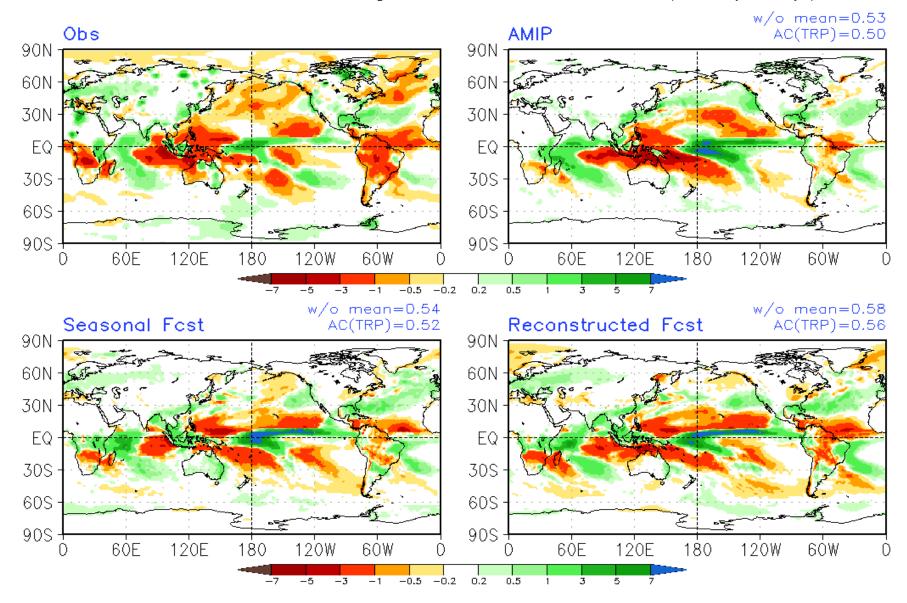
### Model Simulated/Forecast Ensemble Average Anomalies

- AMIP simulations forced with observed sea surface temperatures (100 members ensemble)
- CFSv2 real time operational forecasts
  - <u>Seasonal forecast</u>: the seasonal mean forecasts based on 40 members from the latest 10 days before the target season (0-month-lead). For example, 2016AMJ seasonal mean forecasts are 40 members from 22-31 March2016 initial conditions.
  - <u>Reconstructed forecast</u>: the seasonal mean forecasts constructed from 3 individual monthly forecasts with the latest 10 days initial conditions for each individual monthly forecasts. This approach fr constructing seasonal mean anomalies has more influence from the initial conditions (Kumar et al. 2013). For example, the constructed 2016AMJ seasonal mean forecasts are the average of April2016 forecasts from 22-31 March2016 initial conditions, May2016 forecasts from 21-30 April2016 initial conditions, and June2016 forecasts from 22-31 May2016 initial conditions.
- Numbers at the panels indicate the spatial anomaly correlation (AC). "w/o mean" is AC with area mean removed.

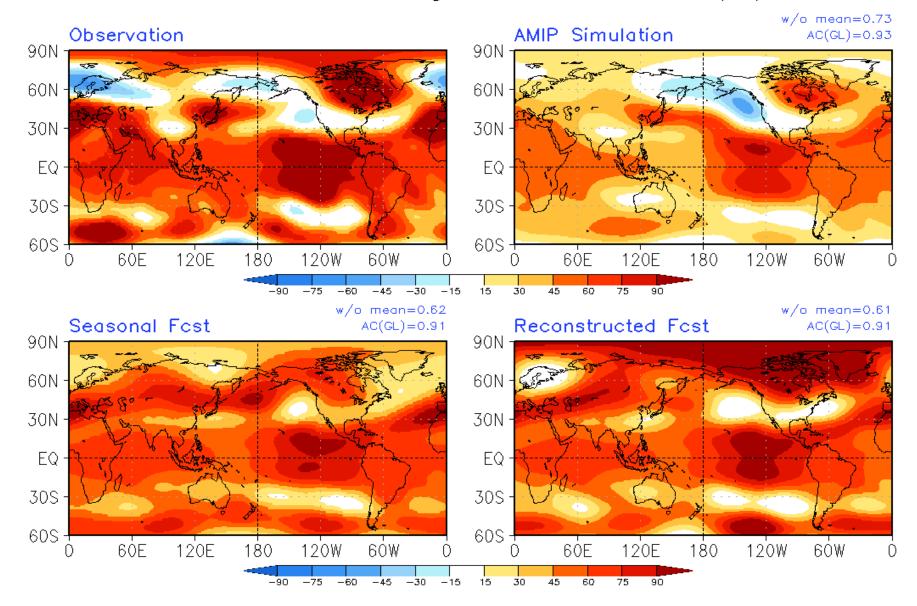
### DJF2023/2024 Observed & Model Simulated/Forecast Ensemble Average Anomalies SST(K)



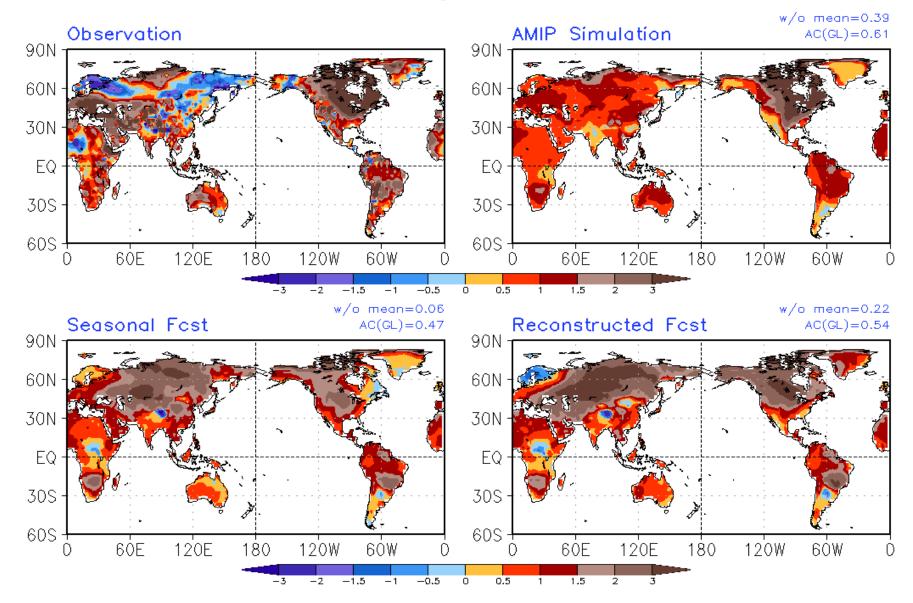
### DJF2023/2024 Observed & Model Simulated/Forecast Ensemble Average Anomalies Prec(mm/day)



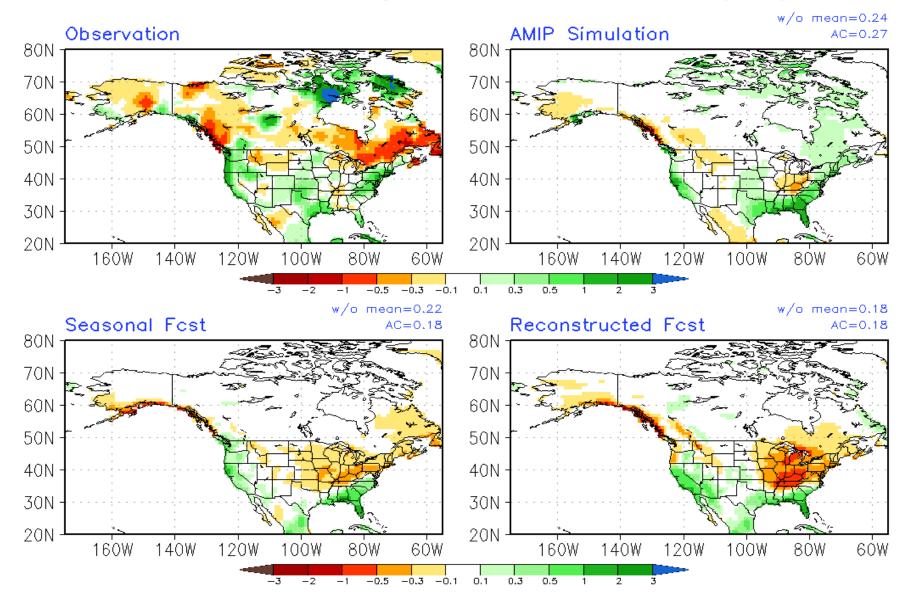
### DJF2023/2024 Observed & Model Simulated/Forecast Ensemble Average Anomalies z200(m)



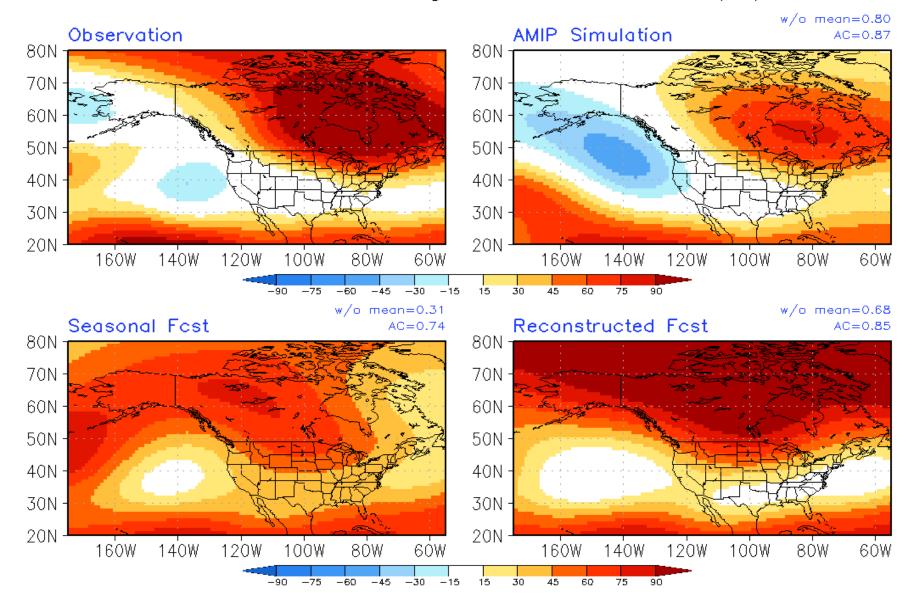
### DJF2023/2024 Observed & Model Simulated/Forecast Ensemble Average Anomalies T2m(K)



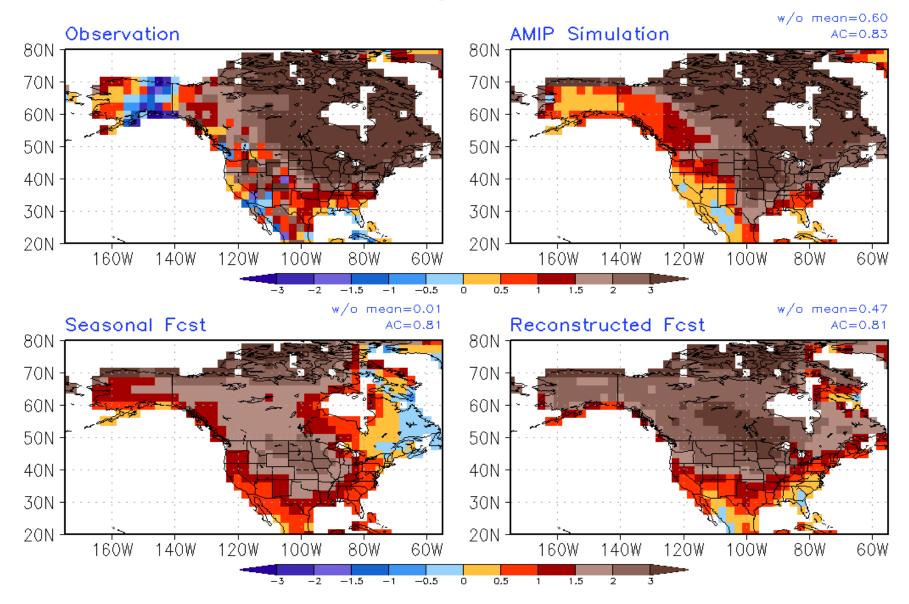
### DJF2023/2024 Observed & Model Simulated/Forecast Ensemble Average Anomalies Prec(mm/day)



### DJF2023/2024 Observed & Model Simulated/Forecast Ensemble Average Anomalies z200(m)



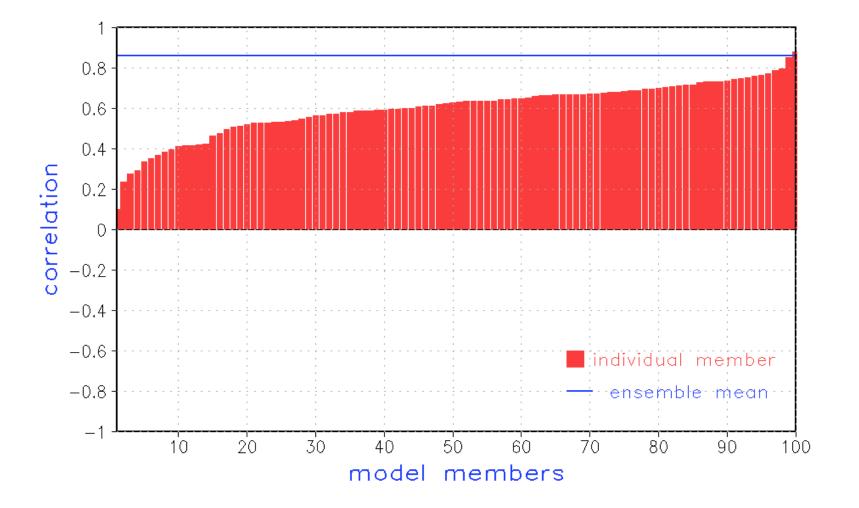
### DJF2023/2024 Observed & Model Simulated/Forecast Ensemble Average Anomalies T2m(K)



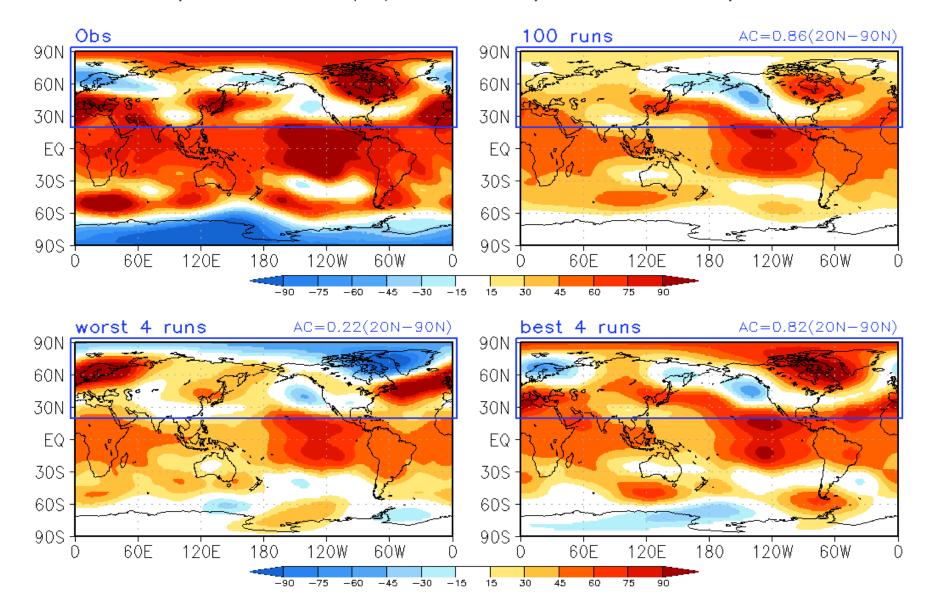
## Model Simulated/Forecast Anomalies: Individual Runs

- In this analysis, anomalies from individual model runs are compared against the observed seasonal mean anomalies. The spatial resemblance between them is quantified based on anomaly correlation (AC).
- The distribution of AC across all model simulations is indicative of probability of observed anomalies to have a predictable (or attributable) component.
- One can also look at best and worst match between model simulated/forecast anomalies to assess the range of possible seasonal mean outcomes.
- For further details see: Kumar, A., M. Chen, M. Hoerling, and J. Eischeid (2013), Do extreme climate events require extreme forcings? Geophys. Res. Lett., 40, 3440-3445. <u>doi:10.1002/grl.50657</u>.

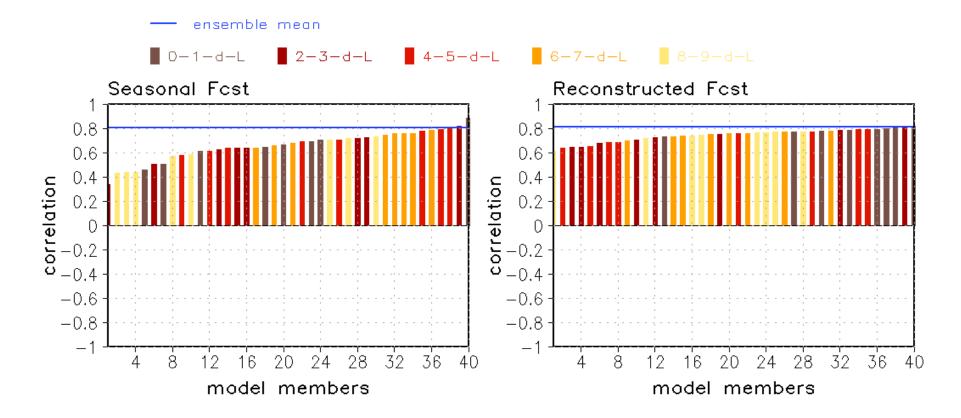
DJF2023/2024 Anomaly Correlation for Individual AMIP Simulation with Observation -- z200(20N-90N)



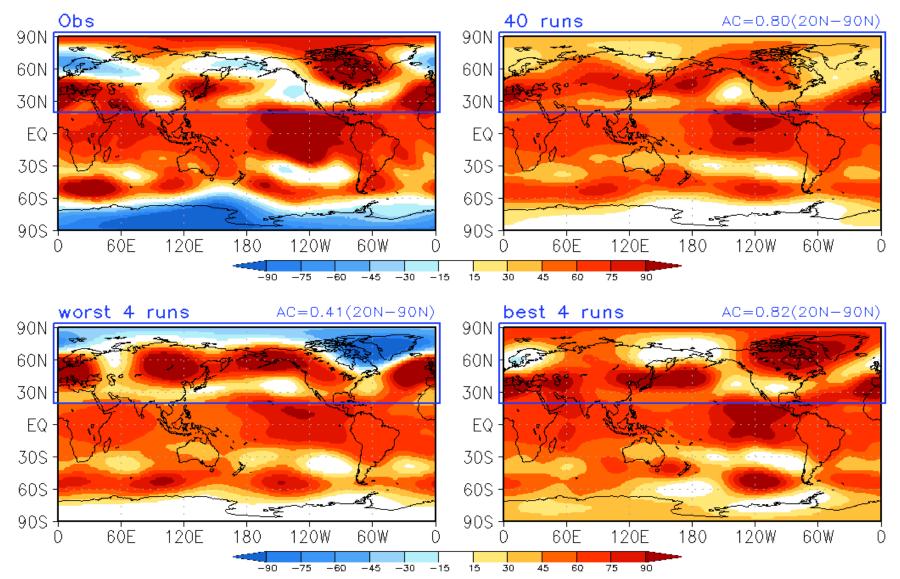
### Observed & AMIP Ensemble Mean Anomalies DJF2023/2024 z200(m) 100 runs/worst 4 runs/best 4 runs



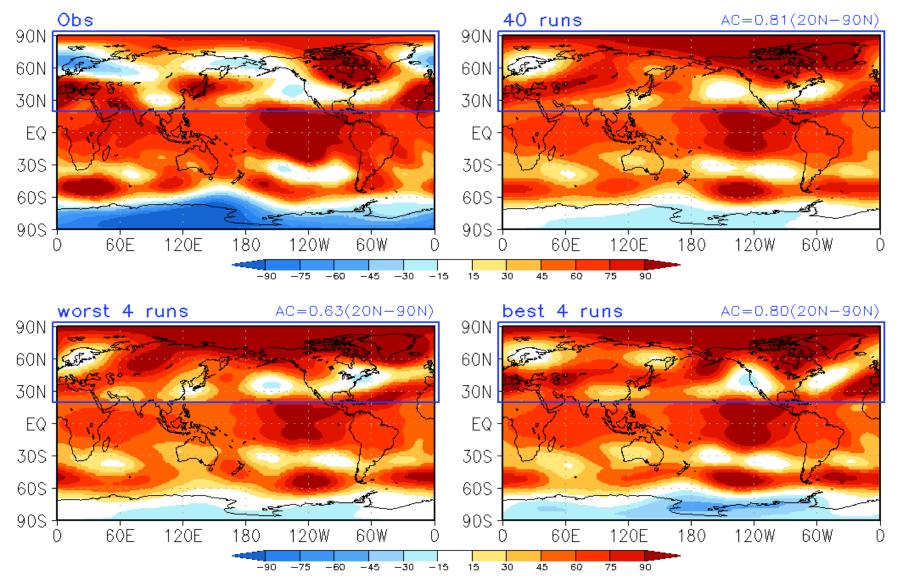
### DJF2023/2024 Anomaly Correlation for Individual CFSv2 Forecast with Observation -- z200 (20N-90N)



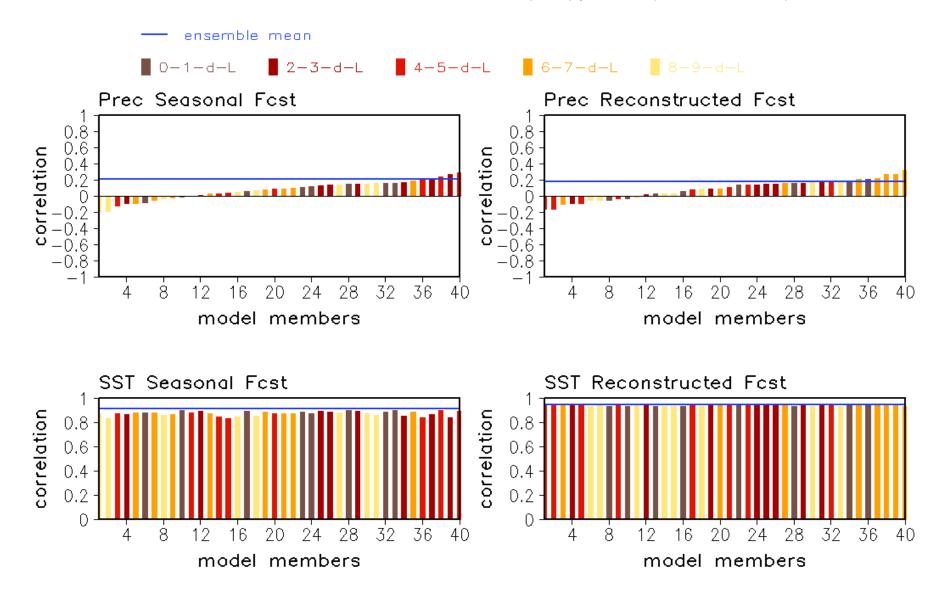
#### Observed & CFSv2 Forecast Ensemble Average Anomalies DJF2023/2024 z200(m) 40 runs/worst 4 runs/best 4 runs Seasonal Forecast



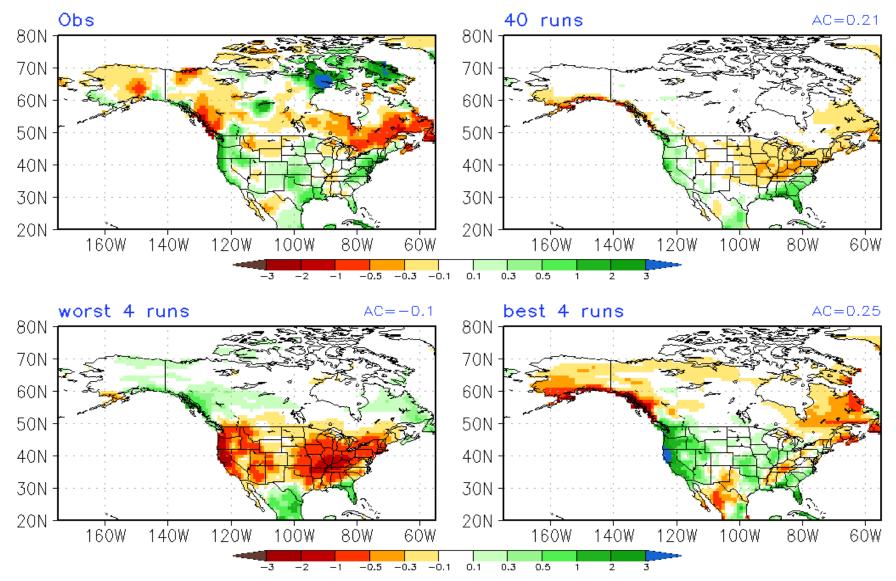
#### Observed & CFSv2 Forecast Ensemble Average Anomalies DJF2023/2024 z200(m) 40 runs/worst 4 runs/best 4 runs Reconstructed Forecast



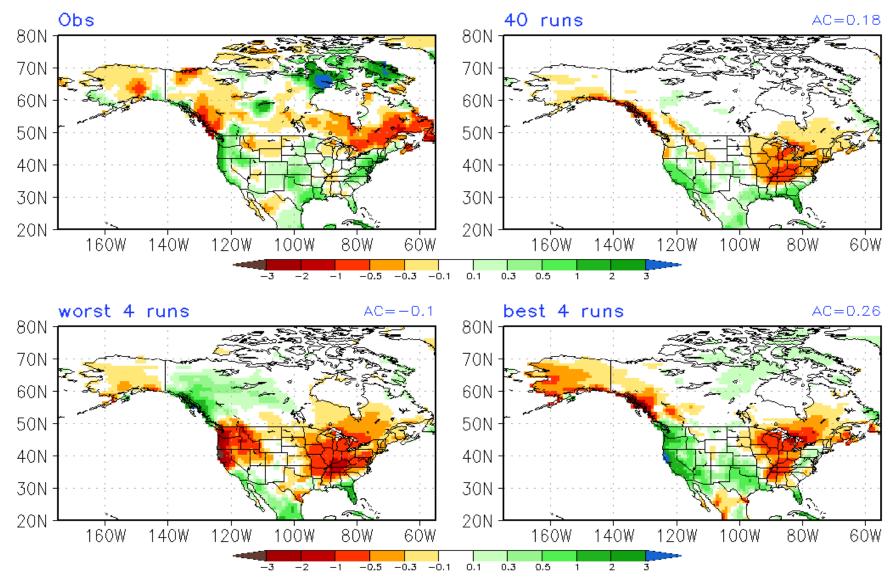
### DJF2023/2024 Anomaly Correlation for Individual CFSv2 Forecast with Observation -- Prec(NA)/SST(30S-30N)



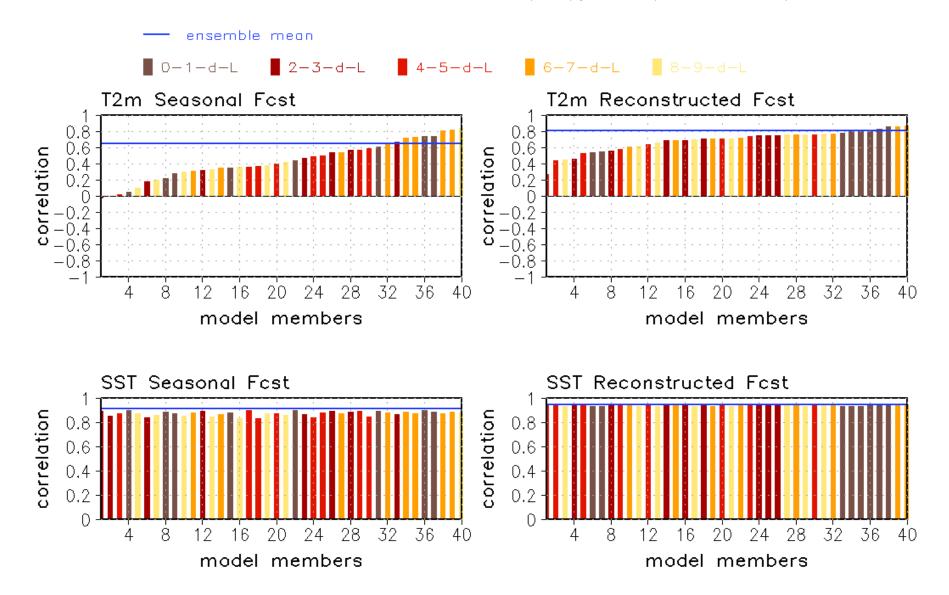
#### Observed & CFSv2 Forecast Ensemble Average Anomalies DJF2023/2024 Prec(mm/day) 40 runs/worst 4 runs/best 4 runs Seasonal Forecast



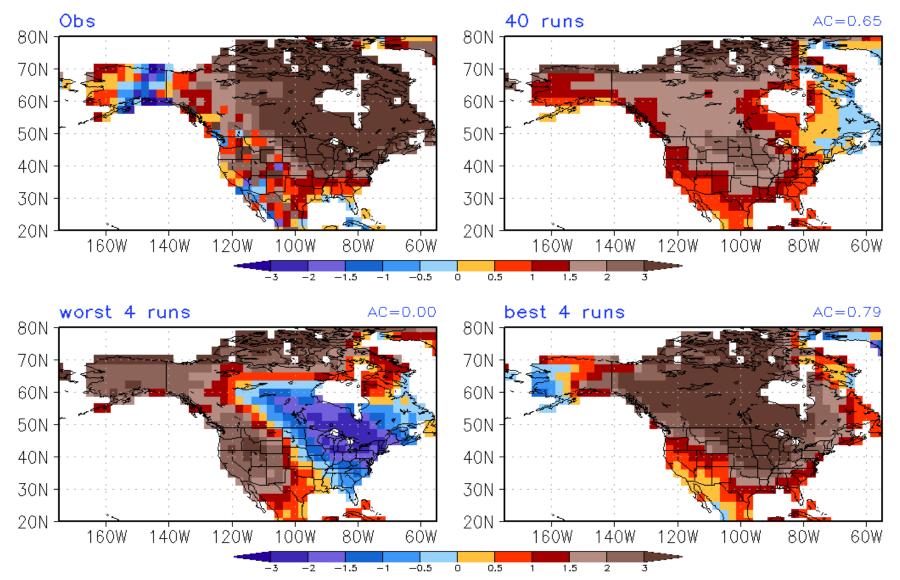
#### Observed & CFSv2 Forecast Ensemble Average Anomalies DJF2023/2024 Prec(mm/day) 40 runs/worst 4 runs/best 4 runs Reconstructed Forecast



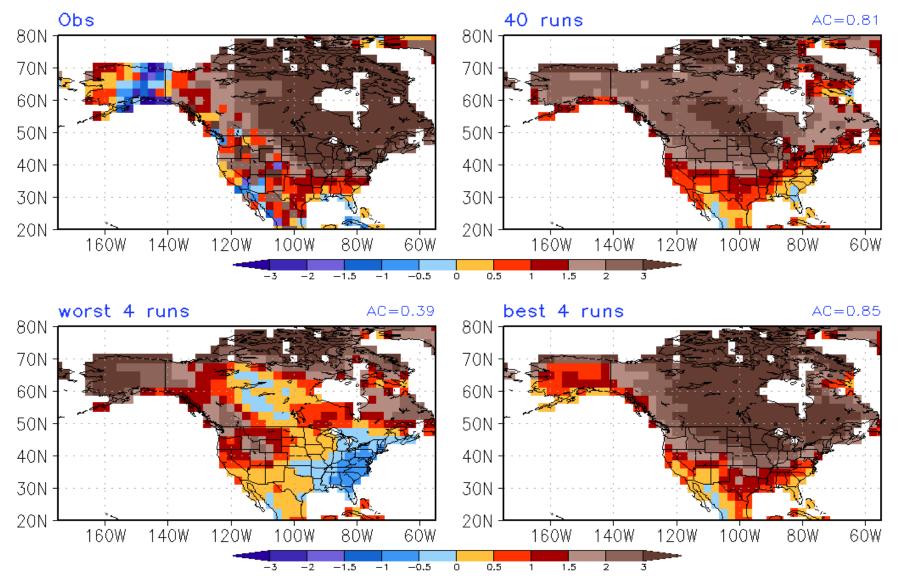
### DJF2023/2024 Anomaly Correlation for Individual CFSv2 Forecast with Observation -- T2m(NA)/SST(30S-30N)



#### Observed & CFSv2 Forecast Ensemble Average Anomalies DJF2023/2024 T2m(K) 40 runs/worst 4 runs/best 4 runs Seasonal Forecast

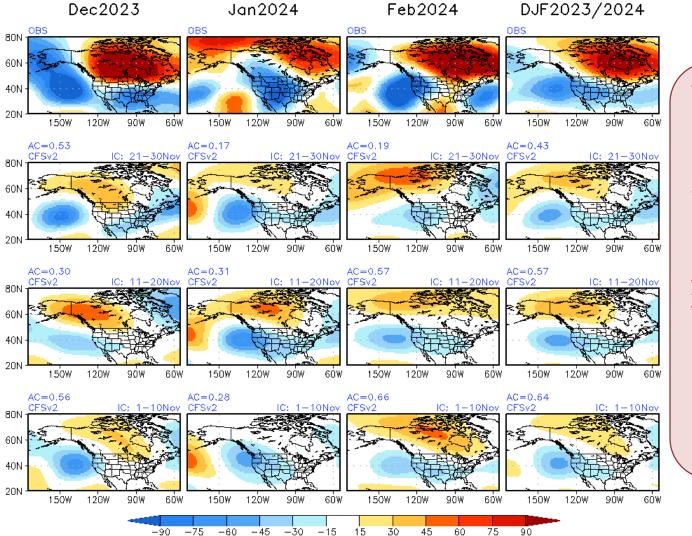


#### Observed & CFSv2 Forecast Ensemble Average Anomalies DJF2023/2024 T2m(K) 40 runs/worst 4 runs/best 4 runs Reconstructed Forecast



## z200(m) Monthly Means from Seasonal Forecast

Monthly Means from Seasonal Fcst (40ensm) DJF2023/2024 z200(m) eddy & Obs



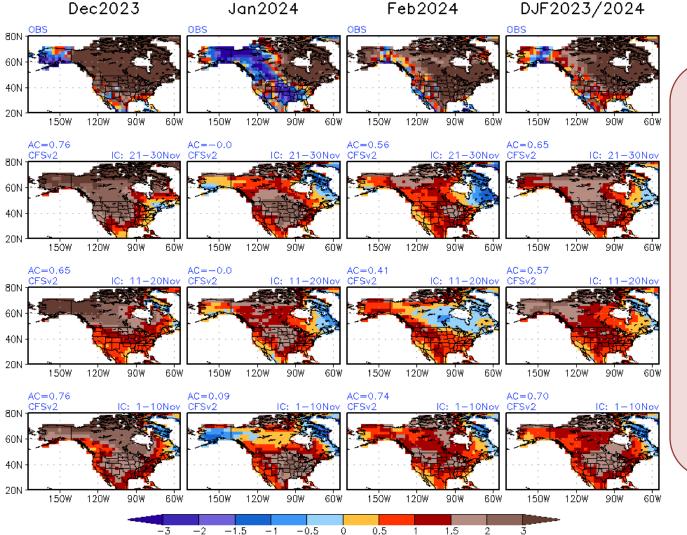
Top row: Observed anomaly.

CFSv2 seasonal forecasts from different initial conditions in the <u>month prior</u> to the target season:

- 2<sup>nd</sup> row: last 10 days of the prior month.
- 3<sup>rd</sup> row: 11<sup>th</sup> 20<sup>th</sup> of the prior month.
- 4<sup>th</sup> row: 1<sup>st</sup> 10<sup>th</sup> of the prior month.

## T2m(k) Monthly Means from Seasonal Forecast

Monthly Means from Seasonal Fcst (40ensm) DJF2023/2024 T2m(K) & Obs



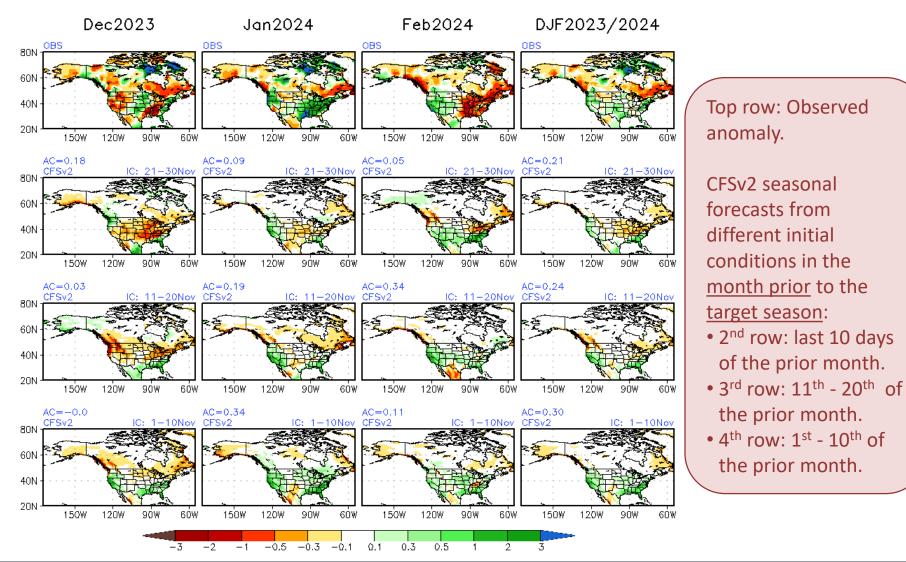
Top row: Observed anomaly.

CFSv2 seasonal forecasts from different initial conditions in the <u>month prior</u> to the target season:

- 2<sup>nd</sup> row: last 10 days of the prior month.
- 3<sup>rd</sup> row: 11<sup>th</sup> 20<sup>th</sup> of the prior month.
- 4<sup>th</sup> row: 1<sup>st</sup> 10<sup>th</sup> of the prior month.

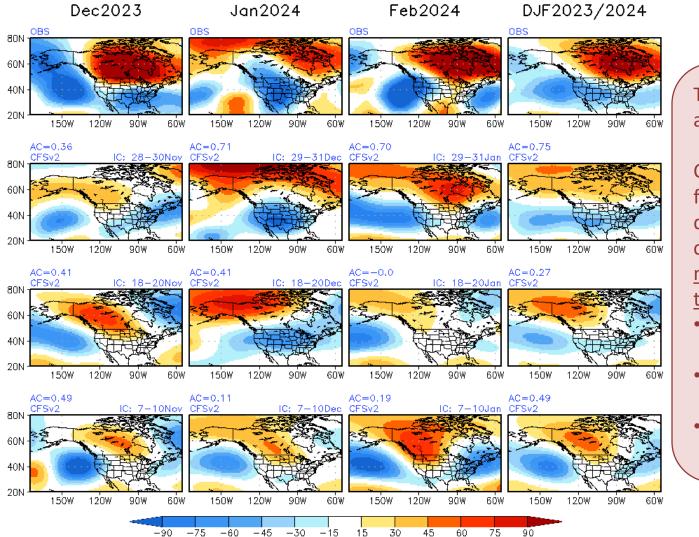
## Prec(mm/day) Monthly Means from Seasonal Forecast

Monthly Means from Seasonal Fcst (40ensm) DJF2023/2024 Prec(mm/day) & Obs



## z200(m) Monthly Means from Monthly Forecast

Monthly Means from Monthly Fcst DJF2023/2024 z200(m) eddy & Obs



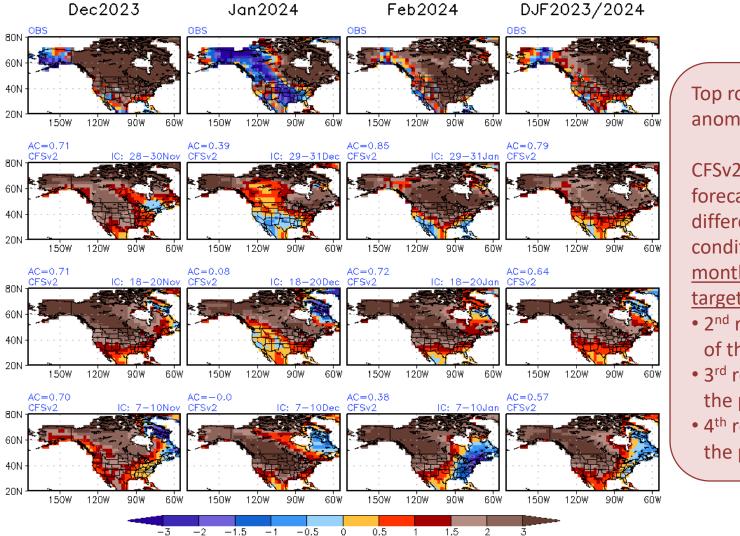
Top row: Observed anomaly.

CFSv2 monthly forecasts from different initial conditions in the <u>month prior</u> to the target month:

- 2<sup>nd</sup> row: last 3 days of the prior month.
- 3<sup>rd</sup> row: 18<sup>th</sup> 20<sup>th</sup> of the prior month.
- 4<sup>th</sup> row: 7<sup>th</sup> 10<sup>th</sup> of the prior month.

## T2m(k) Monthly Means from Monthly Forecast

Monthly Means from Monthly Fcst DJF2023/2024 T2m(K) & Obs



Top row: Observed anomaly.

CFSv2 monthly forecasts from different initial conditions in the <u>month prior</u> to the <u>target month</u>:

- 2<sup>nd</sup> row: last 3 days of the prior month.
- 3<sup>rd</sup> row: 18<sup>th</sup> 20<sup>th</sup> of the prior month.
- 4<sup>th</sup> row: 7<sup>th</sup> 10<sup>th</sup> of the prior month.

## Prec(/mm/day) Monthly Means from Monthly Forecast

Monthly Means from Monthly Fcst DJF2023/2024 Prec(mm/day) & Obs Dec2023 Jan2024 Feb2024 DJF2023/2024 OBS OBS OBS 80N 60N 40N Top row: Observed 20N anomaly. 150W 120W 90W 6ÓW 150W 120W 150W 120W 150W 120W 9ÓW 90W 60W 90W 60W ิด∩ัพ AC=0.12 AC=0.21 AC=0.49 AC=0.11 IC: 28-30Nov IC: 29-31Dec CFSv2 IC: 29-31Jan CFSv2 CFSv2 80N CFSv2 monthly 60N forecasts from 40N different initial 20N conditions in the 150W 150W 150W 120W 90W 6ÓW 120W 9ÓW 6ÓW 150W 120W 120W ิด∩ัพ 90W 60W 90W AC=0.04 CFSv2 AC=-0.0 IC: 18-20Dec CFSv2 AC=0.08 AC = -0.0month prior to the IC: 18-20Nov IC: 18-20Jan CFSv2 80N target month: 60N • 2<sup>nd</sup> row: last 3 days 40N of the prior month. 20N • 3<sup>rd</sup> row: 18<sup>th</sup> – 20<sup>th</sup> of 120W 90W 6ÓW 150W 120W 90W 6Ó₩ 150W 120W 150W 120W 90W 150W 90W 6ÓW 6Ó₩ AC = -0.0AC = -0.0AC=0.25 AC=0.15 the prior month. IC: 7-10Dec CFSv2 IC: 7-10Jan CFSv2 IC: 7-10Nov CFSv2 80N • 4<sup>th</sup> row: 7<sup>th</sup> – 10<sup>th</sup> of 60N the prior month. 40N 20N 150W 120W 9ÓW 150W 120W 9ÓW 60₩ 150W 120W 90W 6ÓW 150W 120W 9ÓW 60W 6Ó₩

2

0.5

0.3

-0.5 -0.3

-3

-2

-1

0.1

-0.1

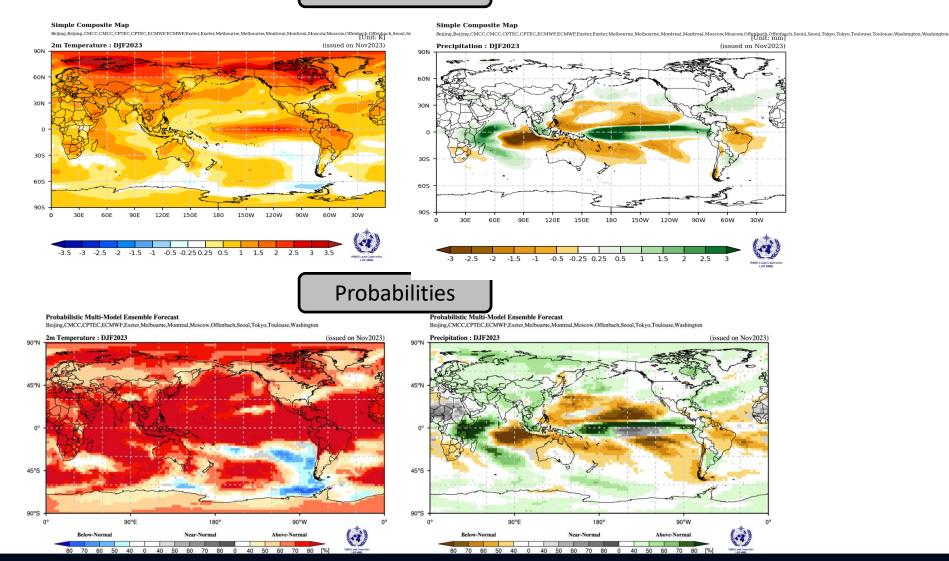
### Seasonal Forecasts from Multi-Model Ensemble Systems

- WMO Lead Center for Long-Range Forecast Multi-Model Ensemble (LC-LRFMME). <u>https://www.wmolc.org/</u>
- Copernicus Climate Change Service (C3S) Multi-model seasonal forecasts. <u>https://climate.copernicus.eu/charts/c3s\_seasonal/</u>
- North American Multi-Model Ensemble (NMME) seasonal forecasts. <u>https://www.cpc.ncep.noaa.gov/products/NMME/</u>

## LC-LRFMM Seasonal Forecasts

(https://www.wmolc.org/)

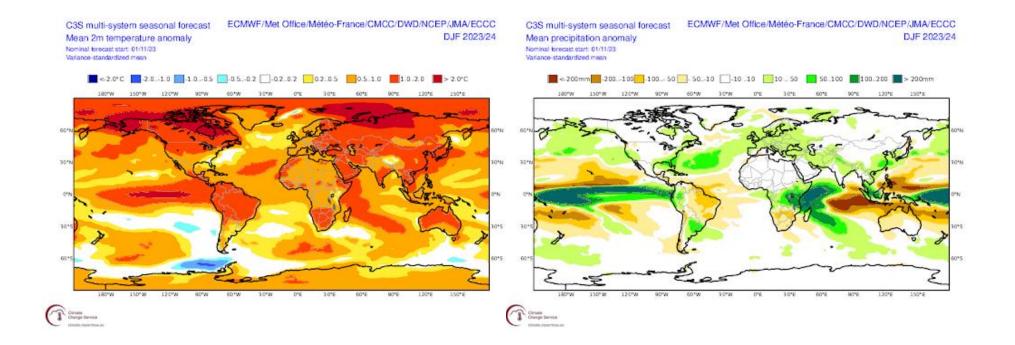
Ensemble means



Climate Prediction Center/NCEP/NWS/NOAA

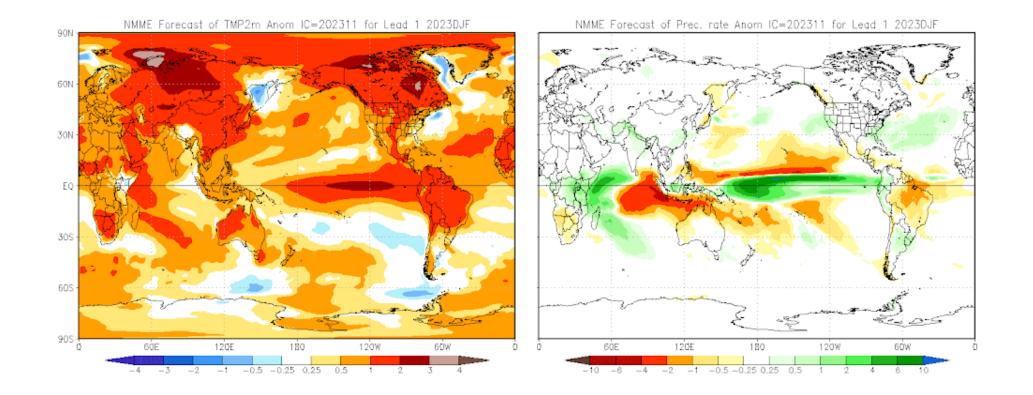
## C3S Seasonal Forecast

(<a href="https://climate.copernicus.eu/charts/c3s\_seasonal/">https://climate.copernicus.eu/charts/c3s\_seasonal/</a>)

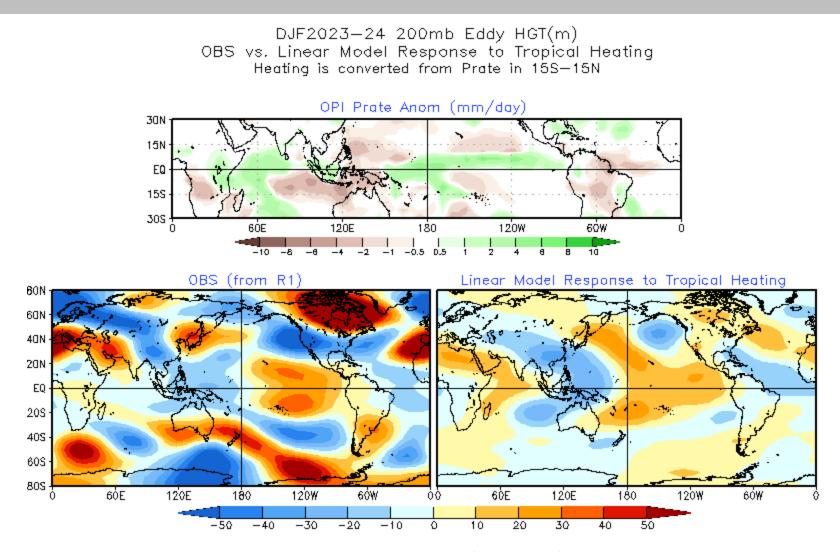


## North American Multi-Model Ensemble Seasonal Forecast

(https://www.cpc.ncep.noaa.gov/products/NMME/)



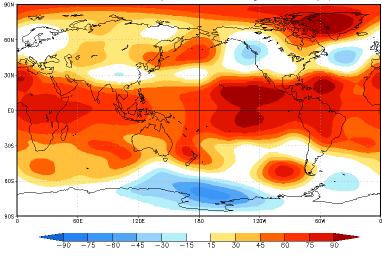
## 200mb Height from Linear Model



Pattern COR: global=0.37, tropics(30S-30N)=0.53

## Seasonal Forecasts from the Constructed Analog Model

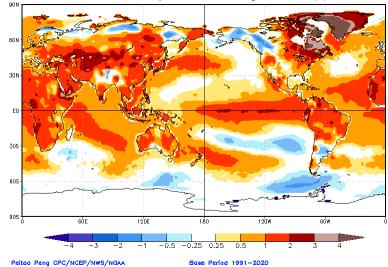
CA HGT200 Prd for DJF2023/2024, ICs through Feb2024(m), Lead -3



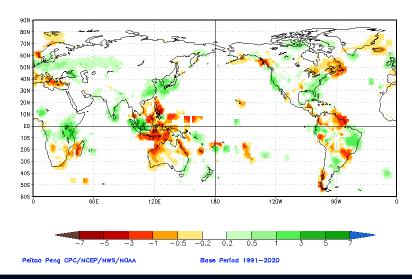
Peitoo Peng CPC/NCEP/NWS/NGAA

Base Period 1991-2020

CA T2m Prd for DJF2023/2024, ICs through Feb2024(K), Lead -3



CA Prec Prd for DJF2023/2024, ICs through Feb2024(mm/day), Lead -3



Background & Methodology

## Attribution of Seasonal Climate Anomalies

#### • Goal

- In the context of prediction of seasonal climate variability, utilize seasonal climate forecasts and atmospheric general circulation model (AGCM) simulations to attribute possible causes for the observed seasonal climate anomalies.
- The analysis can also be considered as an analysis of predictability of the observed seasonal climate anomalies.

## Methodology - 1

- Compare observed seasonal mean anomalies with those from model simulations and forecasts.
- Ensemble averaged model simulated/predicted seasonal mean anomalies are an indication of the predictable (or attributable) component of the corresponding observed anomalies.
- For seasonal mean atmospheric anomalies, predictability could be due to
  - Anomalous boundary forcings [e.g., sea surface temperature (SSTs); soil moisture etc.];
  - Atmospheric initial conditions.
- The influence of anomalous boundary forcings (particularly due to SSTs, can be inferred from the ensemble mean of AGCM simulations forced by observed SSTs, the so called AMIP simulations). This component of predictability (or attributability) is more relevant for longer lead seasonal forecasts.

## Methodology - 2

- The influence of the atmospheric initial state can be inferred from initialized predictions. This component is more relevant for short lead seasonal forecasts.
- The influence of unpredictable component in the atmospheric variability can be assessed from the analysis of individual model simulations, and the extent anomalies in individual runs deviate from the ensemble mean anomalies.
- The relative amplitude of ensemble averaged seasonal mean anomalies to the deviations of seasonal mean anomalies in the individual model runs from the ensemble average is a measure of seasonal predictability (or the extent observed anomalies are attributable).
- Observed anomalies are equivalent to a realization of a single model run, and therefore, analysis of individual model runs also gives an appreciation of how much observed anomalies can deviate from the component that is attributable (Kumar et al. 2013).

### Data

- Observations
  - SST: OI version 2 analysis (Reynolds et al., 2007)
  - Prec: CMAP monthly analysis (Xie and Arkin, 1997)
  - T2m: GHCN-CAMS land surface temperature monthly analysis (Fan and van den Dool, 2008)
  - 200mb height (z200): CFSR (Saha et al., 2010)
- 0-month-lead seasonal mean forecasts from CFSv2 (Saha et al. 2014)
  - <u>Seasonal forecast</u>: the seasonal mean forecasts based on 40 members from the latest 10 days before the target season (0-month-lead);
  - <u>Reconstructed forecast</u>: the seasonal mean forecasts constructed from 3 individual monthly forecasts with the latest 10 days initial conditions for each individual monthly forecasts. This approach for constructing seasonal mean anomalies has more influence from the initial conditions (Kumar et al. 2013);
- Seasonal mean AMIP simulation based on GFS\_FV3 (provided by Dr. Tao Zhang/CPC)
  - 100 members
- All above seasonal mean anomalies are based on 1991-2020 climatology.
- z200 responses to tropical heating in linear model.
- Seasonal mean anomalies of z200, T2m, and Prec forecasted from the Constructed Analog Model.