

# Attribution of Seasonal Climate Anomalies

## March-April-May 2023

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

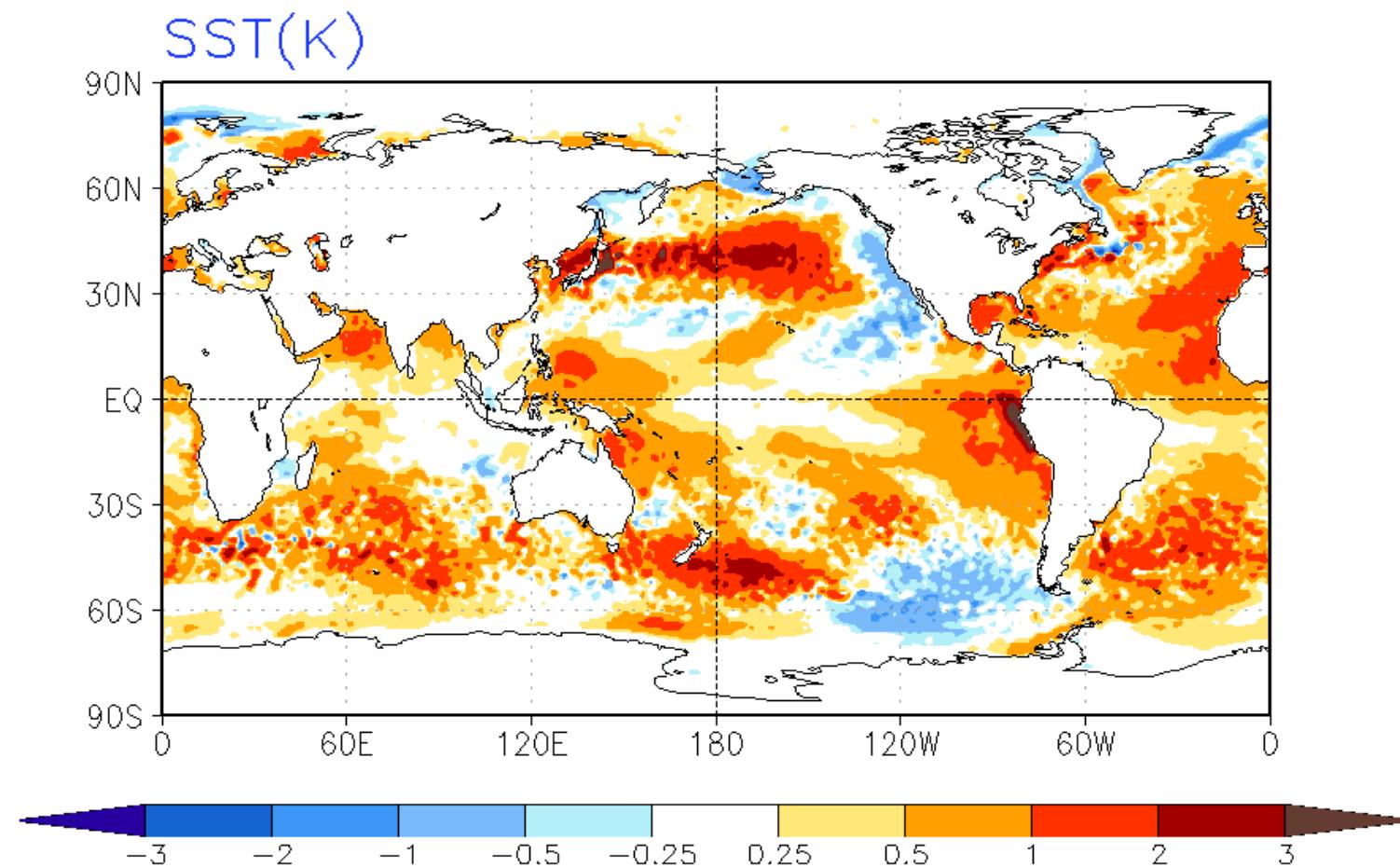
# Summary of Observed Conditions and Outlooks

- The central equatorial Pacific SST anomalies were near normal and were in between above normal SSTs to the east near the coastal regions of South America and to the west near the Maritime continent. The east-west SST gradient, with a minimum in the central Pacific, may be the reason for the below normal rainfall near the dateline. Over the other ocean basins, e.g., North Pacific, western Pacific, South Pacific and Atlantic ocean, SST anomalies were above normal (slide 4). The CFSv2 predicted the SST warm anomalies over the equatorial eastern Pacific and far eastern Pacific along the South America coastal area, although the prediction had a cold biases compared to observations (slide 10);
- The AMIP simulation and the initialized forecasts, and other MME forecasts well captured the large scale distribution of observed precipitation anomalies in tropical latitudes – below (above) normal anomalies in the equatorial eastern Indian Ocean (Maritime Continent and equatorial western Pacific) and dry conditions in the equatorial central Pacific Ocean (slides 11, 37-39).
- The AMIP and initialized CFSv2 forecasts missed the z200 negative anomalies that extended from the polar region to the central Asia region and Alaska. The erroneous prediction of height anomalies led to failed prediction of the observed cold temperature anomalies over the regions of central Asia and Alaska (slides 12,13,15,16).
- The AMIP and initialized forecasts captured most of the observed North America temperature anomalies but missed most of the observed precipitation anomalies over the NA (slides 14, 16).
- The ridge over the western Canada in May 2023 could only be predicted in shortest lead forecasts (slides 30, 33).
- May 2023 monthly mean forecasts from the shortest leads show improvements for predicting North America z200, temperature, and precipitation anomalies (slides 33, 34,35).

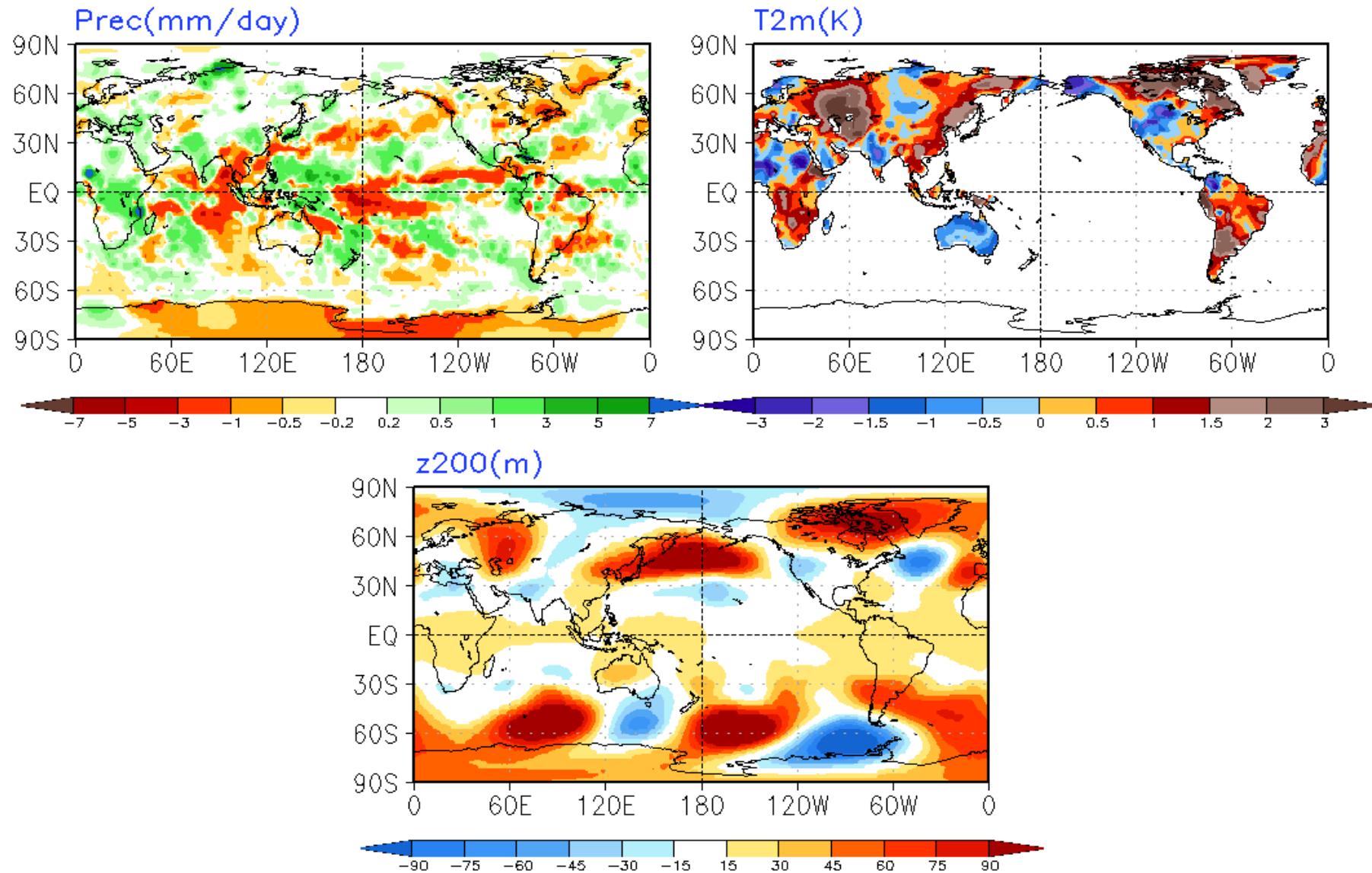
Observed Seasonal Anomalies

Global and North America

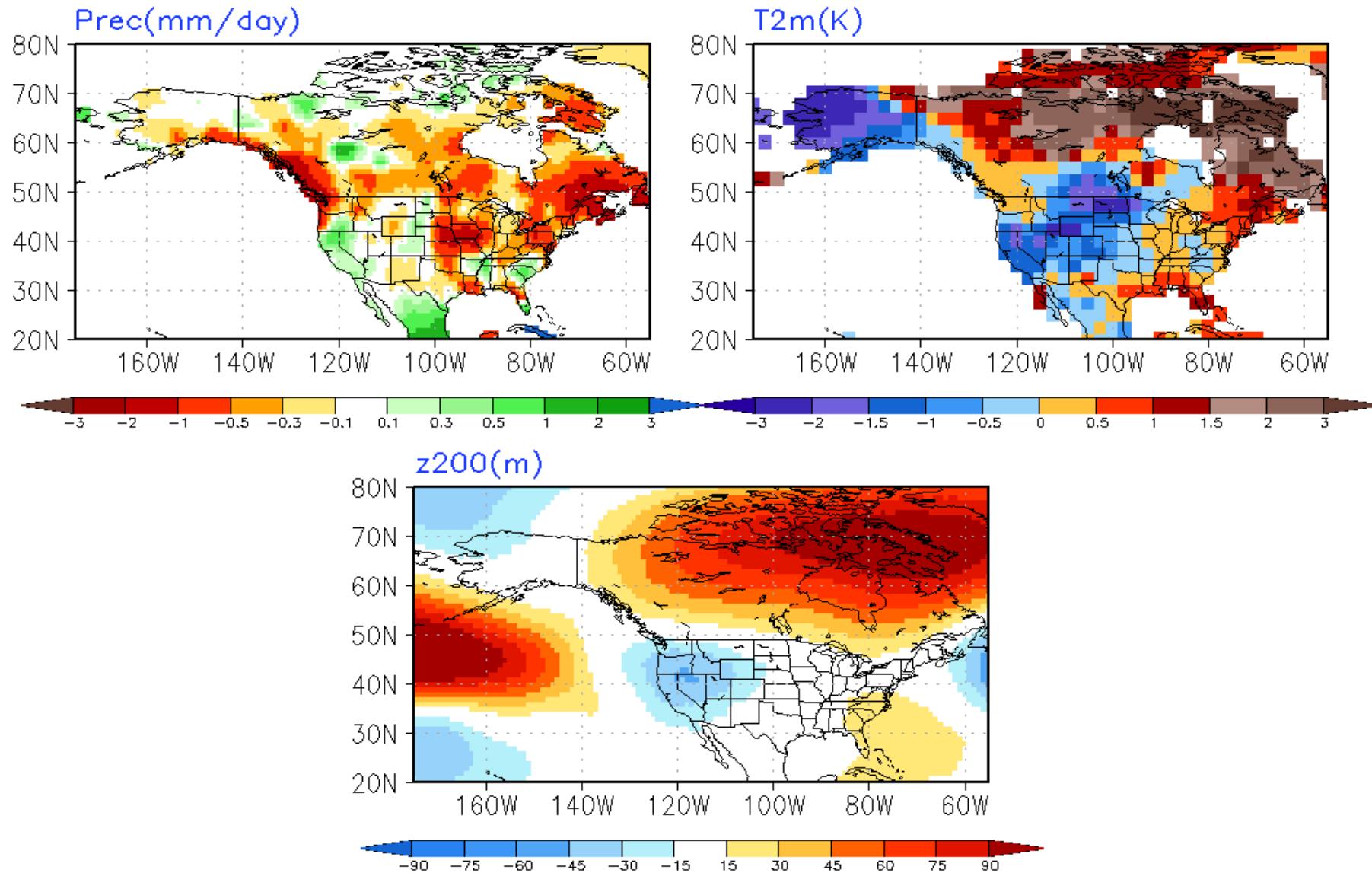
# Observed Anomaly MAM2023



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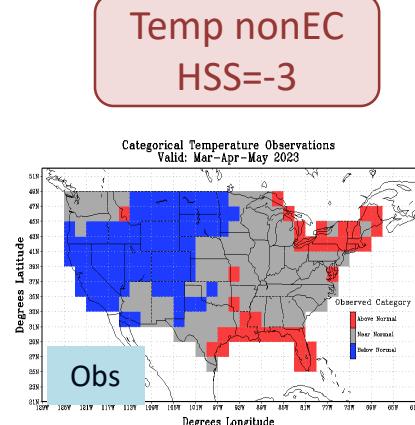


# Observed Anomaly MAM2023



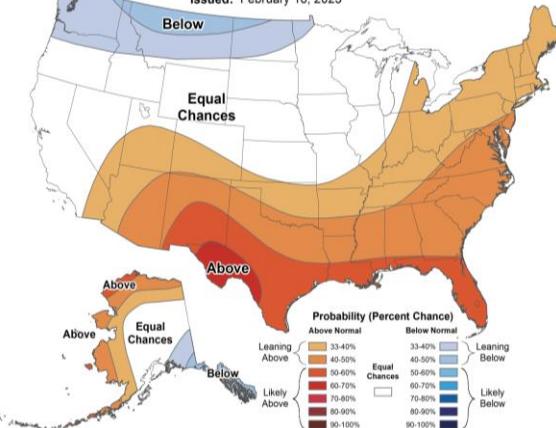
# CPC Seasonal Outlooks and NMME Forecasts

CPC



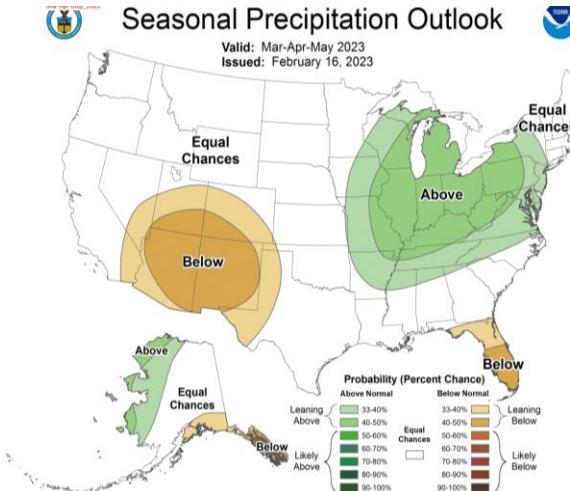
Seasonal Temperature Outlook

Valid: Mar-Apr-May 2023  
Issued: February 16, 2023

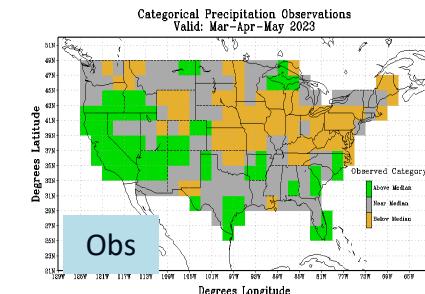


Seasonal Precipitation Outlook

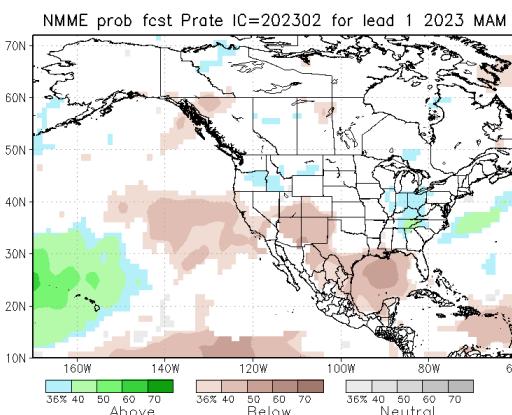
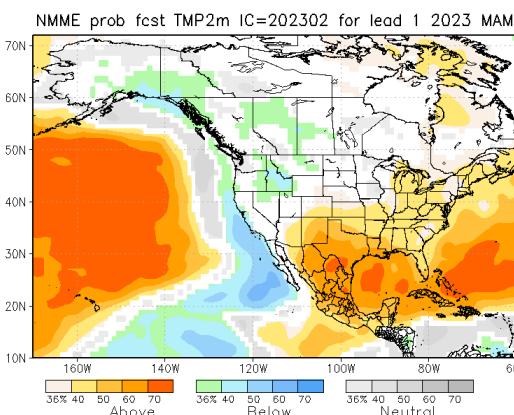
Valid: Mar-Apr-May 2023  
Issued: February 16, 2023



Prec nonEC  
HSS=-34



NMME



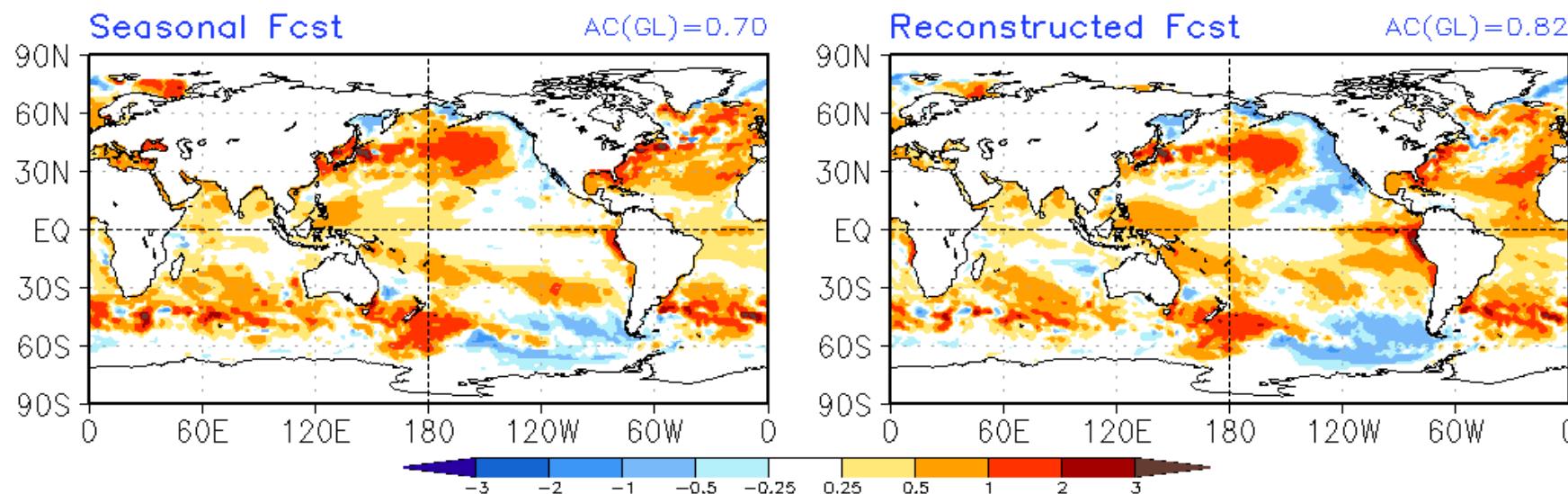
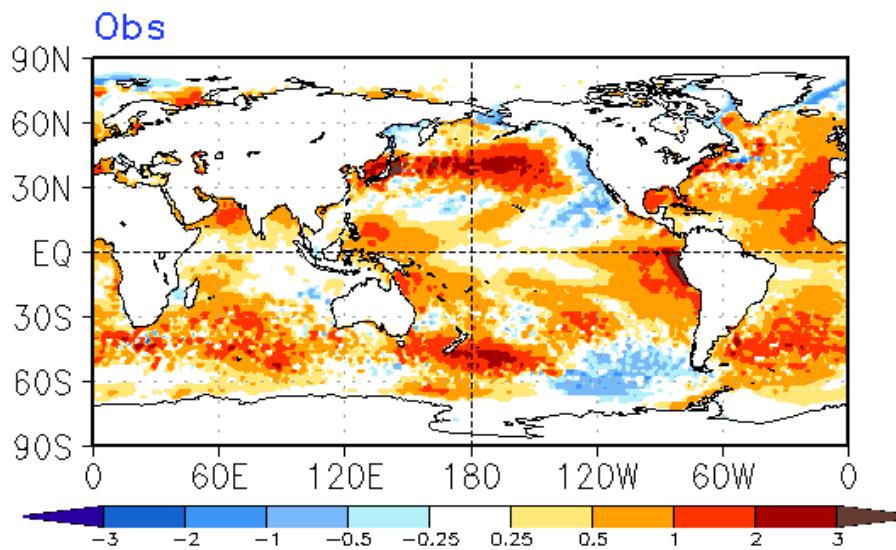
For the rationale behind CPC outlooks see: [https://www.cpc.ncep.noaa.gov/products/archives/long\\_lead/PMD/2023/202302\\_PMD90D](https://www.cpc.ncep.noaa.gov/products/archives/long_lead/PMD/2023/202302_PMD90D)

## Model Simulated/Forecast Ensemble Mean Anomalies

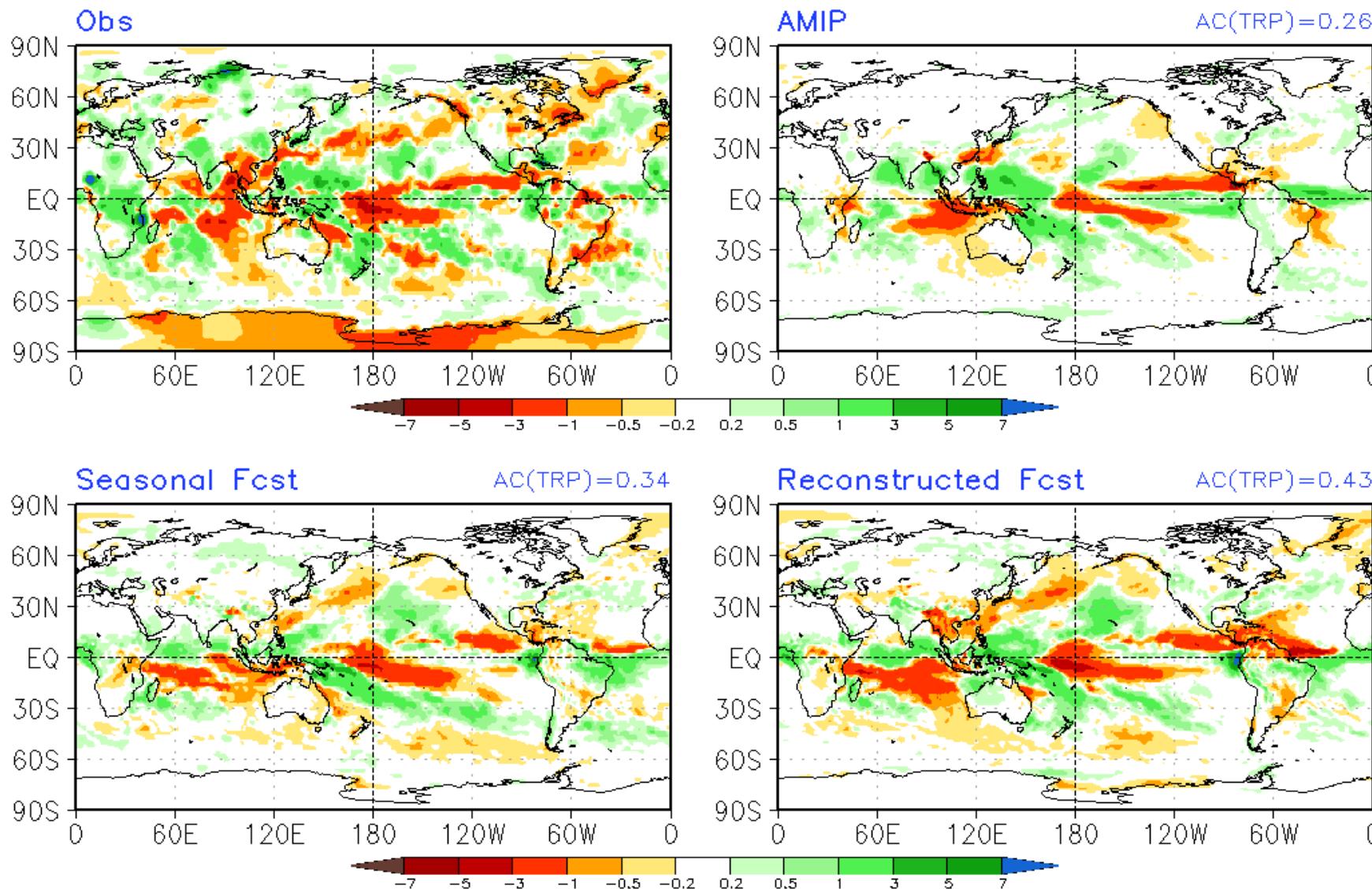
# Model Simulated/Forecast Ensemble Average Anomalies

- AMIP simulations forced with observed sea surface temperatures (100 members ensemble)
- CFSv2 real time operational forecasts
  - Seasonal forecast: 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.
  - Reconstructed forecast: 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). 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).

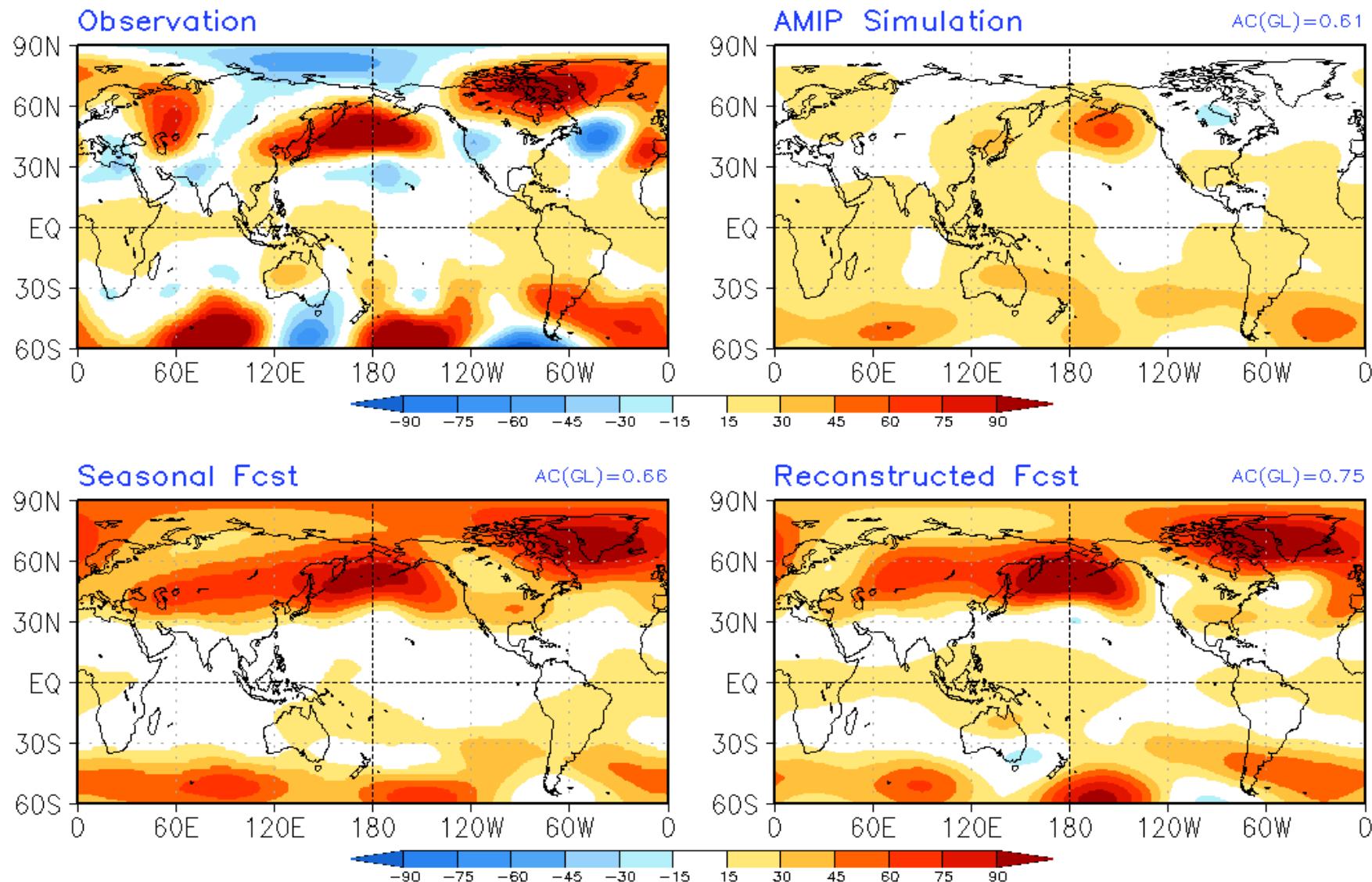
# MAM2023 Observed & Model Simulated/Forecast Ensemble Average Anomalies SST(K)



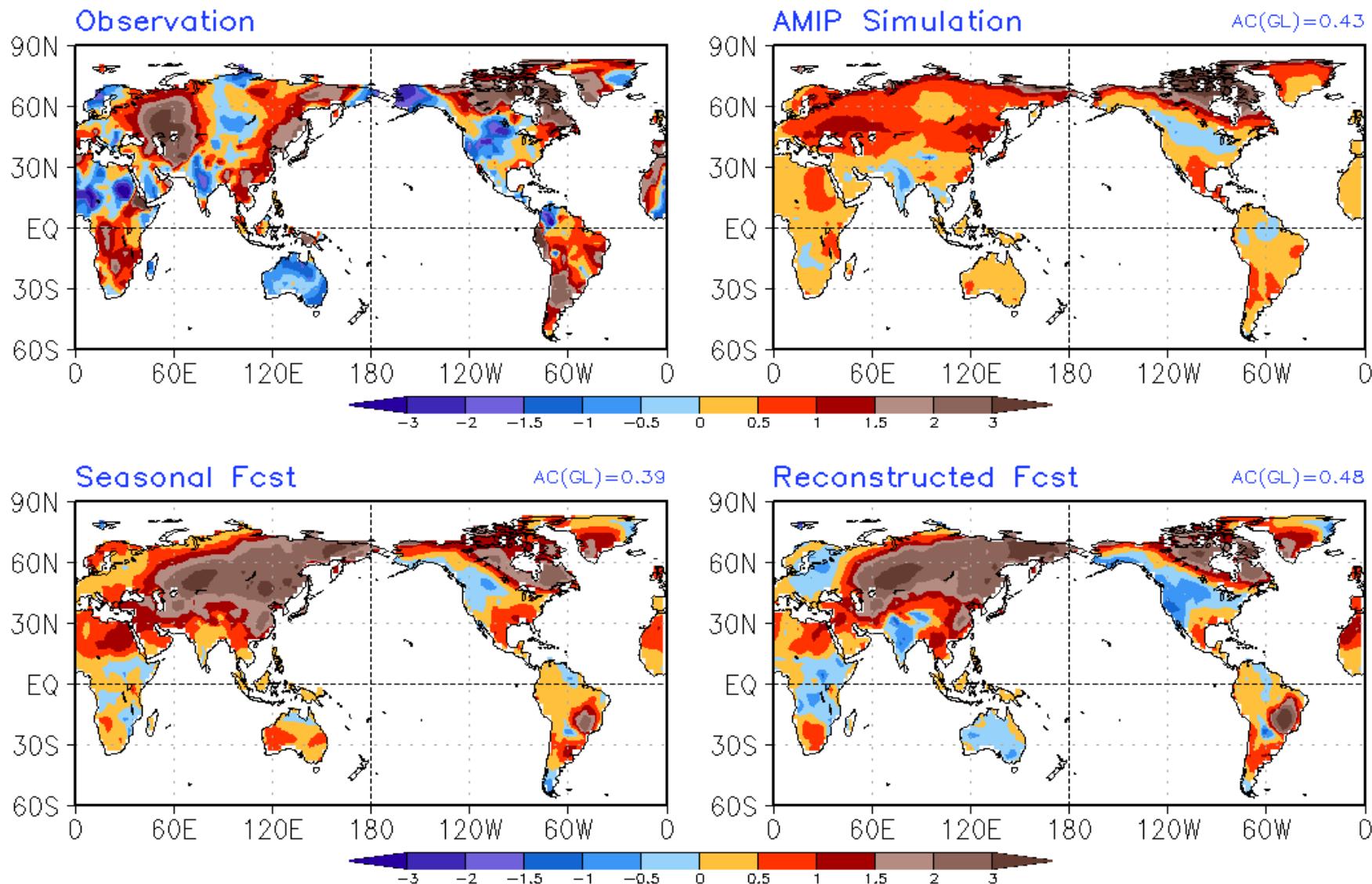
# MAM2023 Observed & Model Simulated/Forecast Ensemble Average Anomalies Prec(mm/day)



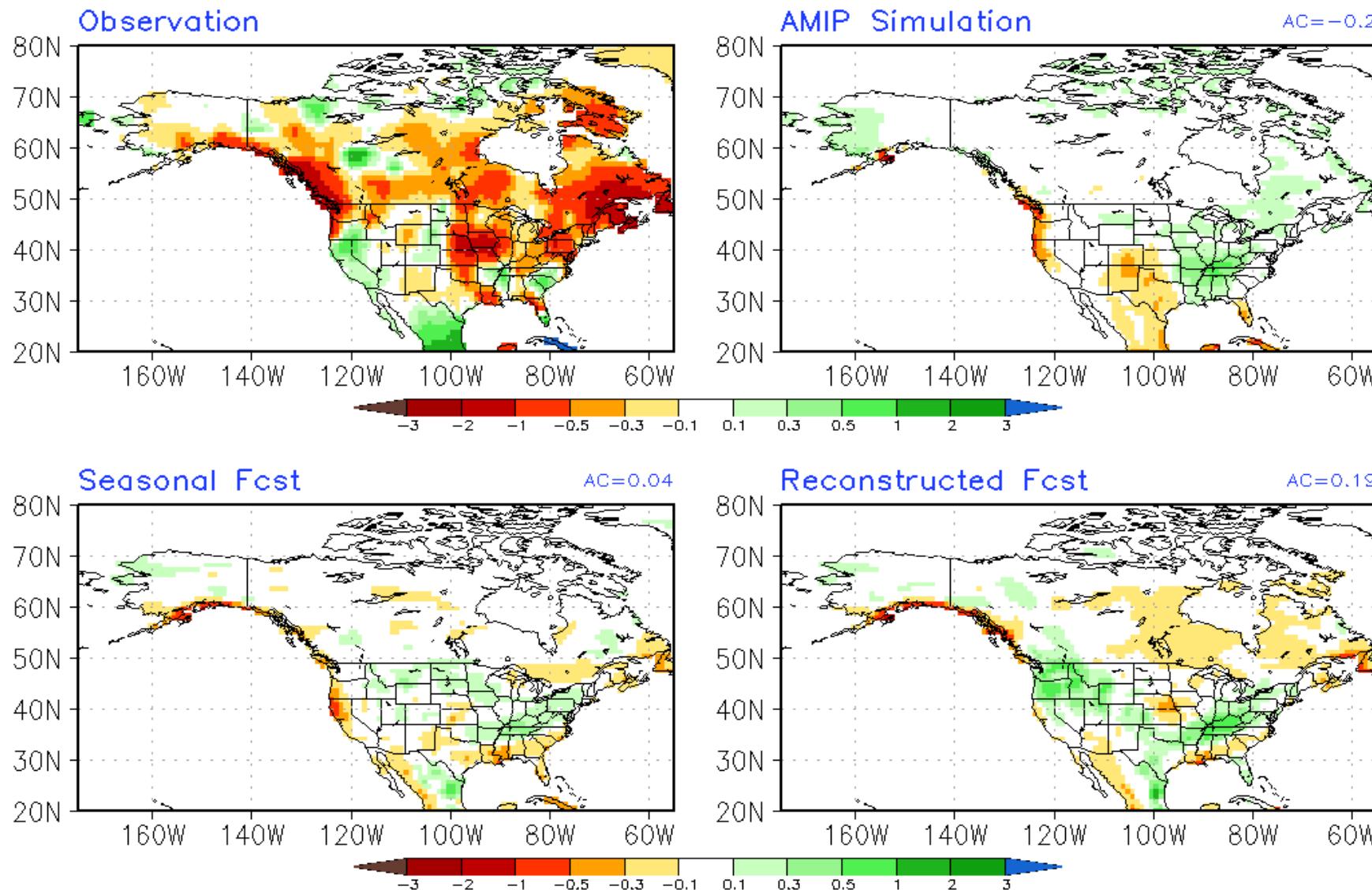
# MAM2023 Observed & Model Simulated/Forecast Ensemble Average Anomalies z200(m)



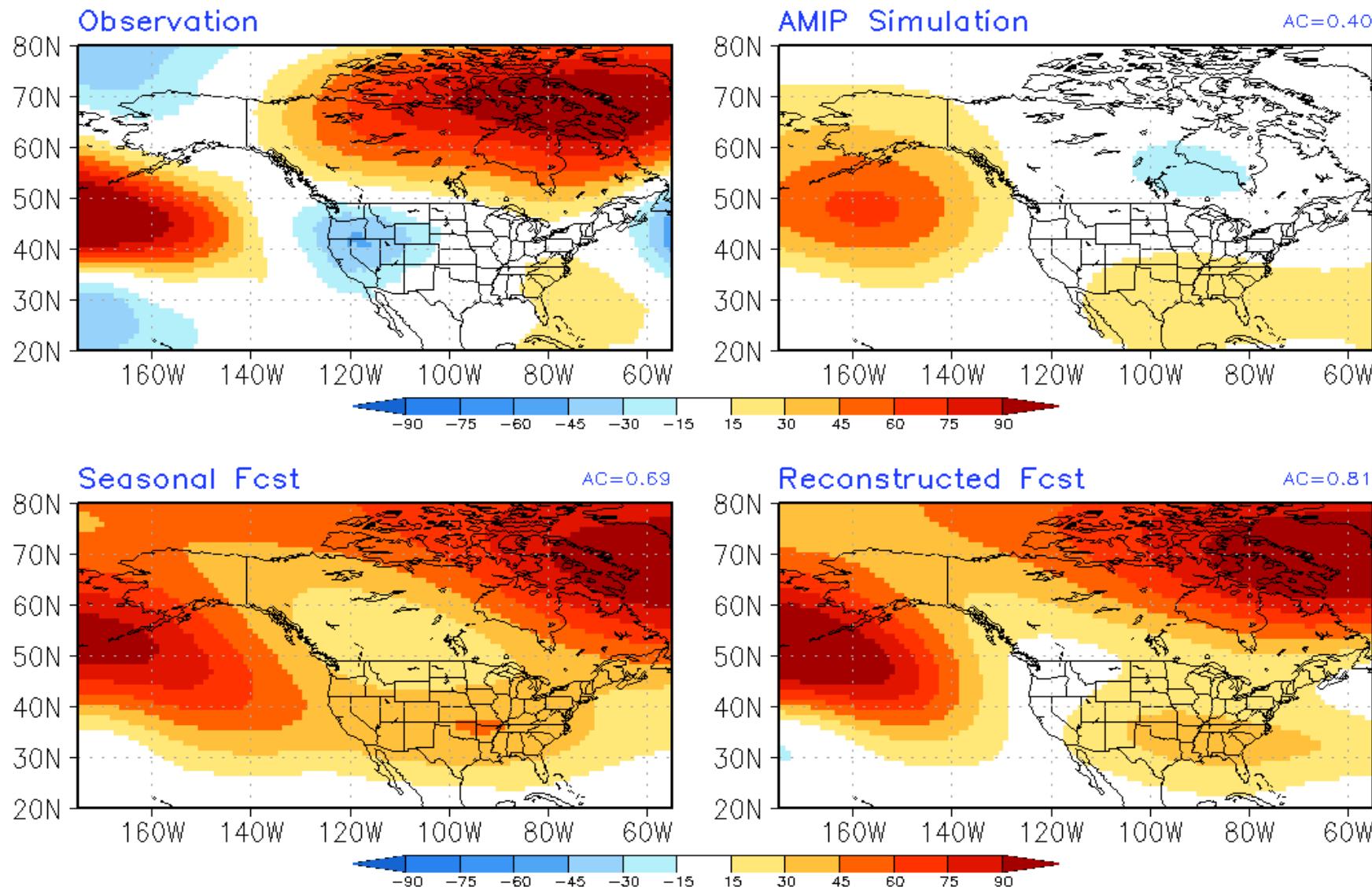
# MAM2023 Observed & Model Simulated/Forecast Ensemble Average Anomalies T2m(K)



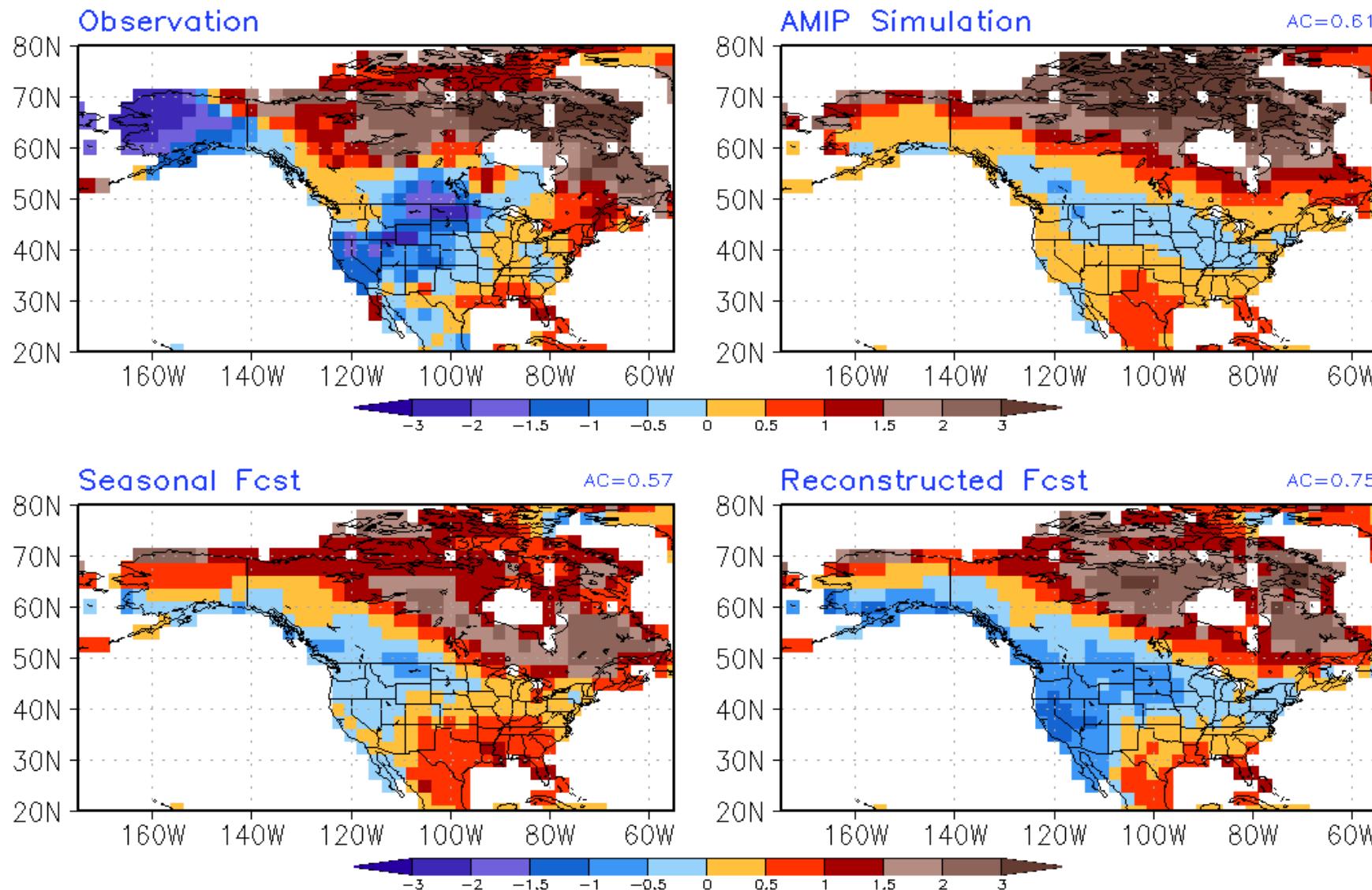
# MAM2023 Observed & Model Simulated/Forecast Ensemble Average Anomalies Prec(mm/day)



# MAM2023 Observed & Model Simulated/Forecast Ensemble Average Anomalies z200(m)



# MAM2023 Observed & Model Simulated/Forecast Ensemble Average Anomalies T2m(K)

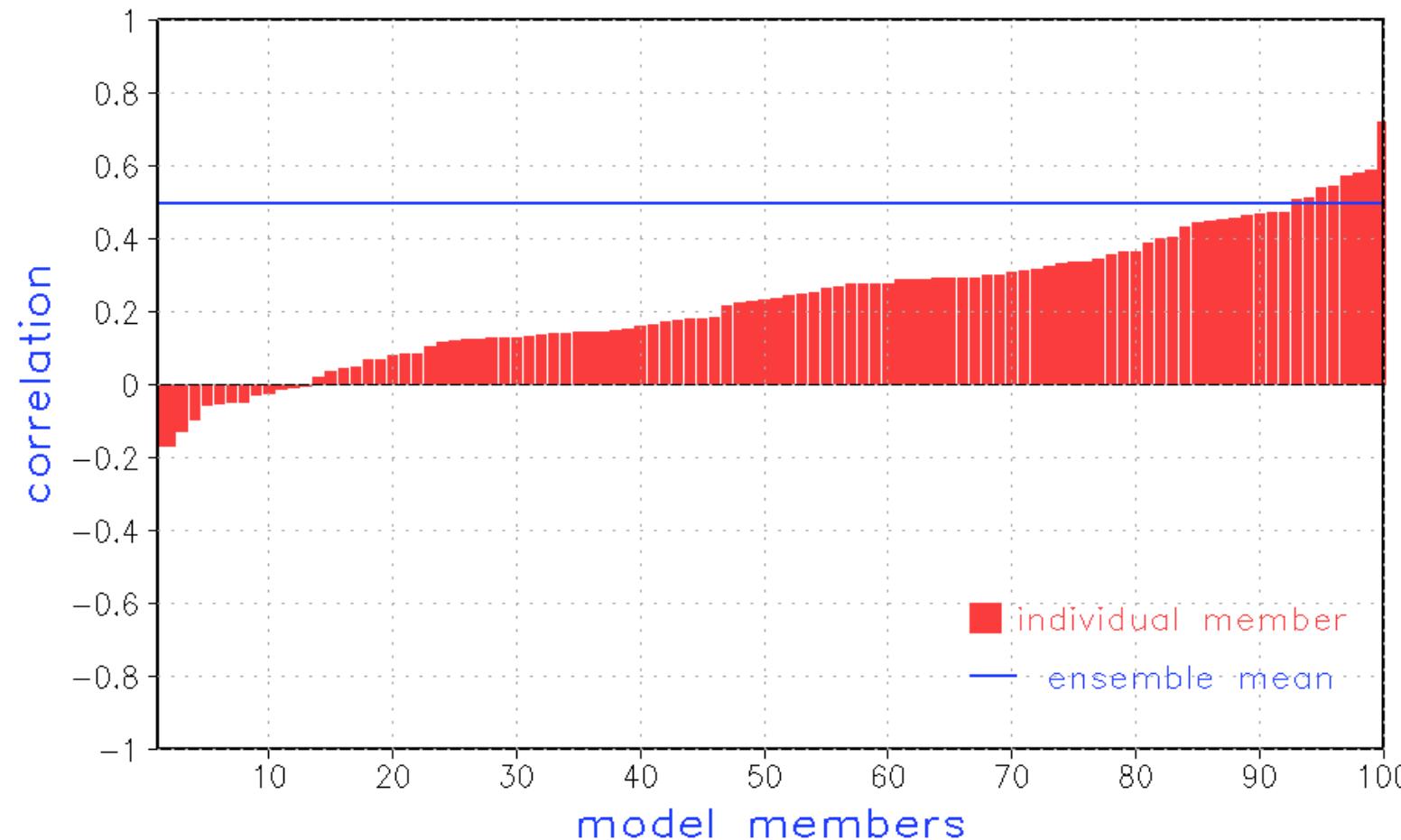


## Model Simulated/Forecast Anomalies: Individual Runs

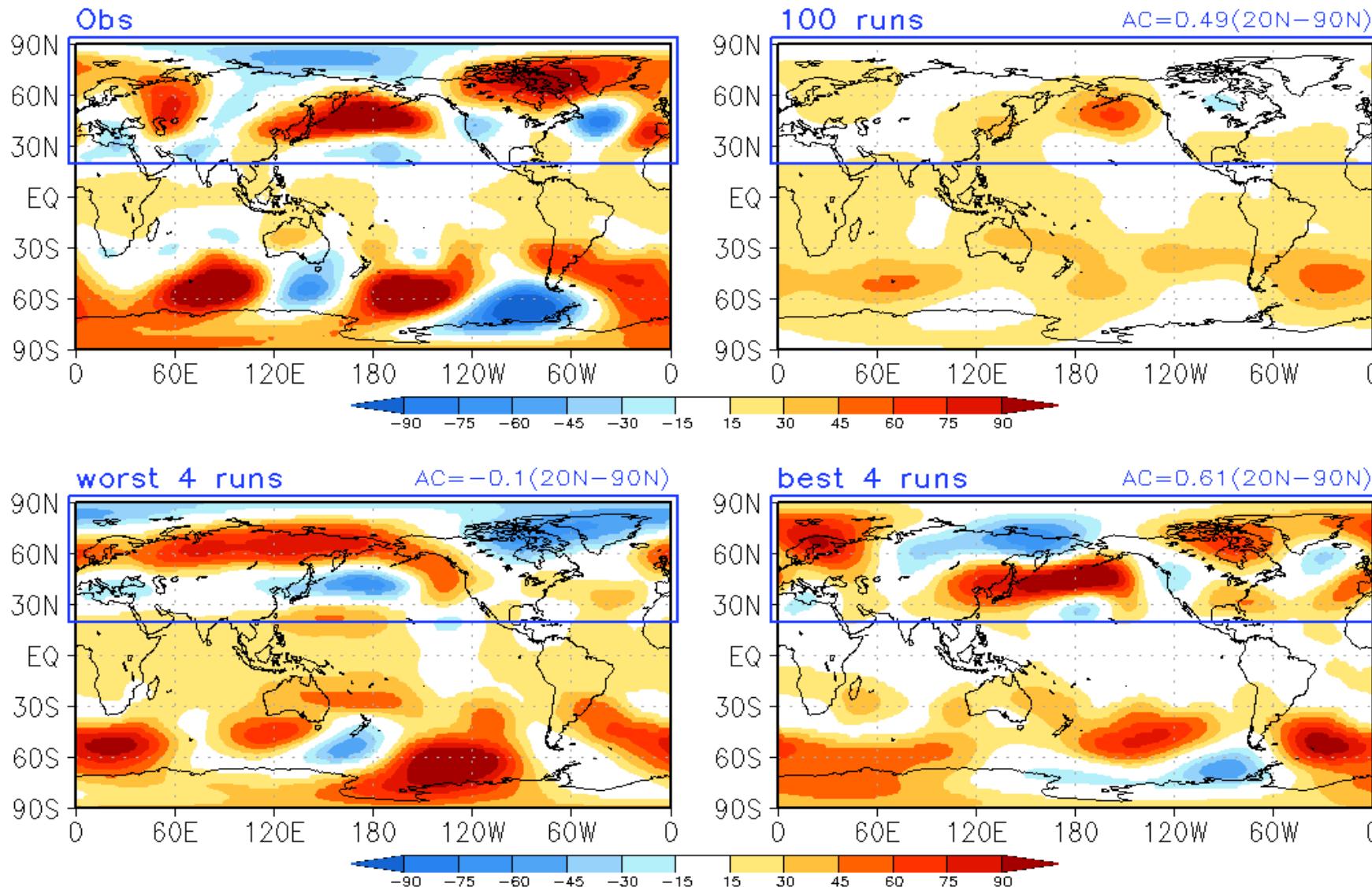
## Model Simulated/Forecast Anomalies: Individual Runs

- 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. [doi:10.1002/grl.50657](https://doi.org/10.1002/grl.50657).

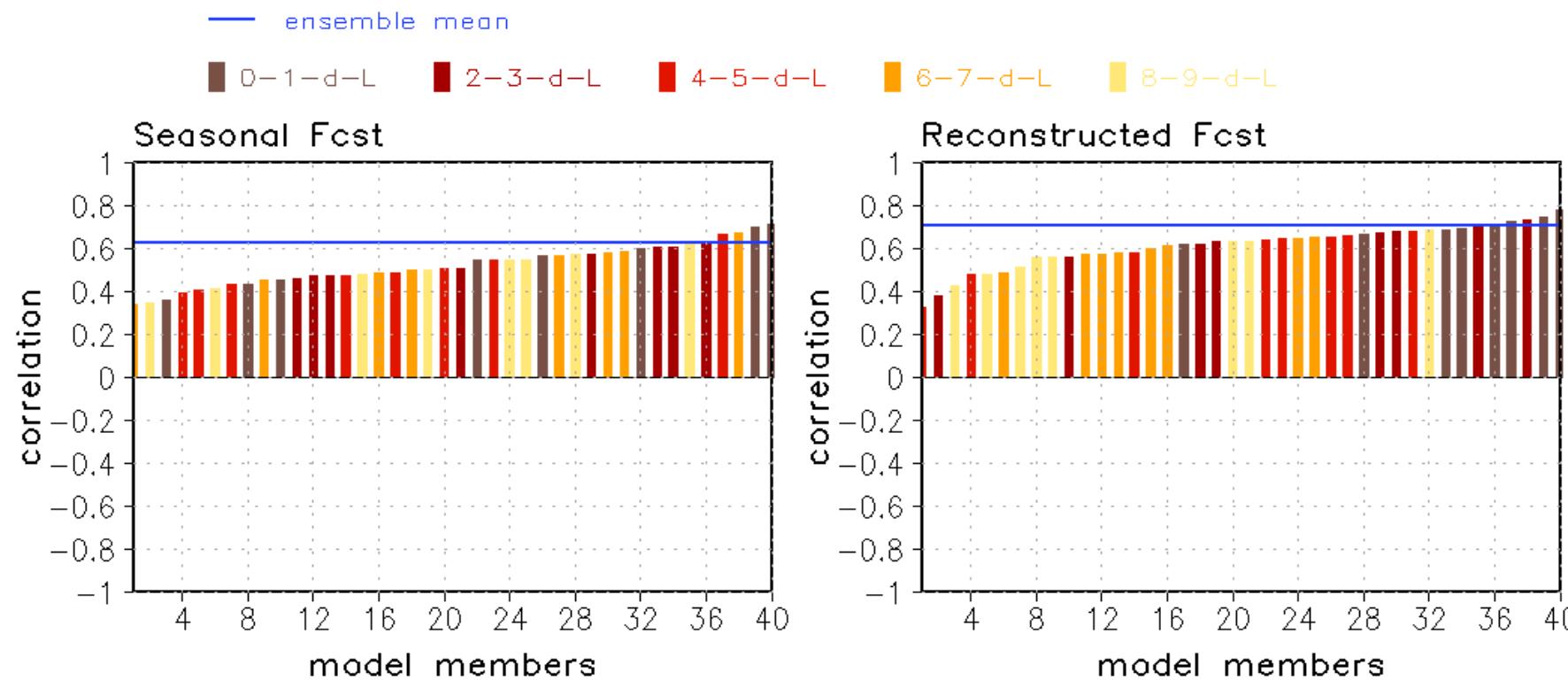
MAM2023 Anomaly Correlation for Individual AMIP Simulation  
with Observation --  $z200(20N-90N)$



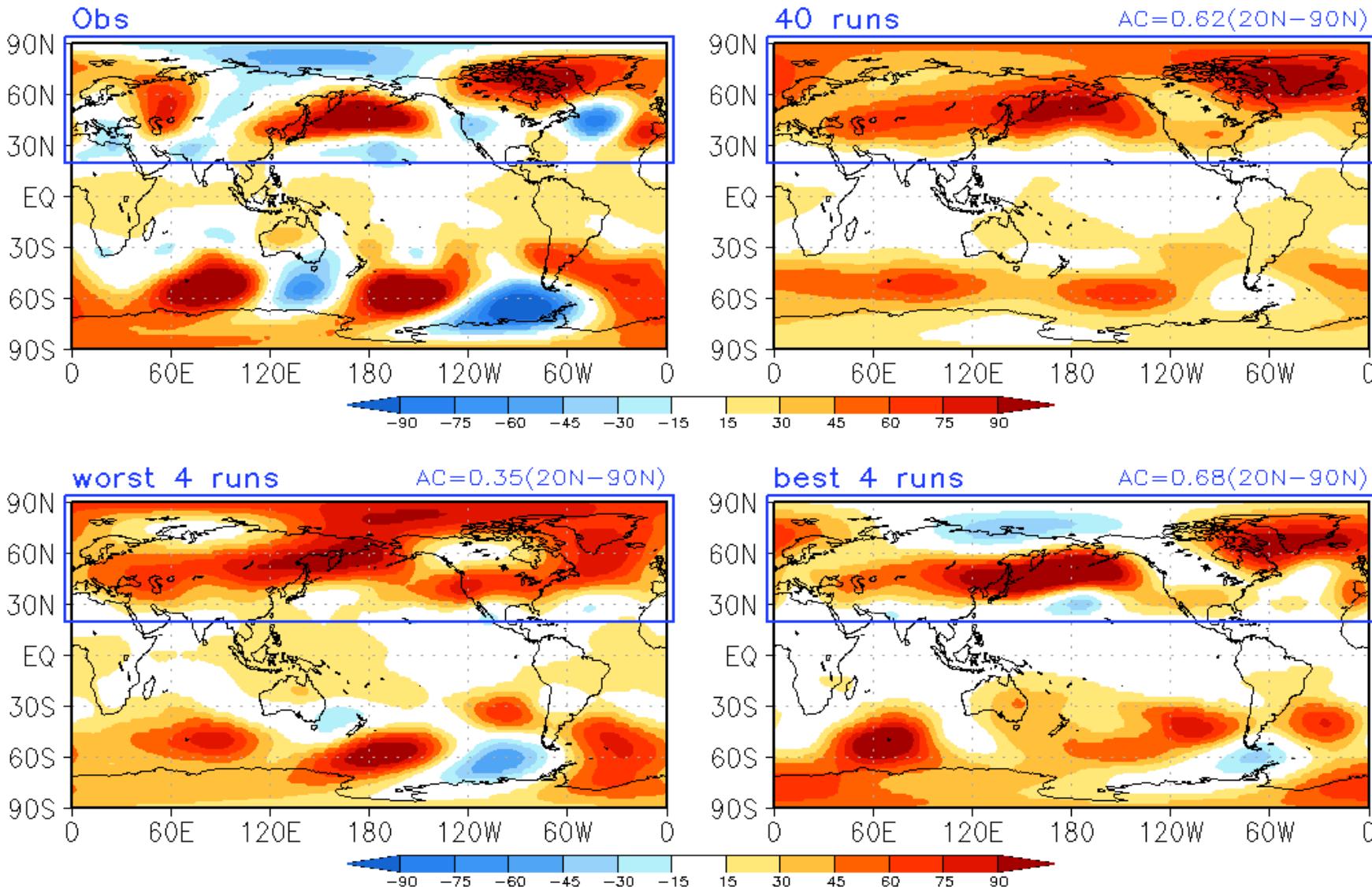
Observed & AMIP Ensemble Mean Anomalies  
MAM2023  $z200(\text{m})$  100 runs/worst 4 runs/best 4 runs



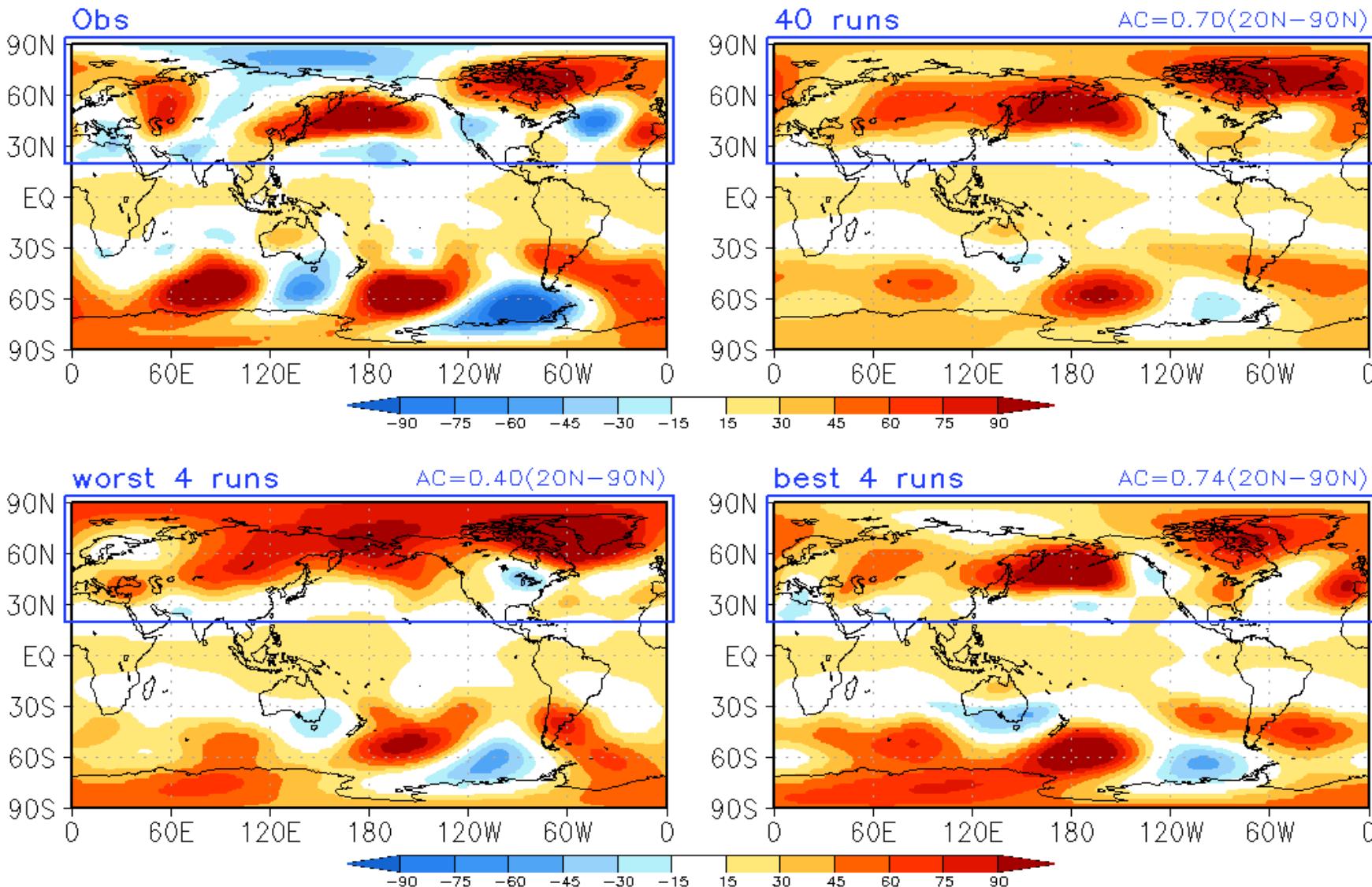
# MAM2023 Anomaly Correlation for Individual CFSv2 Forecast with Observation -- z200 (20N–90N)



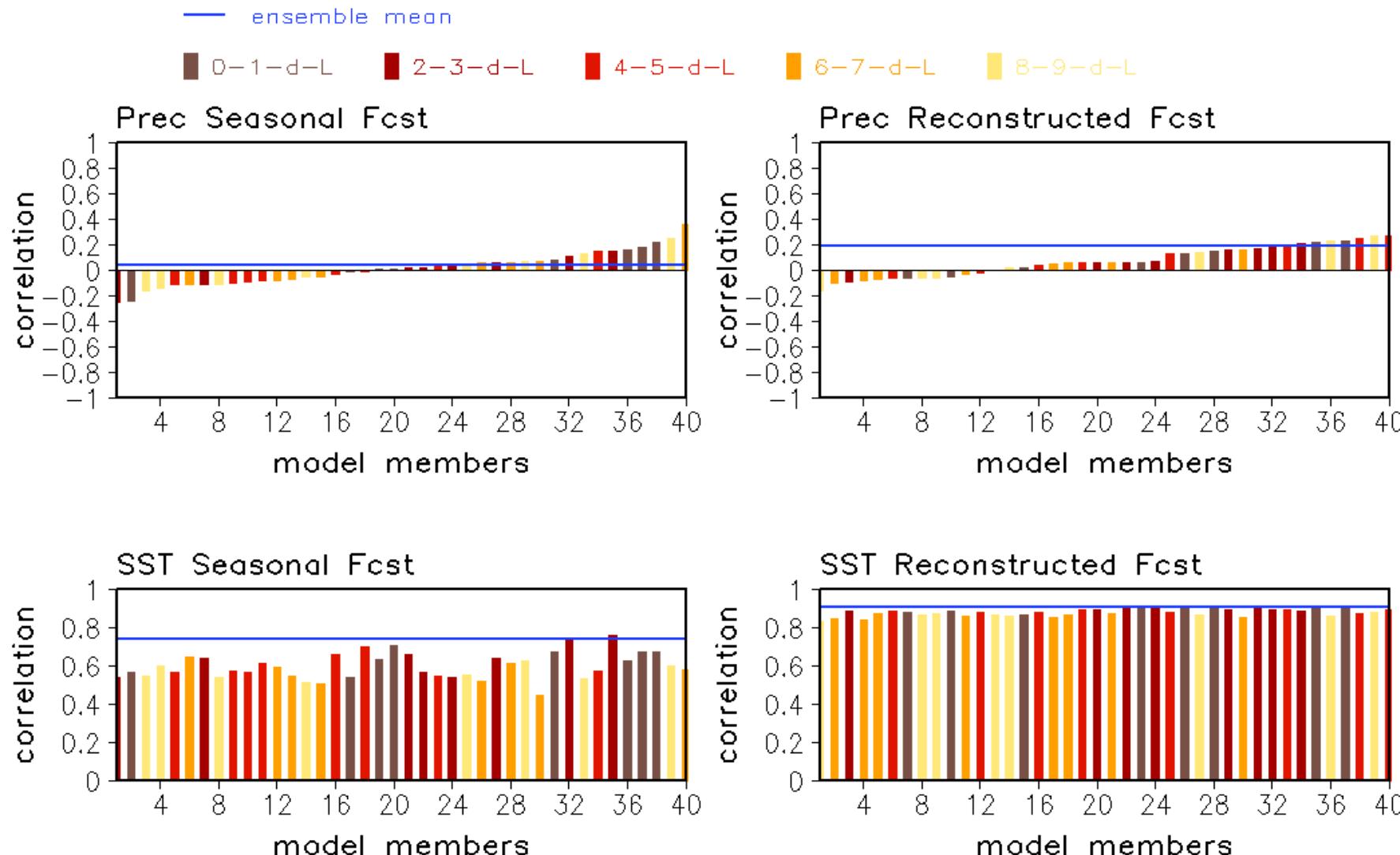
Observed & CFSv2 Forecast Ensemble Average Anomalies  
MAM2023 z200(m) 40 runs/worst 4 runs/best 4 runs  
Seasonal Forecast



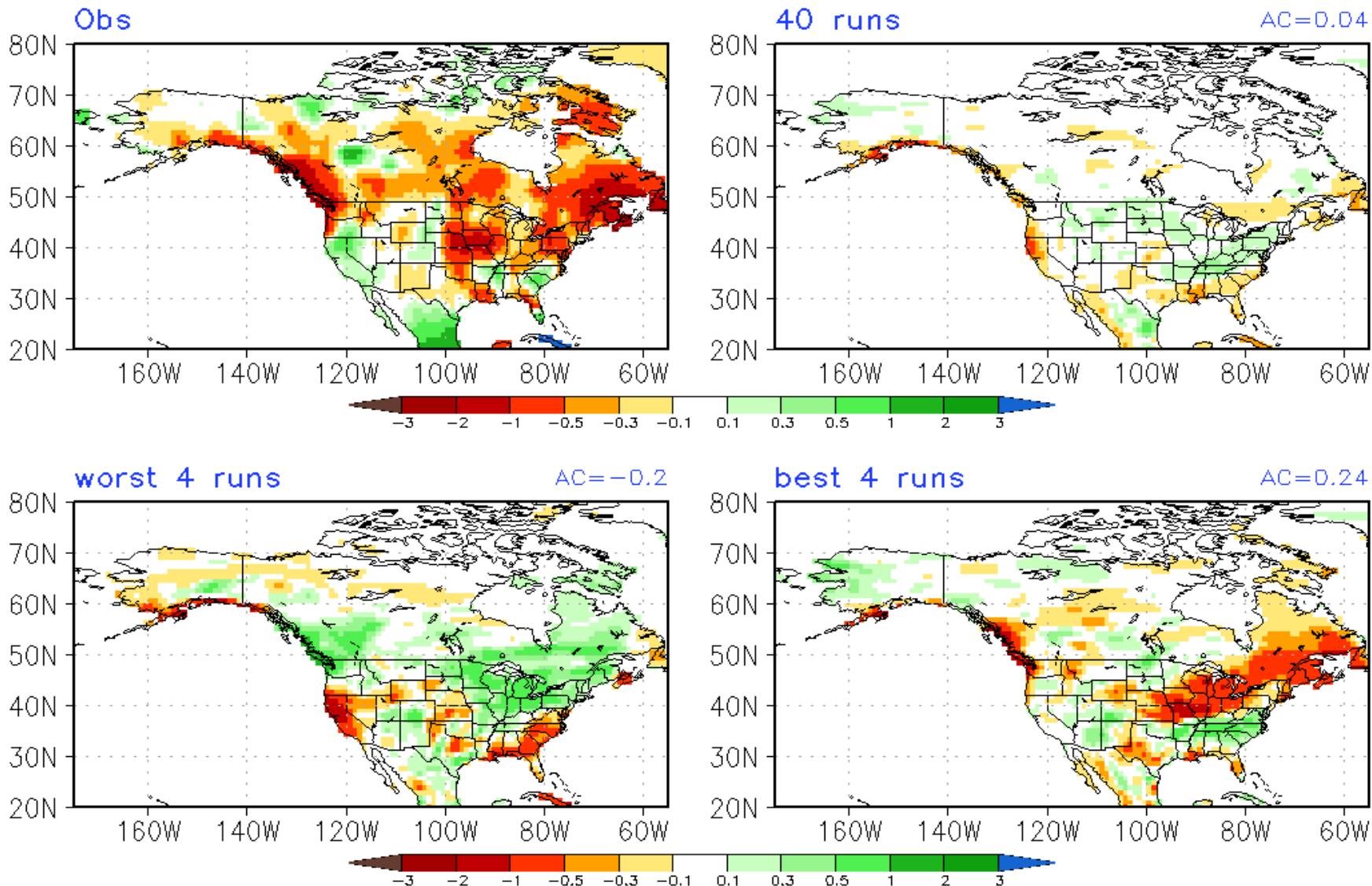
Observed & CFSv2 Forecast Ensemble Average Anomalies  
MAM2023 z200(m) 40 runs/worst 4 runs/best 4 runs  
Reconstructed Forecast



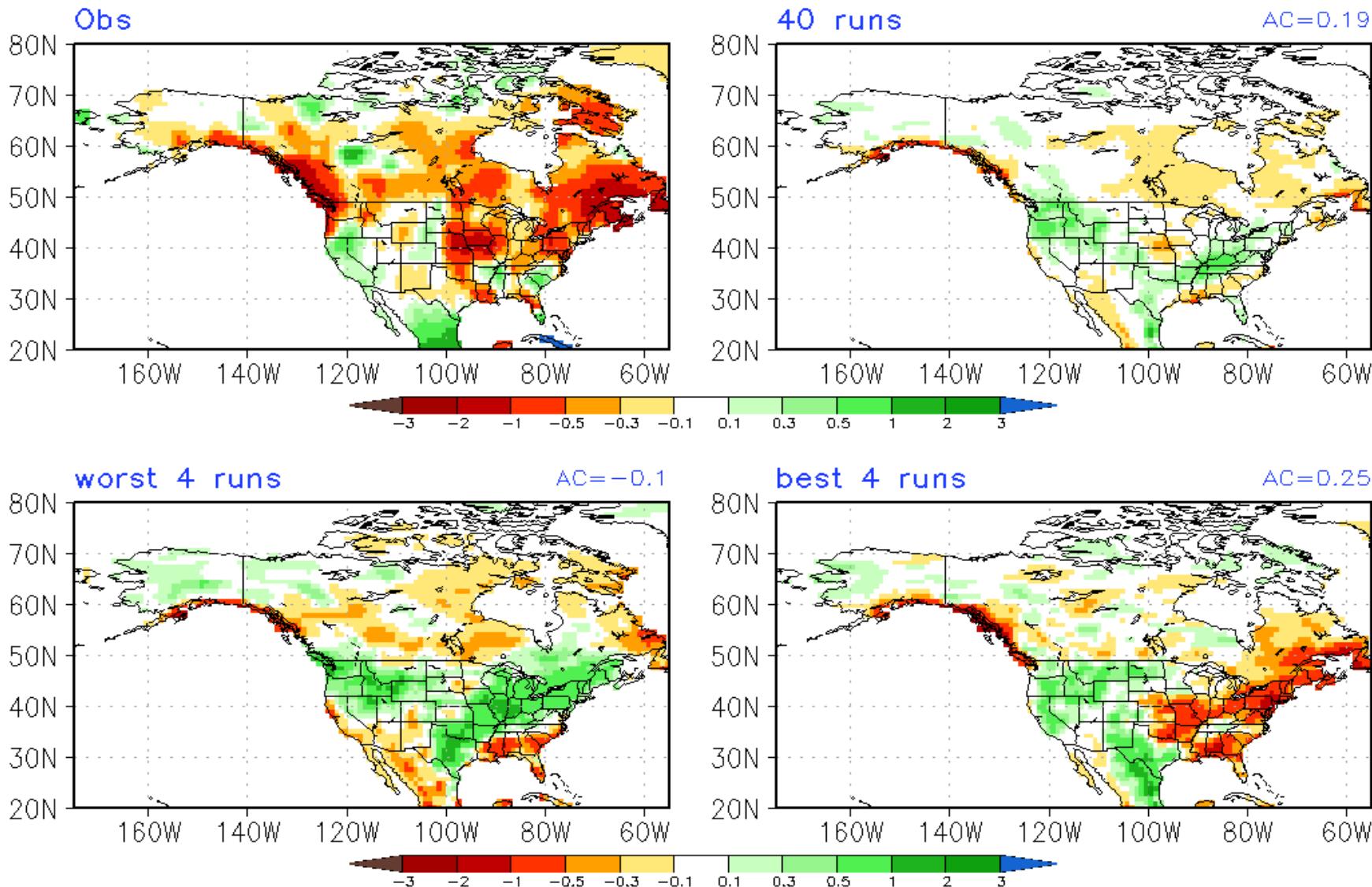
# MAM2023 Anomaly Correlation for Individual CFSv2 Forecast with Observation -- Prec(NA)/SST(30S–30N)



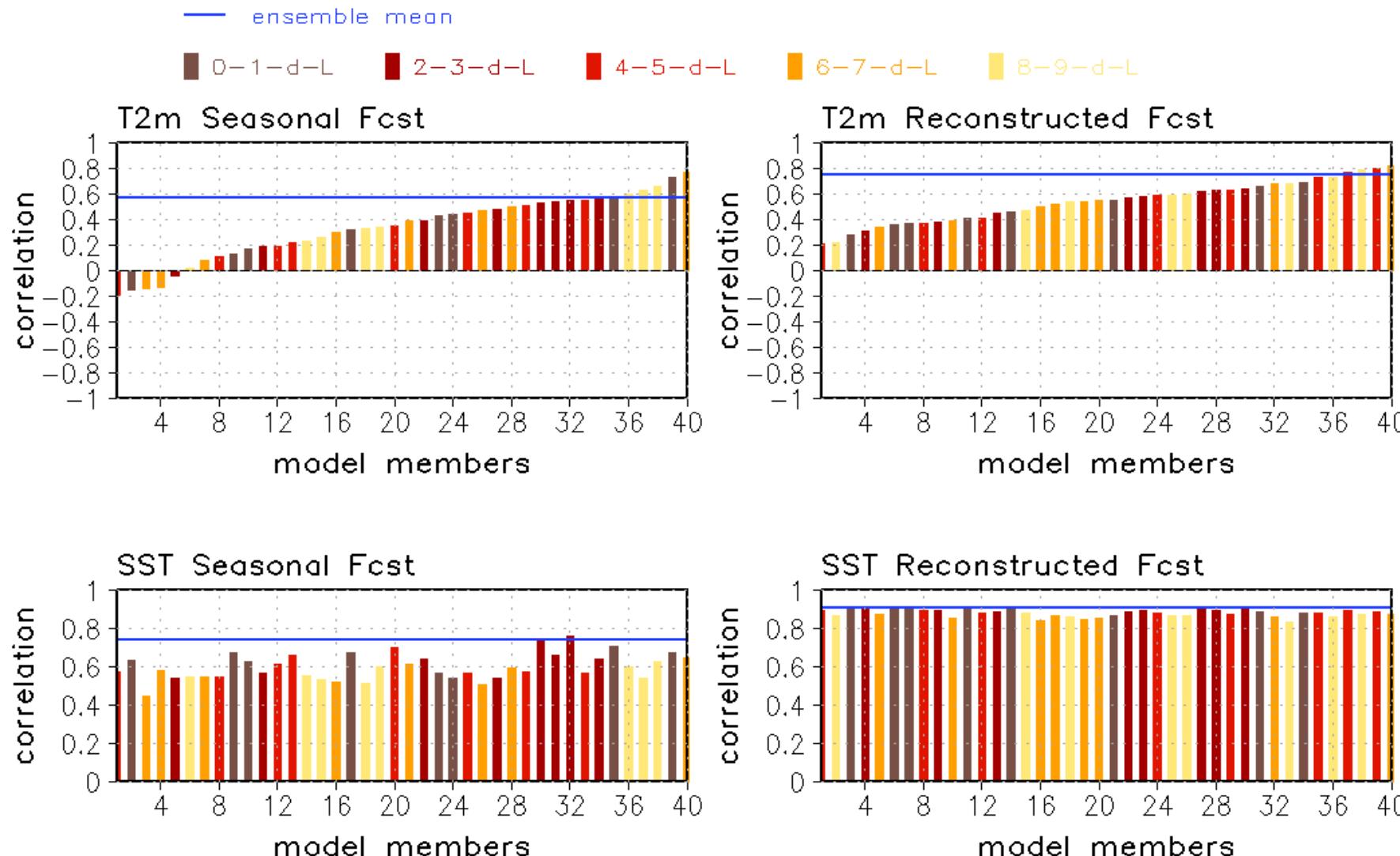
Observed & CFSv2 Forecast Ensemble Average Anomalies  
MAM2023 Prec(mm/day) 40 runs/worst 4 runs/best 4 runs  
**Seasonal Forecast**



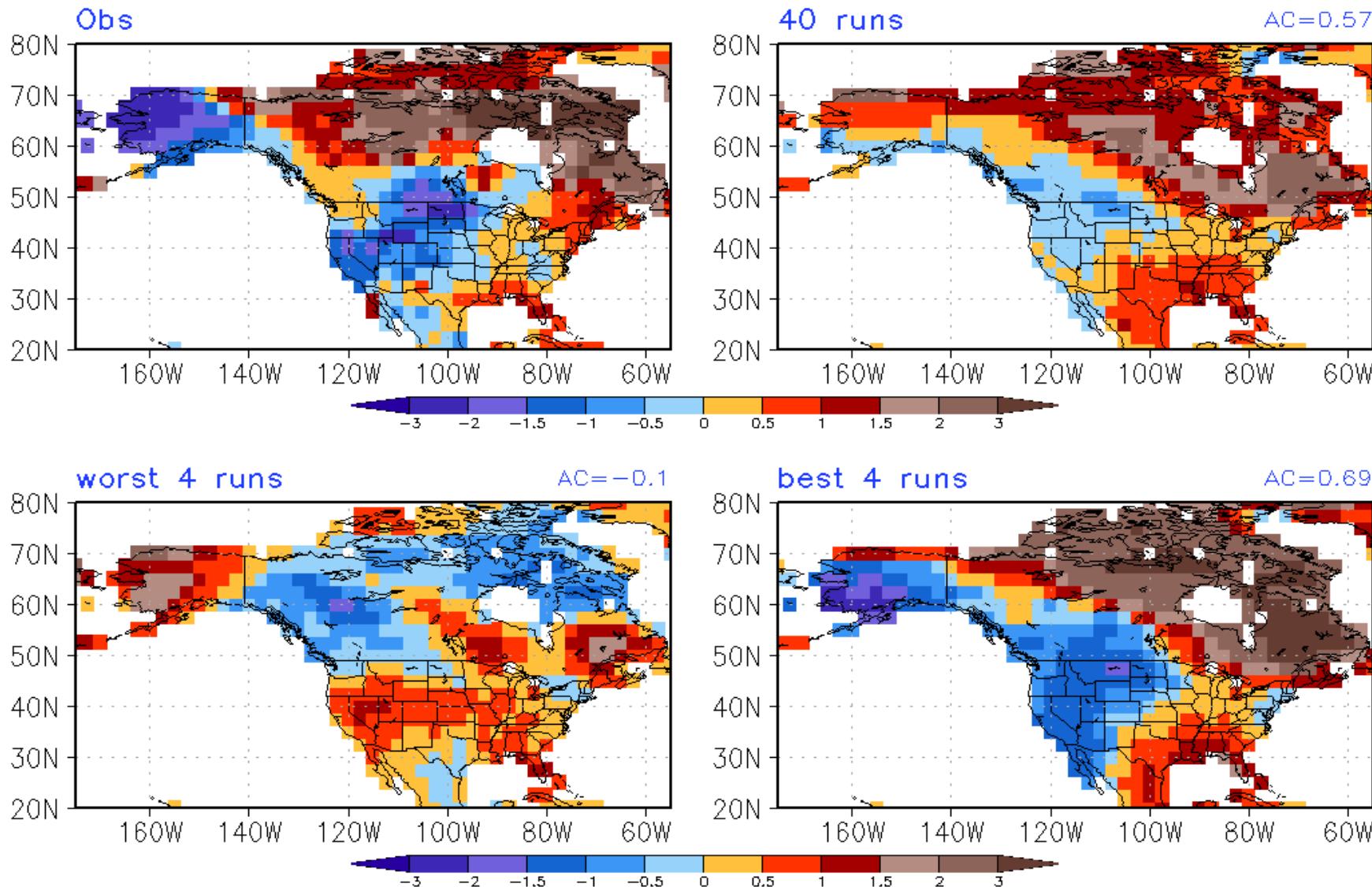
Observed & CFSv2 Forecast Ensemble Average Anomalies  
MAM2023 Prec(mm/day) 40 runs/worst 4 runs/best 4 runs  
Reconstructed Forecast



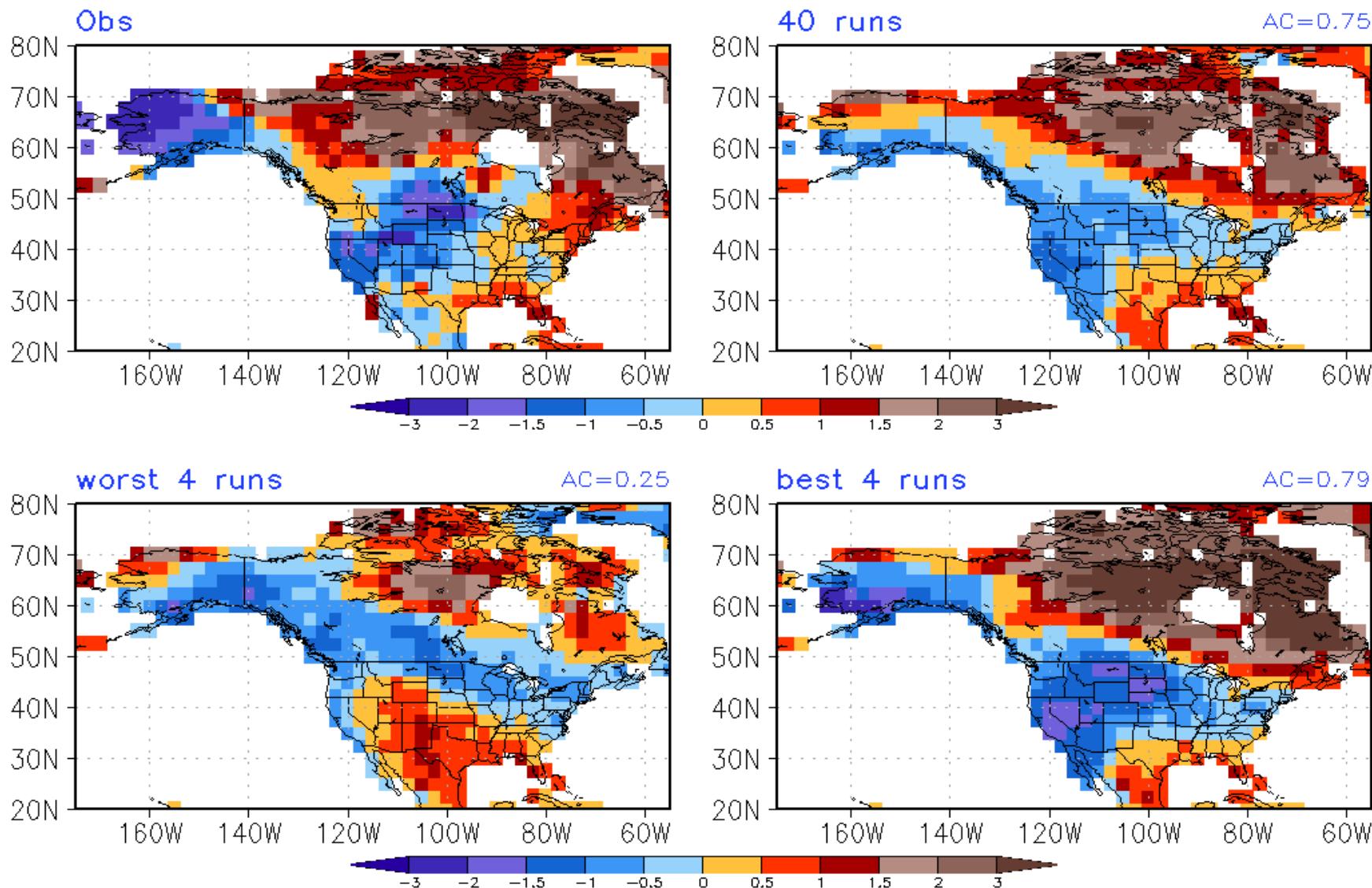
# MAM2023 Anomaly Correlation for Individual CFSv2 Forecast with Observation -- T2m(NA)/SST(30S–30N)



Observed & CFSv2 Forecast Ensemble Average Anomalies  
MAM2023 T2m(K) 40 runs/worst 4 runs/best 4 runs  
**Seasonal Forecast**

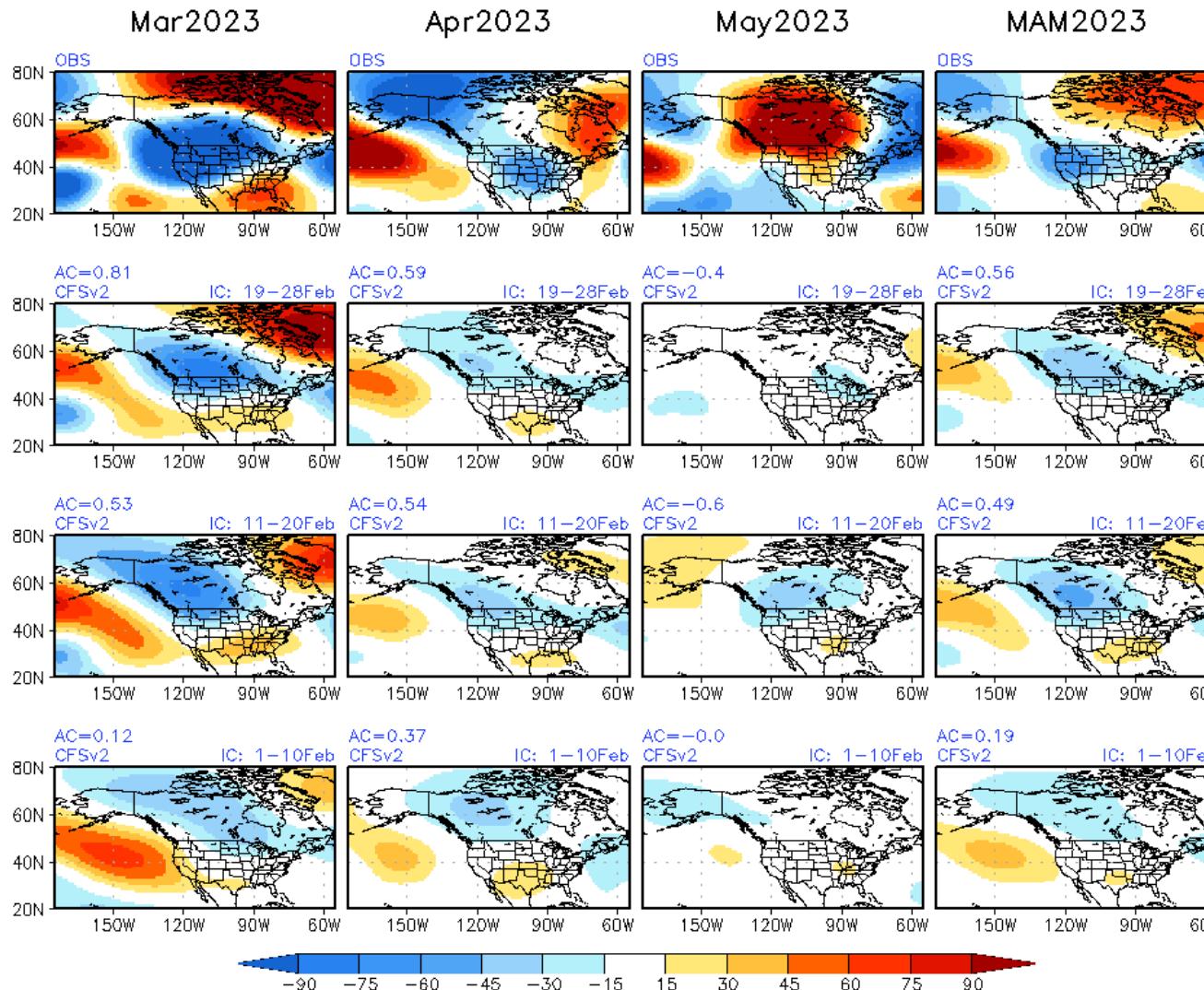


Observed & CFSv2 Forecast Ensemble Average Anomalies  
MAM2023 T2m(K) 40 runs/worst 4 runs/best 4 runs  
**Reconstructed Forecast**



# $z200(m)$ Monthly Means from *Seasonal Forecast*

Monthly Means from Seasonal Fcst (40ensm) MAM2023  $z200(m)$  eddy & Obs



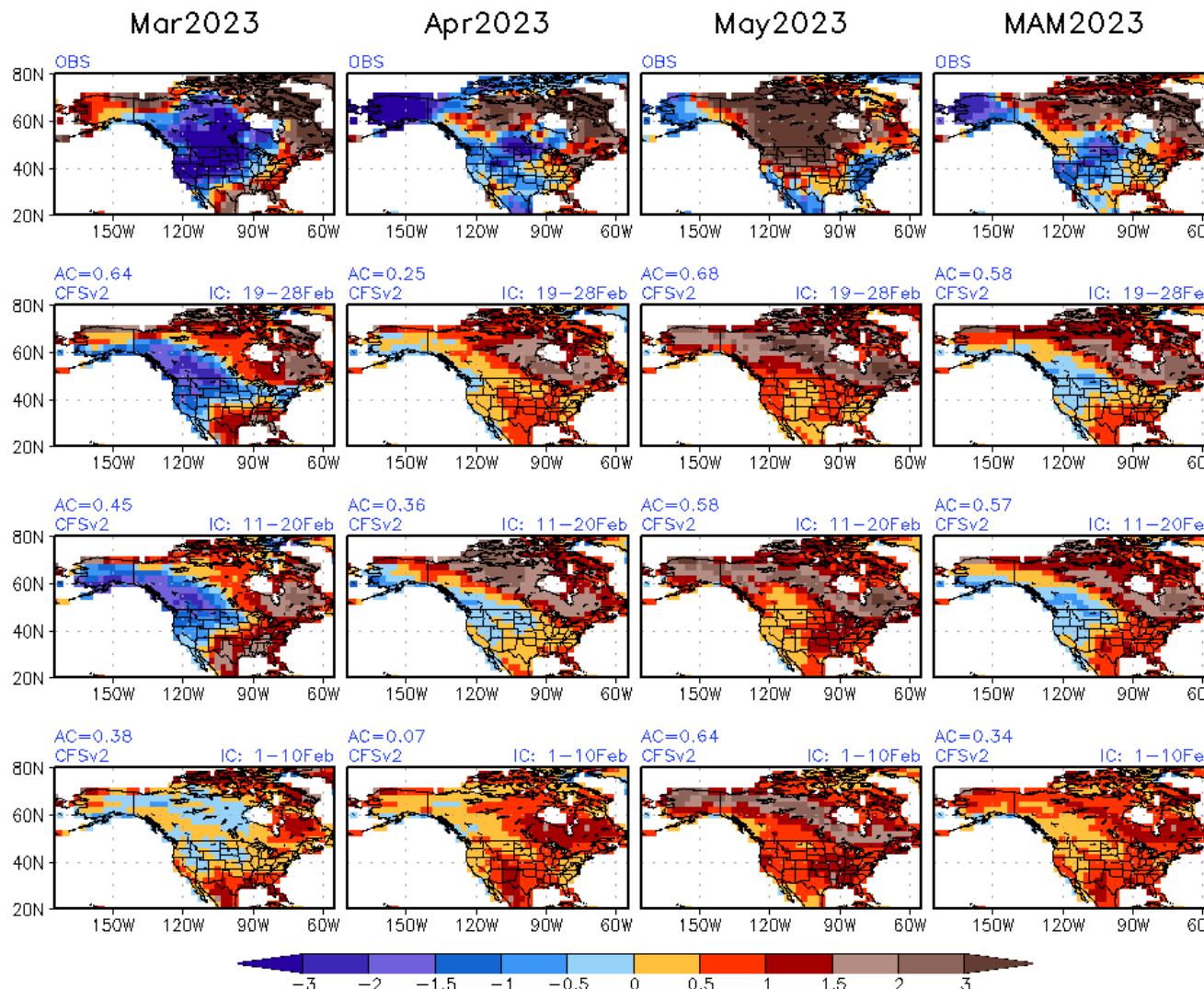
Top row: Observed anomaly.

CFSv2 seasonal forecasts from different initial conditions in the month prior 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) MAM2023 T2m(K) & Obs



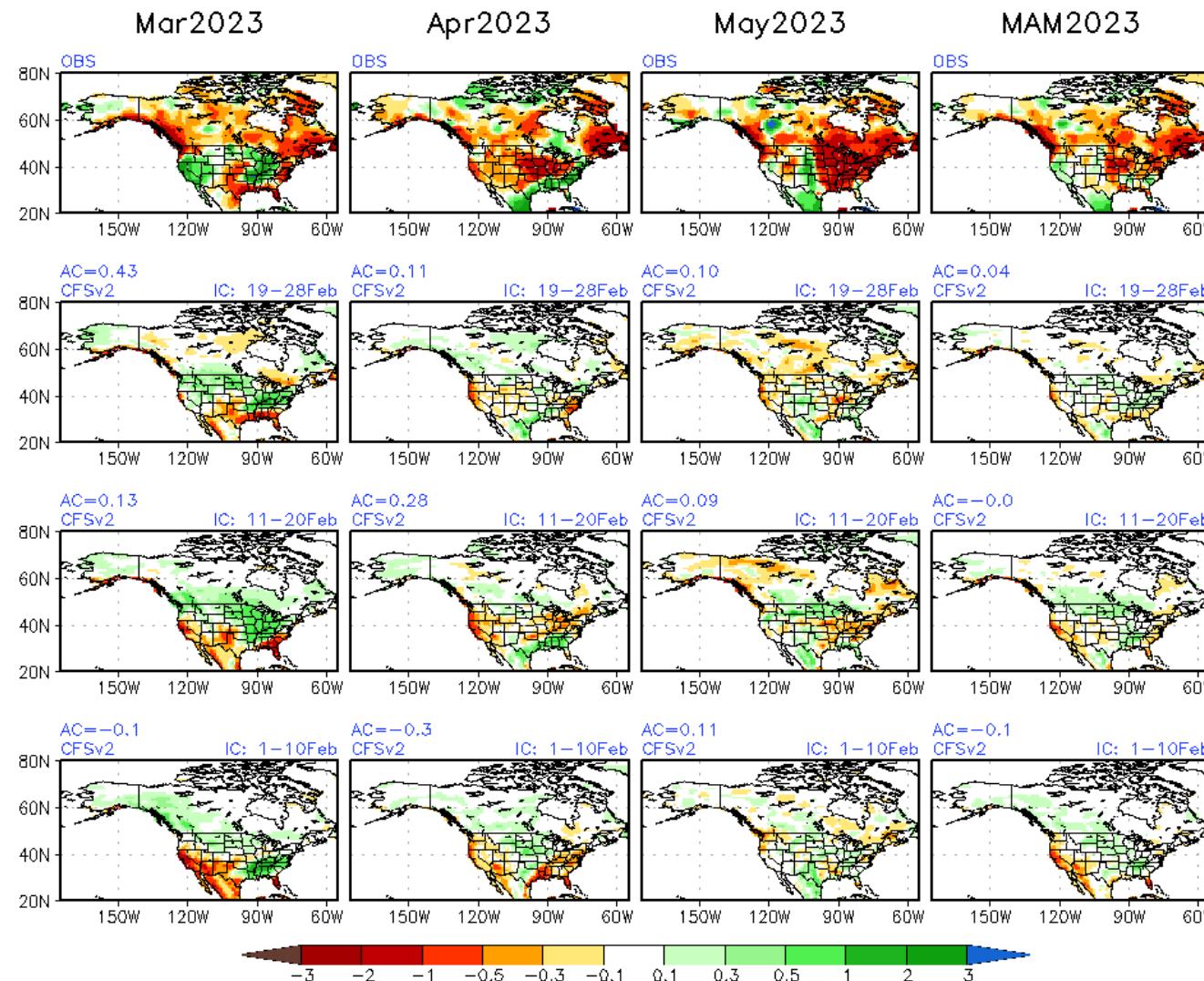
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- 4<sup>th</sup> row: 1<sup>st</sup> - 10<sup>th</sup> of the prior month.

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

Monthly Means from Seasonal Fcst (40ensm) MAM2023 Prec(mm/day) & Obs

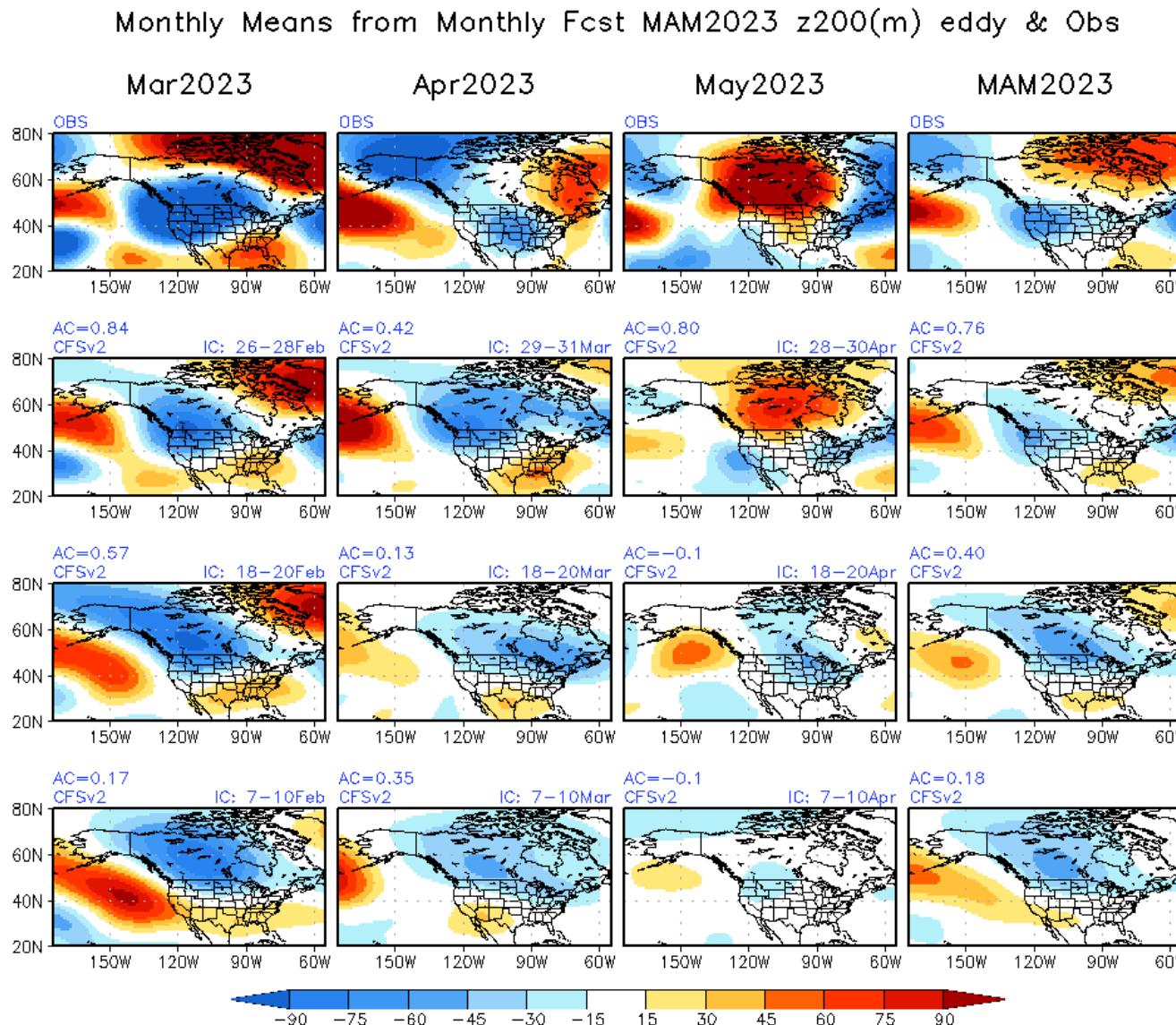


Top row: Observed anomaly.

CFSv2 seasonal forecasts from different initial conditions in the month prior to the target season:

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- 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.

# $z200(m)$ Monthly Means from Monthly Forecast



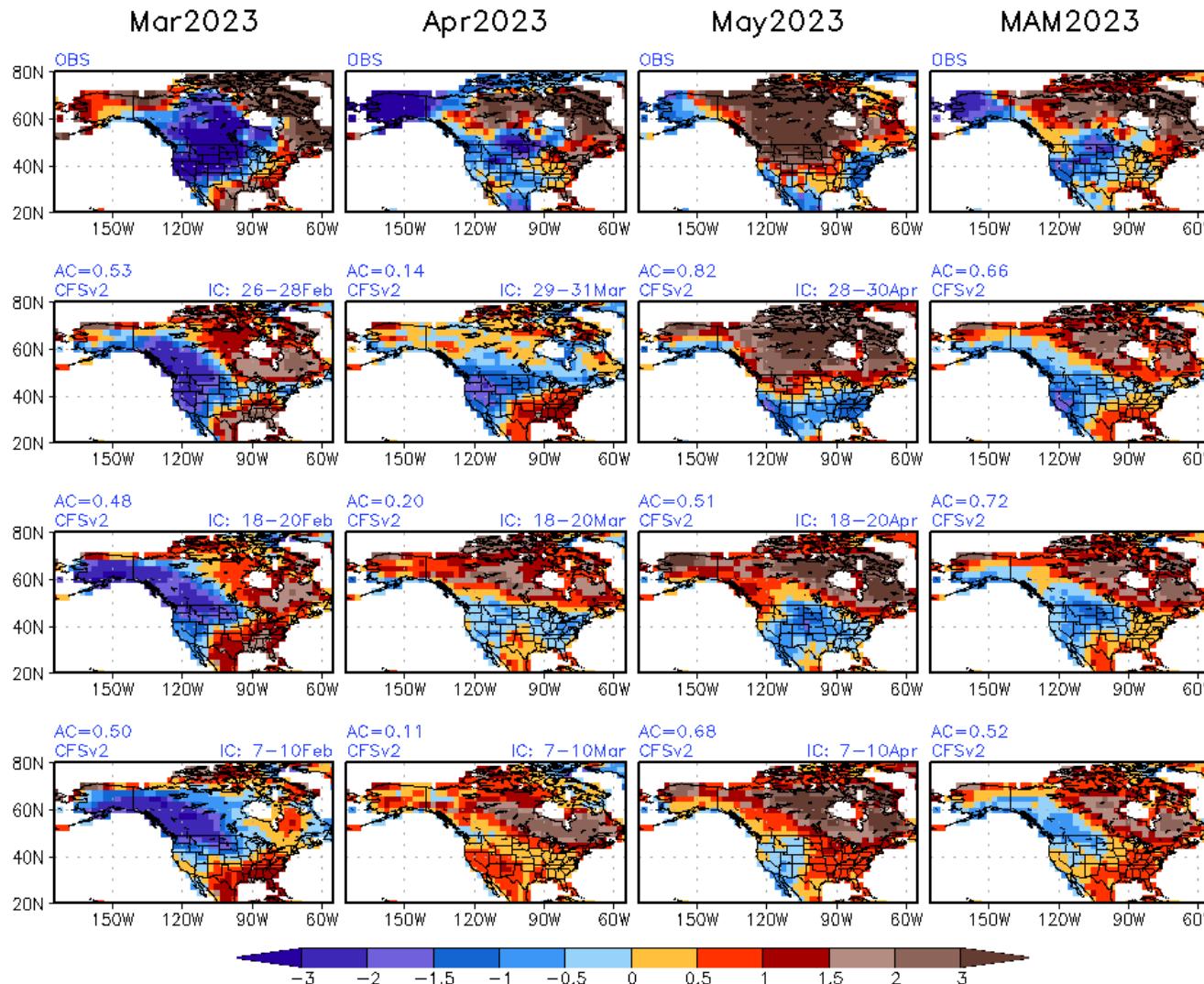
Top row: Observed anomaly.

CFSv2 monthly forecasts from different initial conditions in the month prior 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 MAM2023 T2m(K) & Obs

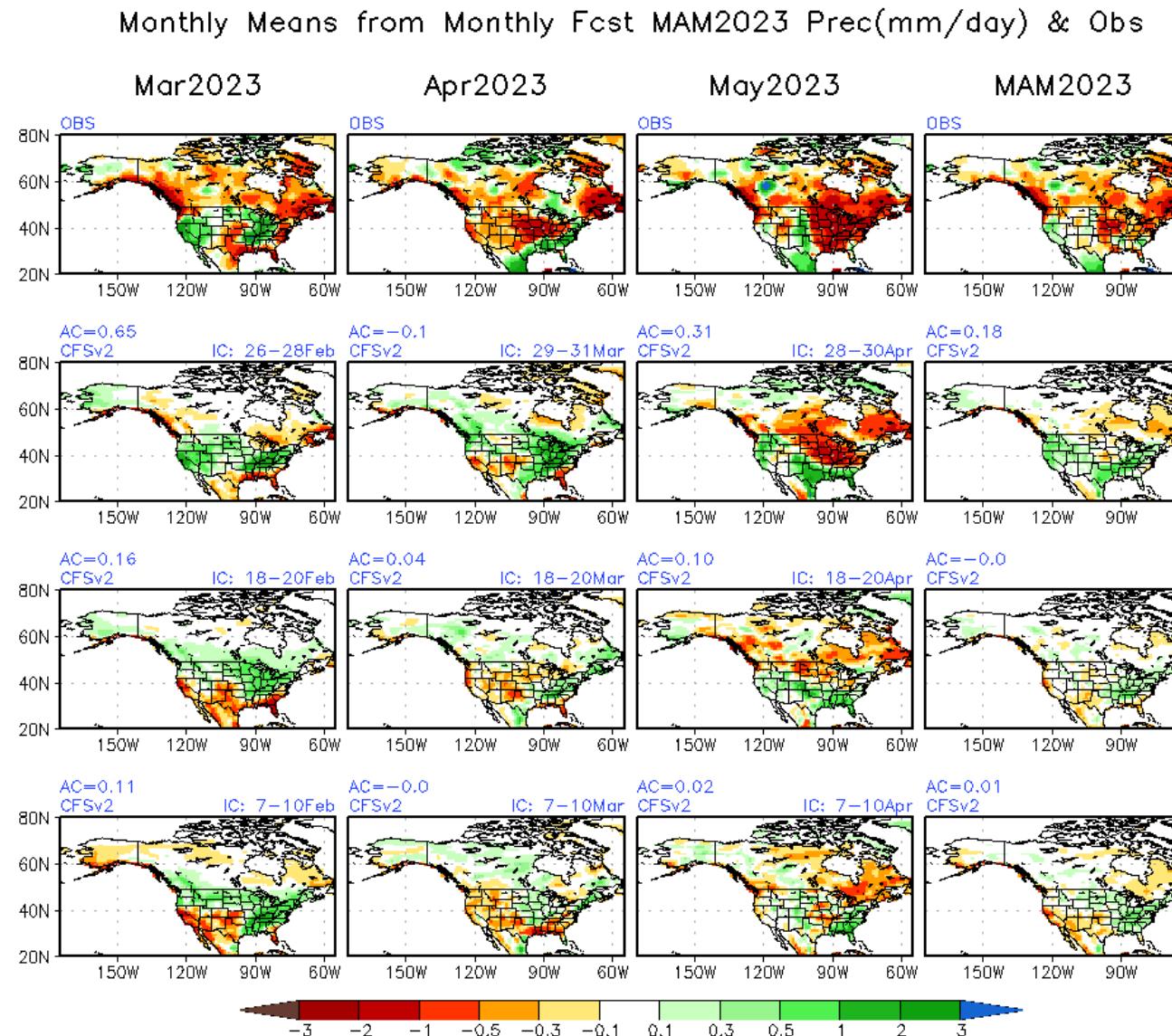


Top row: Observed anomaly.

CFSv2 monthly forecasts from different initial conditions in the month prior 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.

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



Top row: Observed anomaly.

CFSv2 monthly forecasts from different initial conditions in the month prior 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.

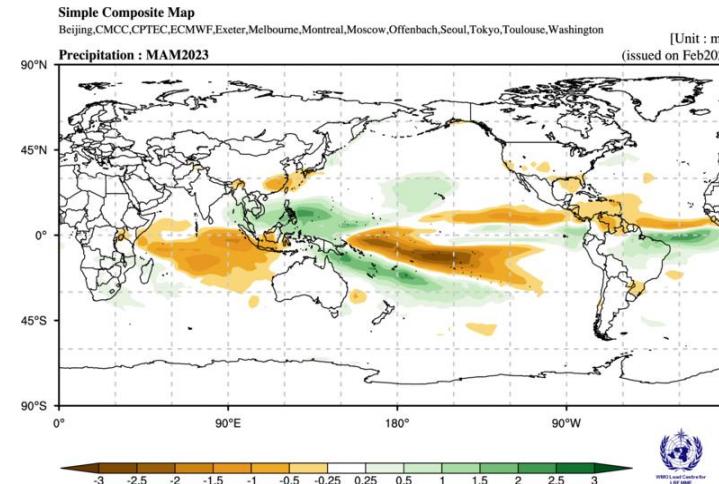
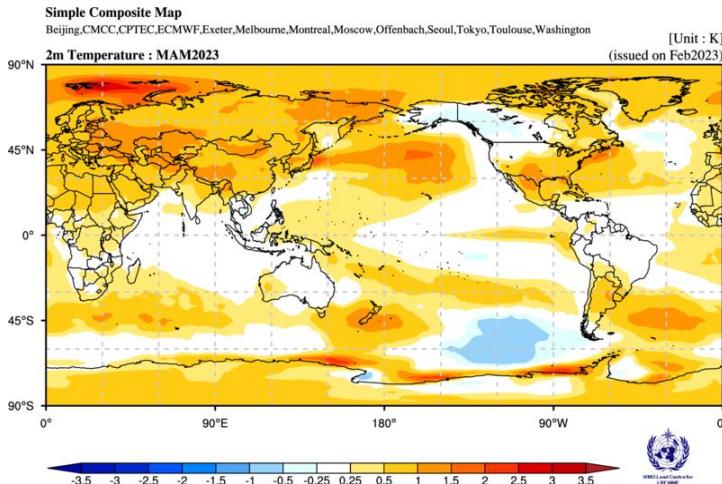
## Seasonal Forecasts from Multi-Model Ensemble Systems

- WMO Lead Center for Long-Range Forecast Multi-Model Ensemble (LC-LRFMME).  
<https://www.wmclc.org/>
- Copernicus Climate Change Service (C3S) Multi-model seasonal forecasts.  
[https://climate.copernicus.eu/charts/c3s\\_seasonal/](https://climate.copernicus.eu/charts/c3s_seasonal/)
- North American Multi-Model Ensemble (NMME) seasonal forecasts.  
<https://www.cpc.ncep.noaa.gov/products/NMME/>

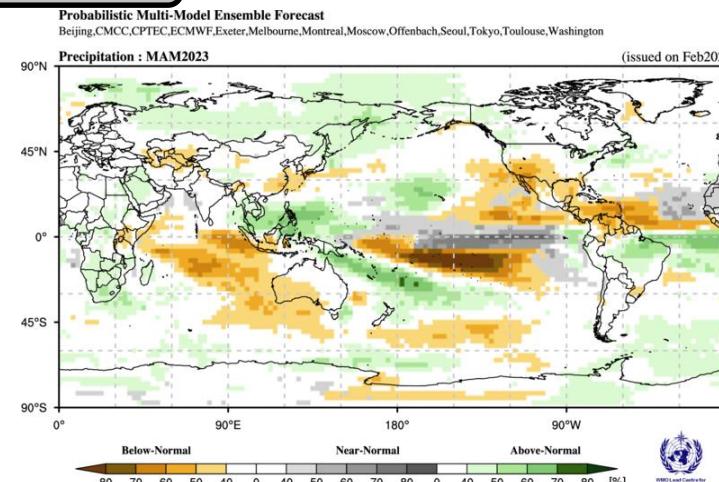
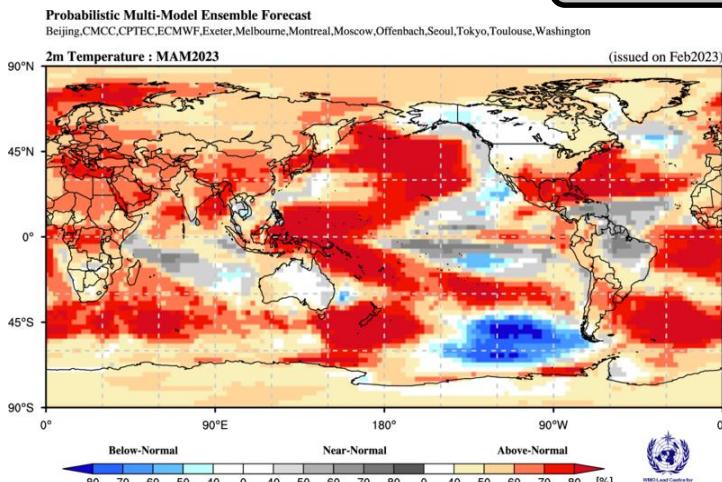
# LC-LRFMM Seasonal Forecasts

(<https://www.wmorc.org/>)

## Ensemble means

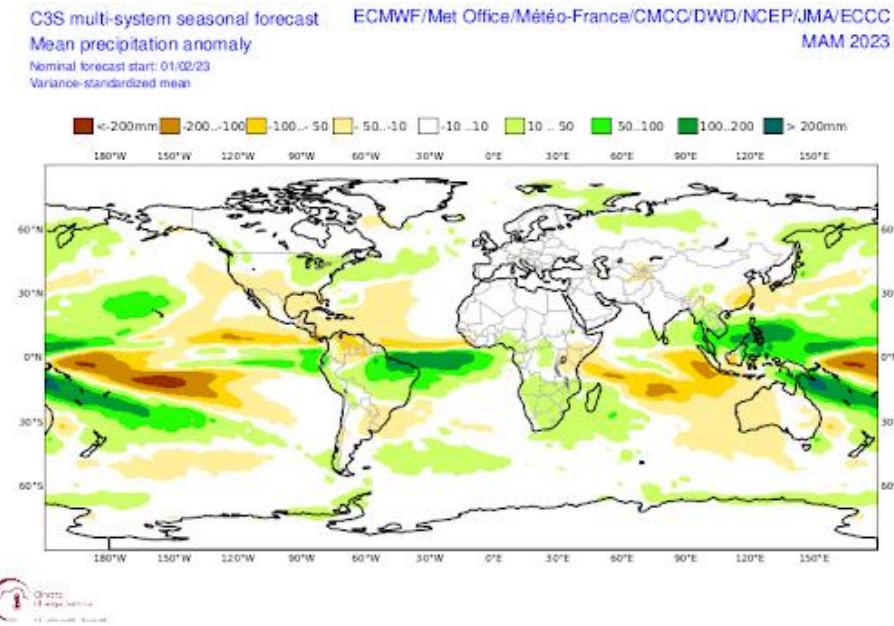
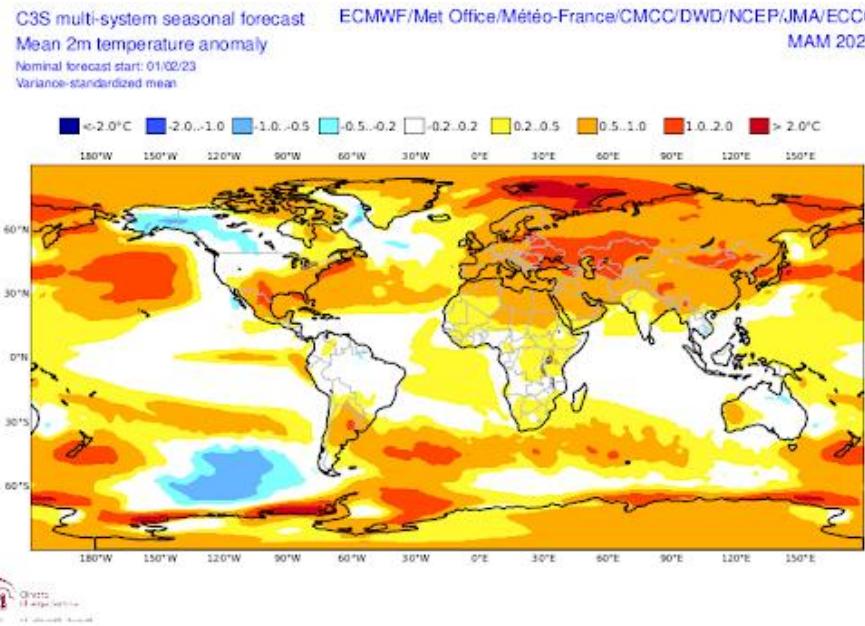


## Probabilities



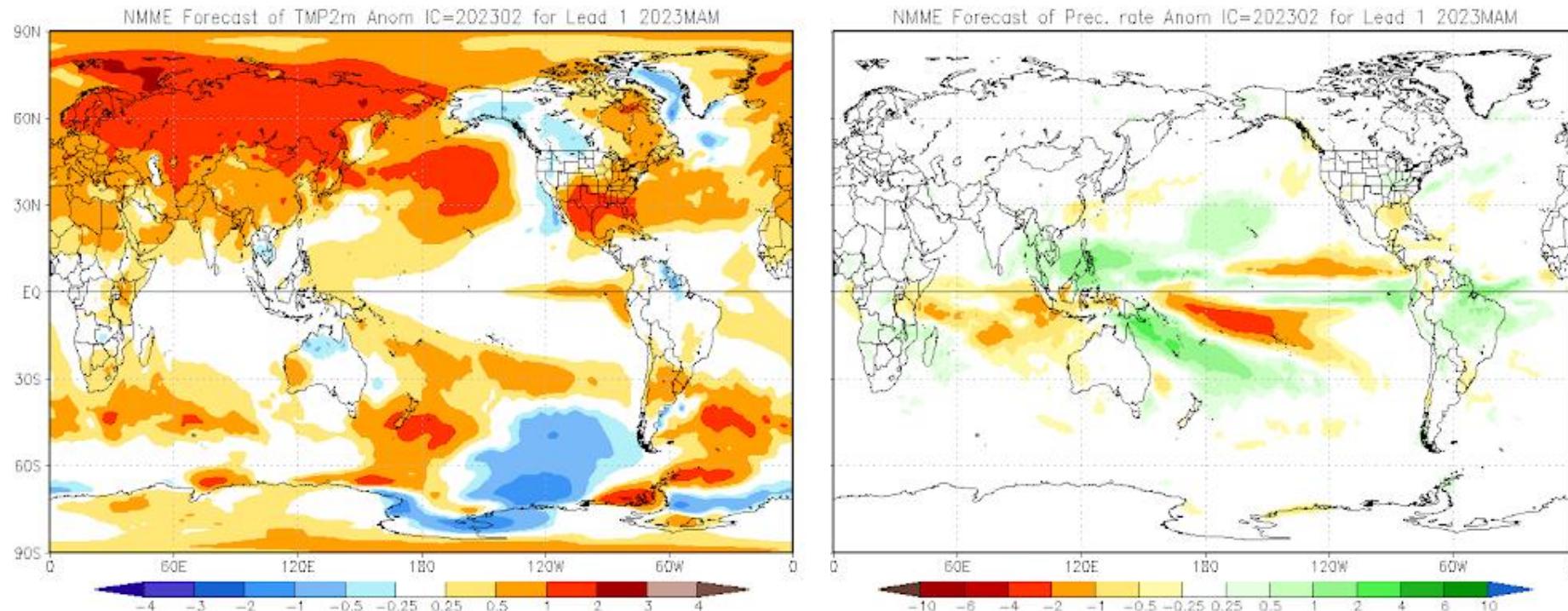
# C3S Seasonal Forecast

([https://climate.copernicus.eu/charts/c3s\\_seasonal/](https://climate.copernicus.eu/charts/c3s_seasonal/))



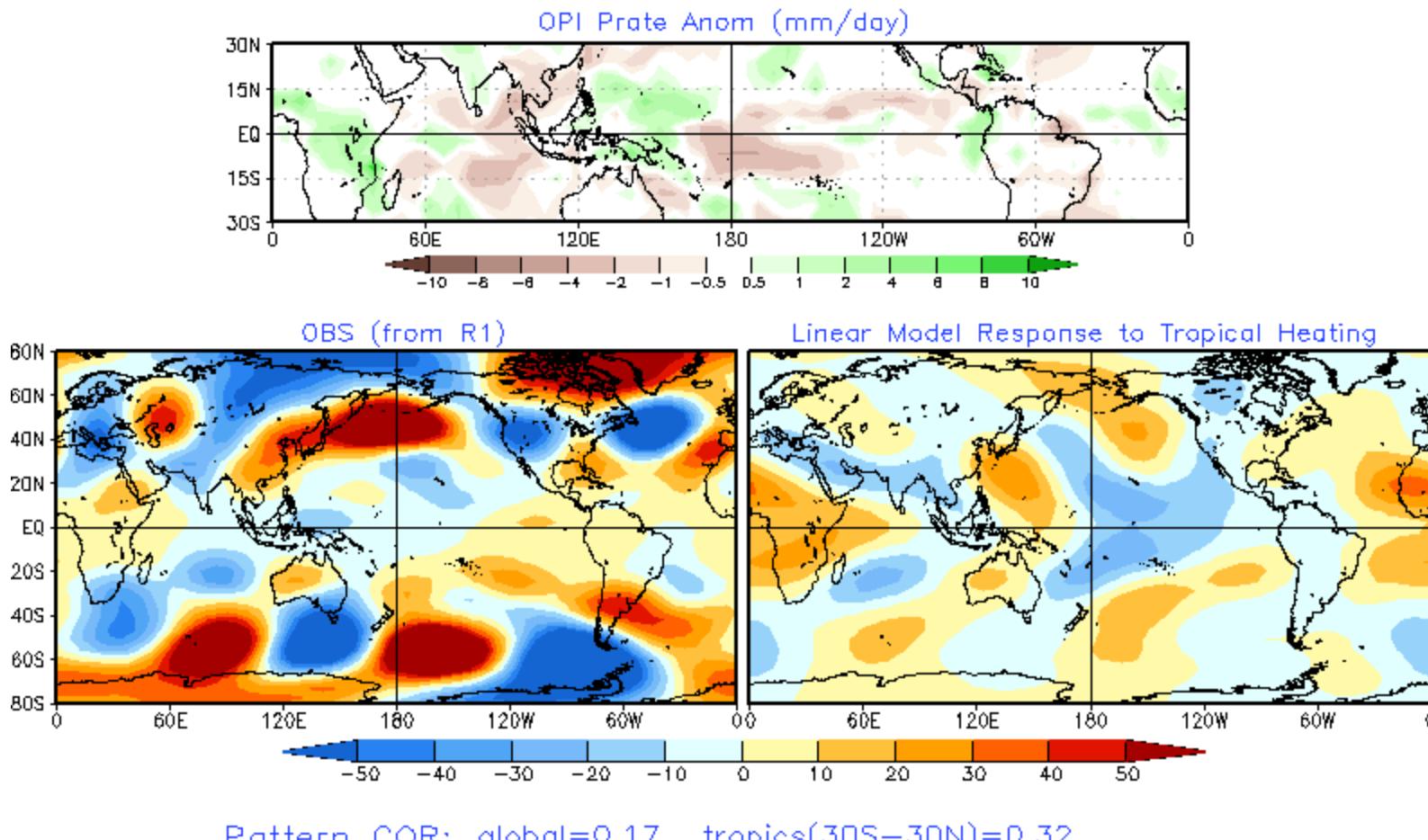
# North American Multi-Model Ensemble Seasonal Forecast

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

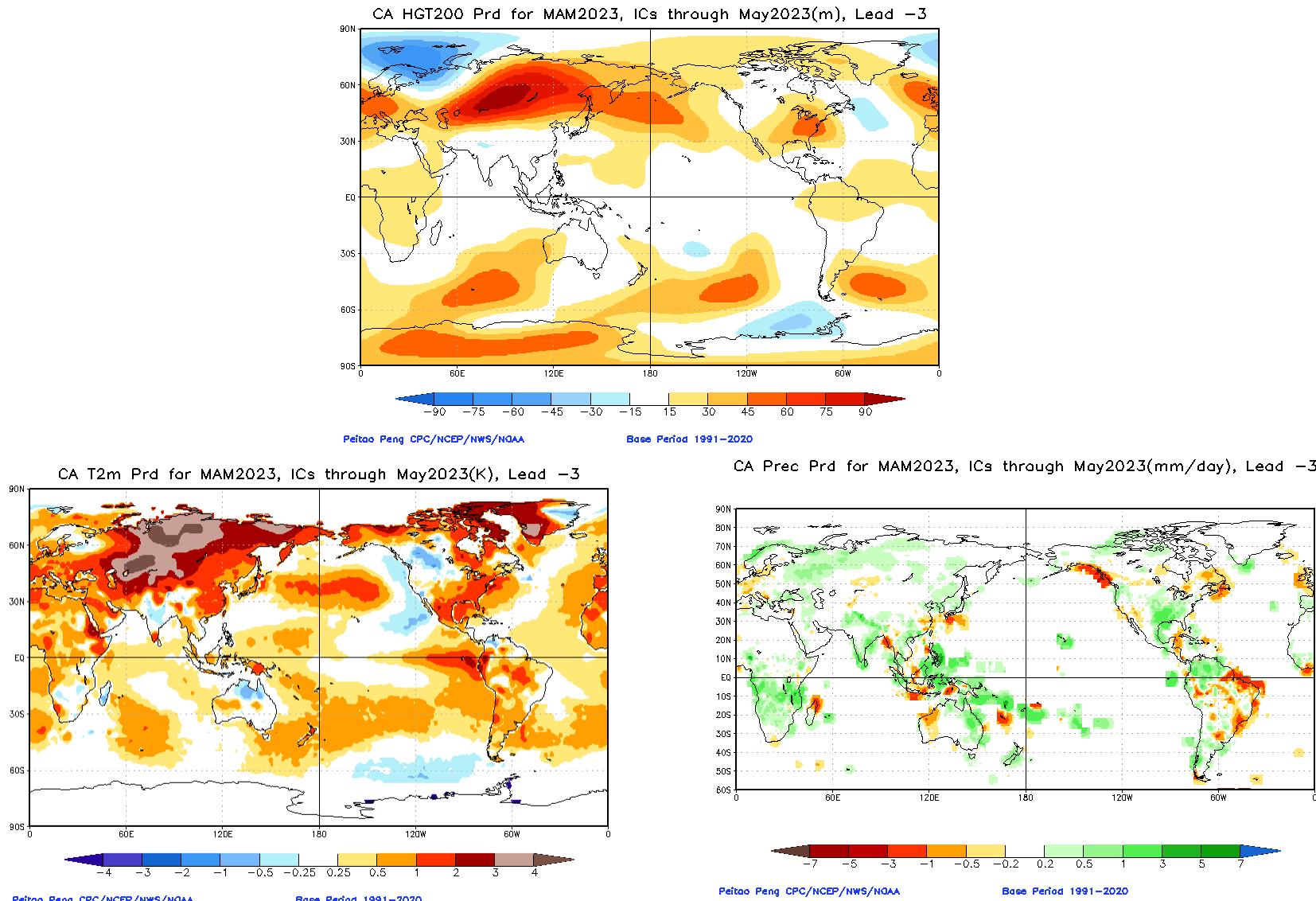


# 200mb Height from Linear Model

MAM2023 200mb Eddy HGT(m)  
OBS vs. Linear Model Response to Tropical Heating  
Heating is converted from Prate in 15S–15N



# Seasonal Forecasts from the Constructed Analog Model



## 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)
  - Seasonal forecast: the seasonal mean forecasts based on 40 members from the latest 10 days before the target season (0-month-lead);
  - Reconstructed forecast: 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 (provided by Dr. Peitao Peng/CPC)
- Seasonal mean anomalies of z200, T2m, and Prec forecasted from the Constructed Analog Model (provided by Dr. Peitao Peng/CPC)