

# Attribution of Seasonal Climate Anomalies December-January-February 2022-2023

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

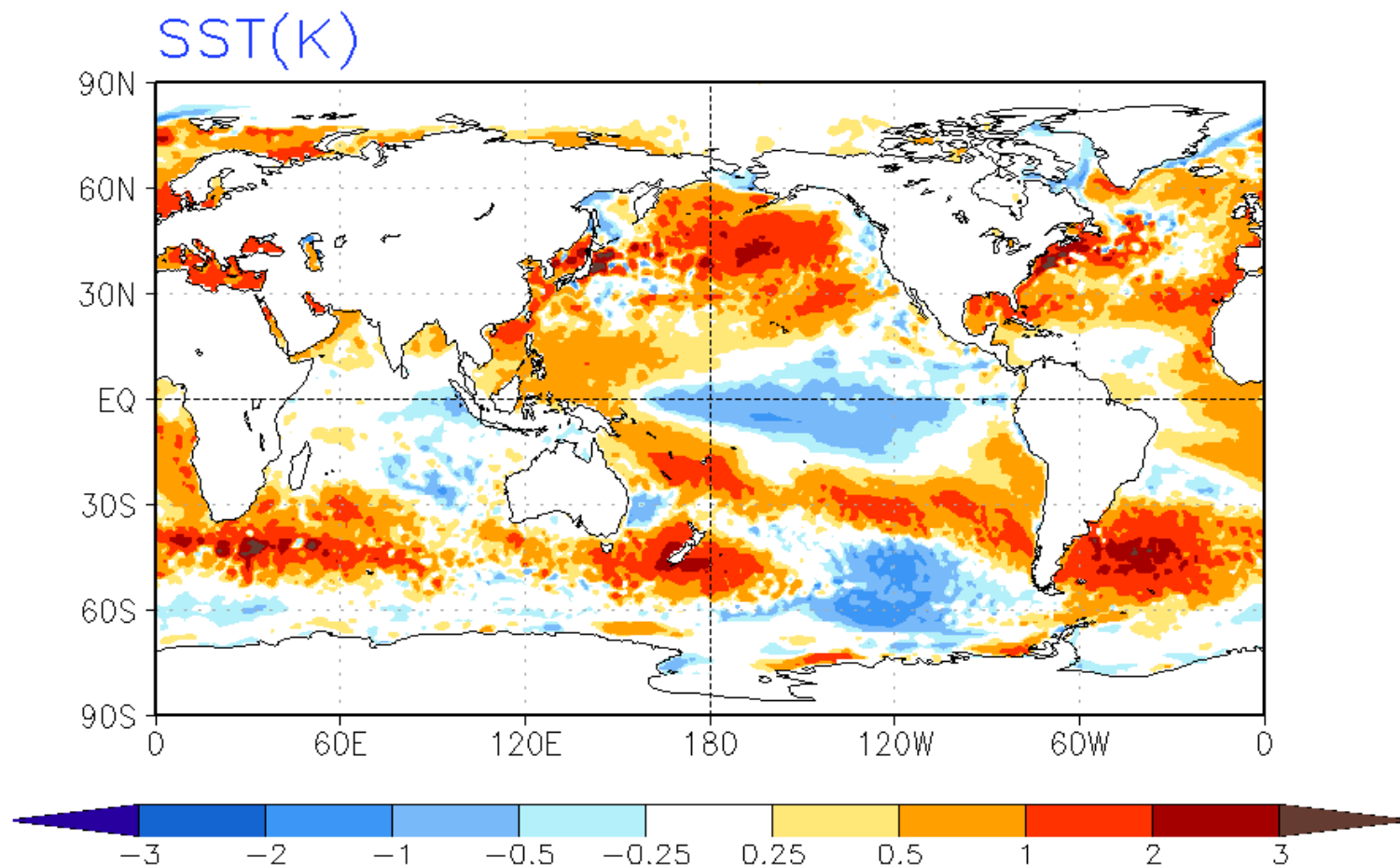
# Summary of Observed Conditions and Outlooks

- Equatorial tropical Pacific SST anomalies continued in La Nina conditions but with weaker amplitude relative to the previous seasons; in the equatorial and north Atlantic, and North Pacific, SST anomalies continued above normal, while SST anomalies in the equatorial Indian Ocean were weak (slide 4). The large-scale distribution of SST anomalies was predicted well (slide 10);
- AMIP simulations and initialized CFSv2, and other MME forecasts, all replicated the large-scale distribution of observed precipitation anomalies in tropical latitudes ([a reflection of La Niña conditions](#)) including above normal anomalies in the equatorial eastern Indian Ocean, Maritime Continent and dry conditions in the equatorial western, central Pacific Ocean (slides 11, 37-39).
- Both AMIP and the initialized CFSv2 predicted the large-scale distribution of observed 200mb height anomalies in tropics, however, misplaced the negative anomalies over the northeast Asia and western North America region. The erroneous prediction of height anomalies led to failed prediction of the observed cold temperature anomalies over the northeast Asia and the western US (slides 12,13,15,16).
- The spatial pattern of forecast North America precipitation anomalies in the AMIP simulations and the initialized CFSv2 and NMME forecasts were consistent with [the La Nina composite](#). The observed anomalies over the US western region, however, differed from the La Niña composite leading to poor skill (slides 7, 14).
- February 2023 monthly mean forecasts from the shortest leads show much better skill for predicting North America z200 and temperature (slides 33, 34).

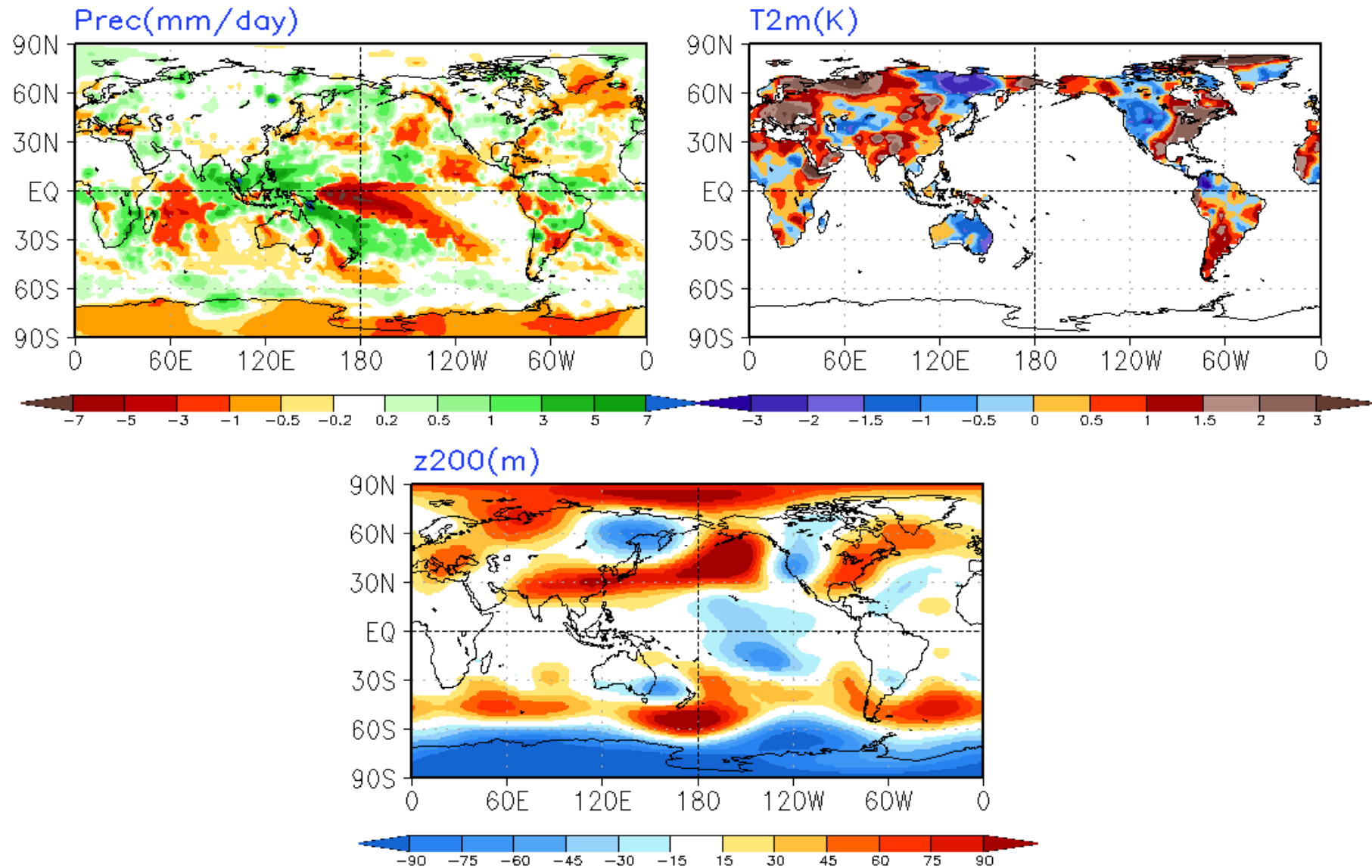
# Observed Seasonal Anomalies

## Global and North America

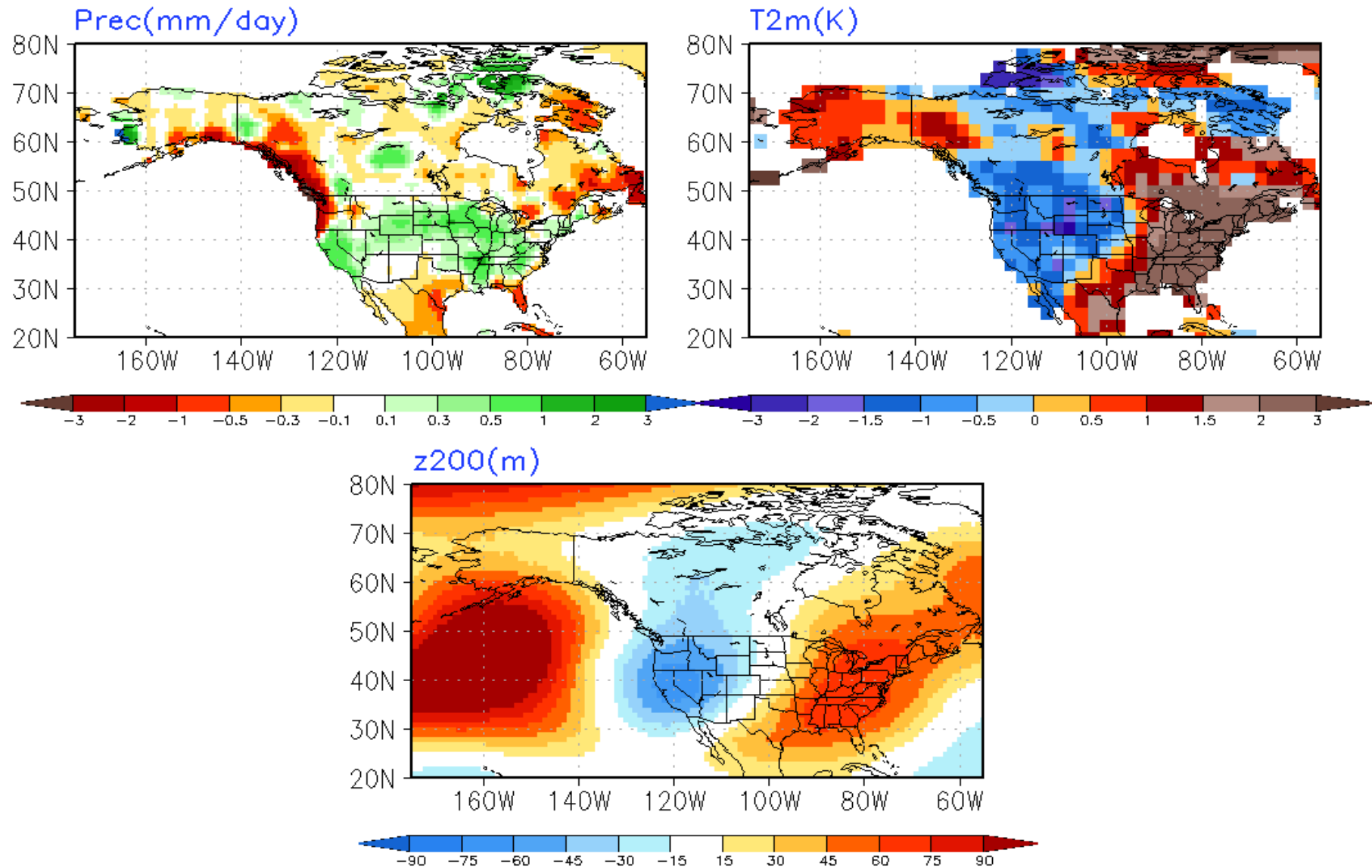
# Observed Anomaly DJF2022/2023



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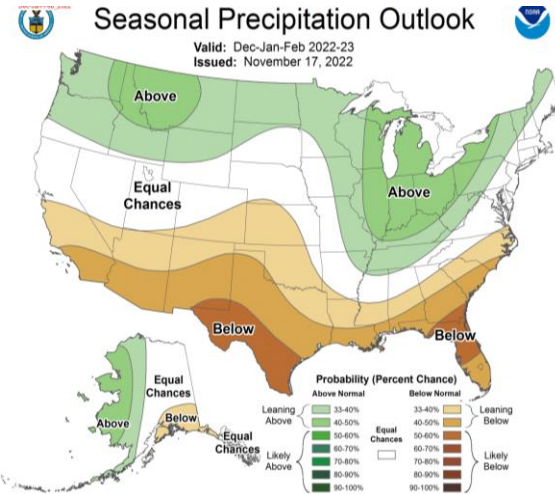
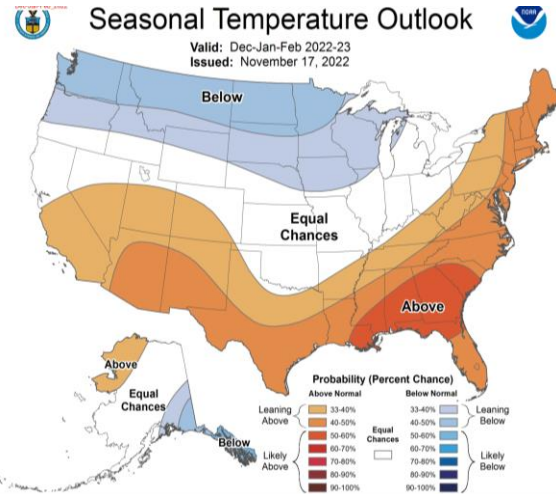
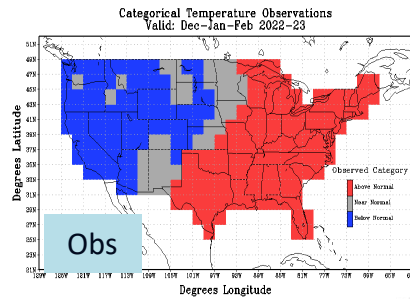
# Observed Anomaly DJF2022/2023



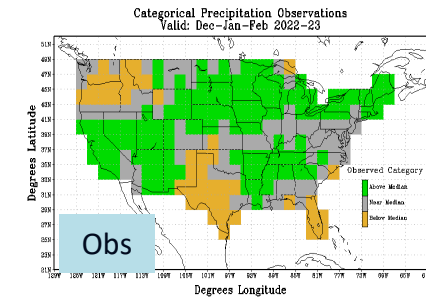
# CPC Seasonal Outlooks and NMME Forecasts

CPC

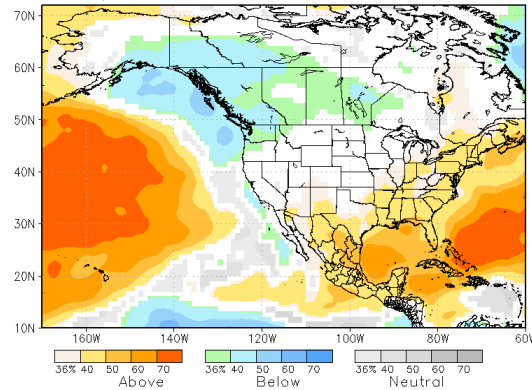
Temp nonEC  
HSS=39



Prec nonEC  
HSS=12

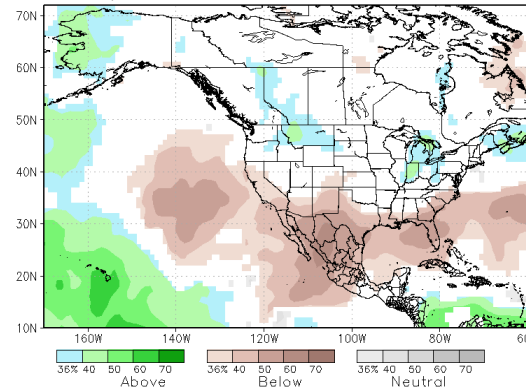


NMME prob fcst TMP2m IC=202211 for lead 1 2022 DJF



NMME

NMME prob fcst Prate IC=202211 for lead 1 2022 DJF



For the rationale behind CPC outlooks see: [https://www.cpc.ncep.noaa.gov/products/archives/long\\_lead/PMD/2022/202211\\_PMD90D](https://www.cpc.ncep.noaa.gov/products/archives/long_lead/PMD/2022/202211_PMD90D)

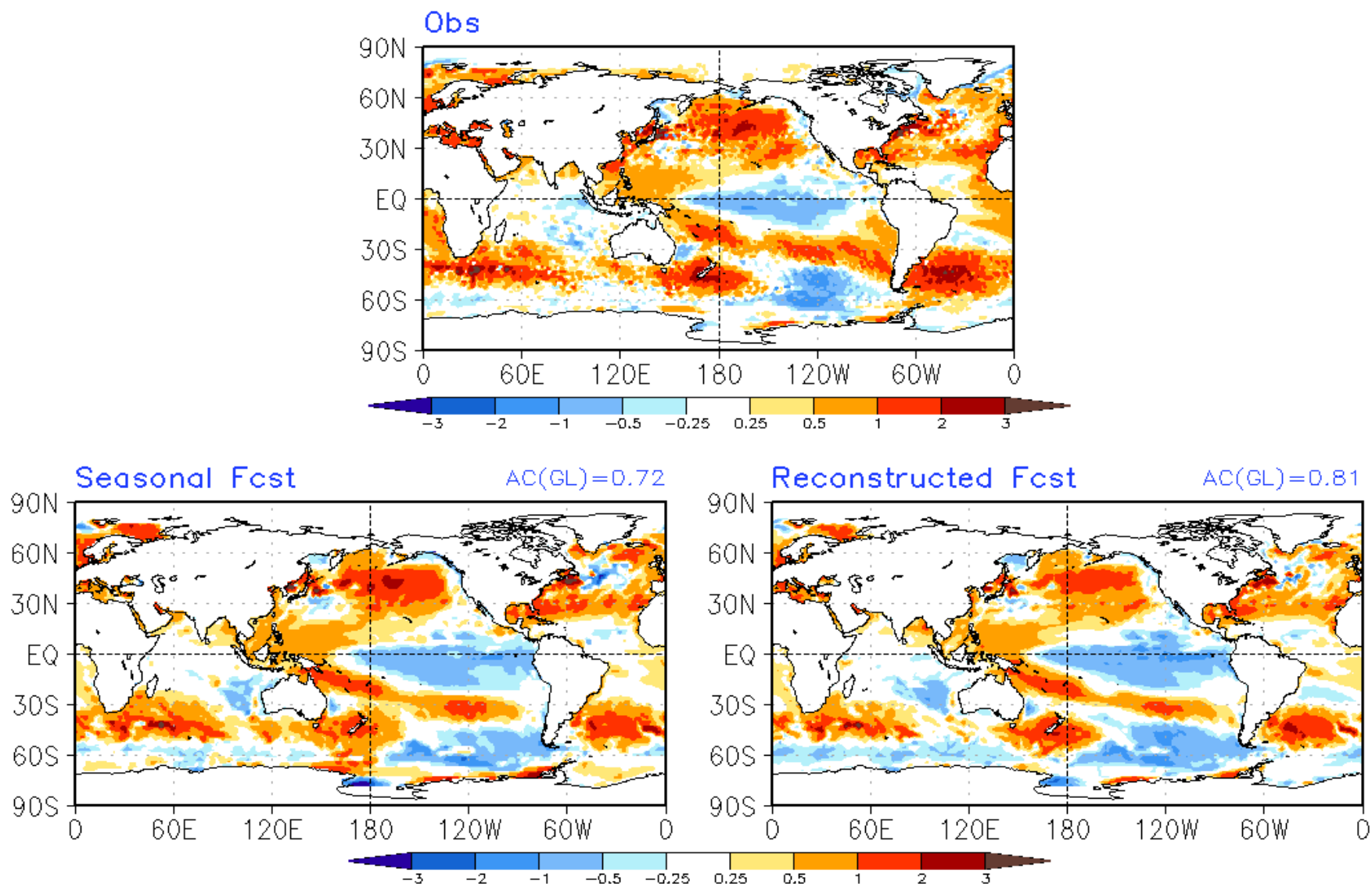
## Model Simulated/Forecast Ensemble Mean Anomalies



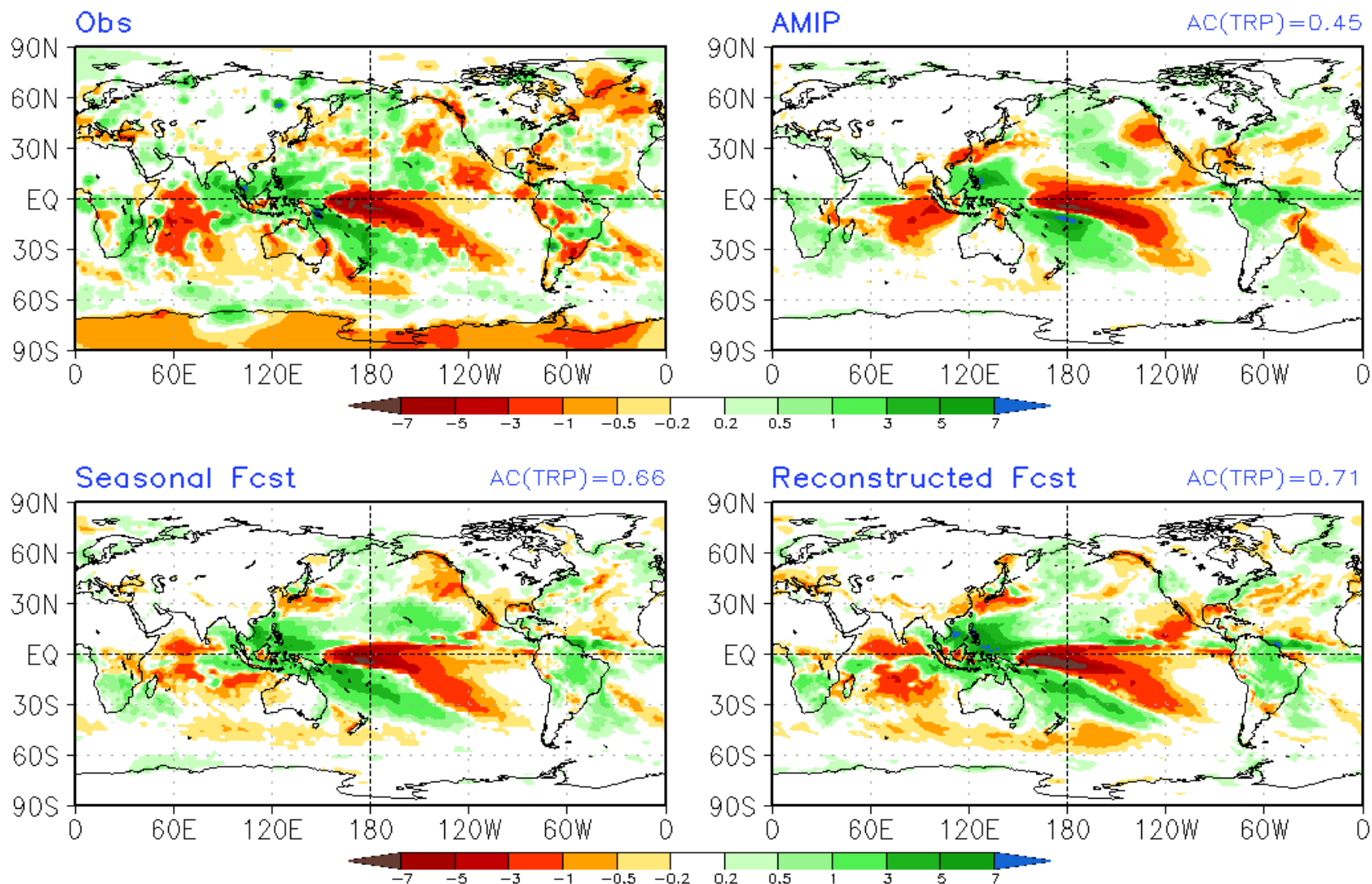
# Model Simulated/Forecast Ensemble Average Anomalies

- **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).

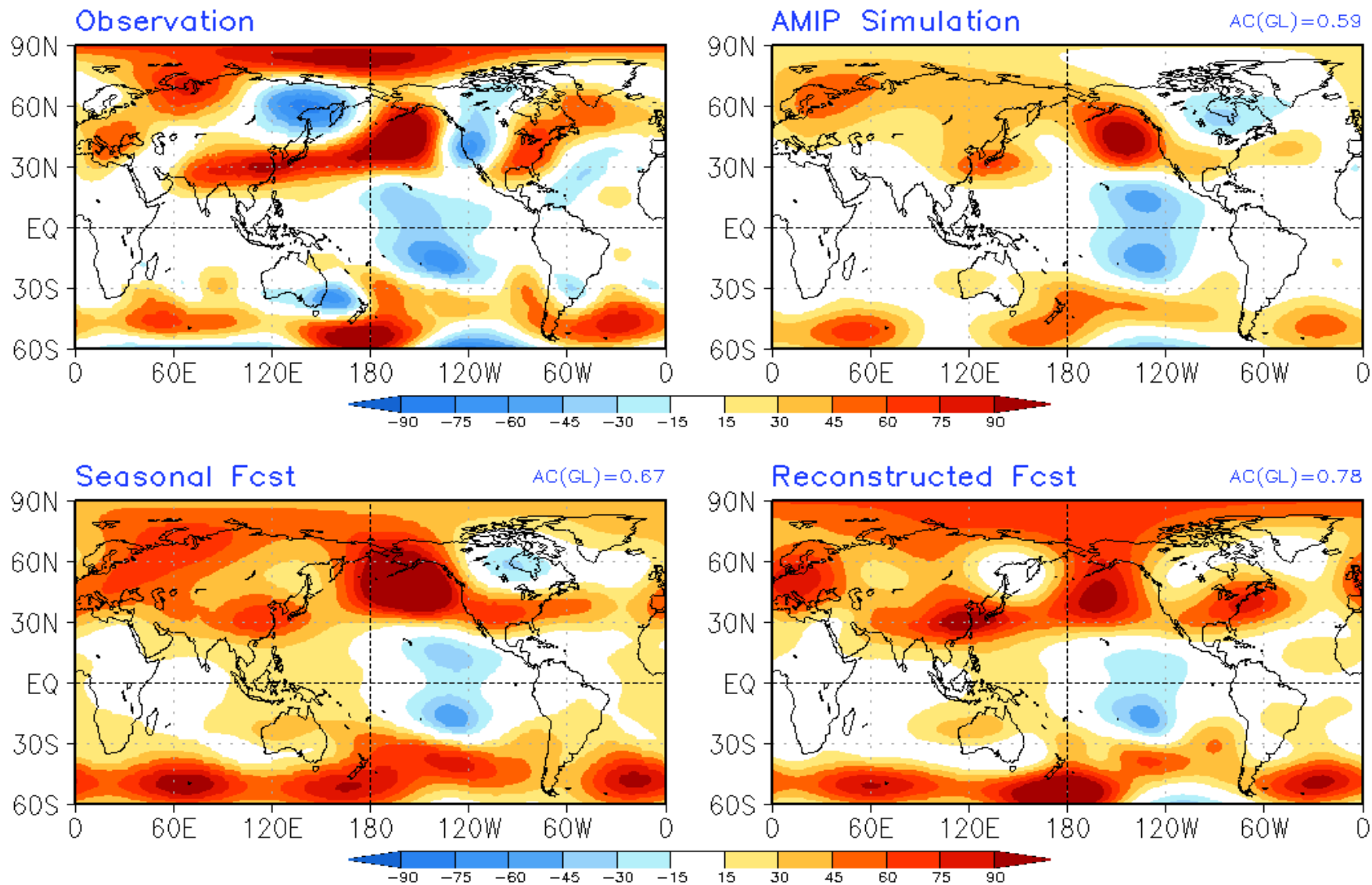
# DJF2022/2023 Observed & Model Simulated/Forecast Ensemble Average Anomalies SST(K)



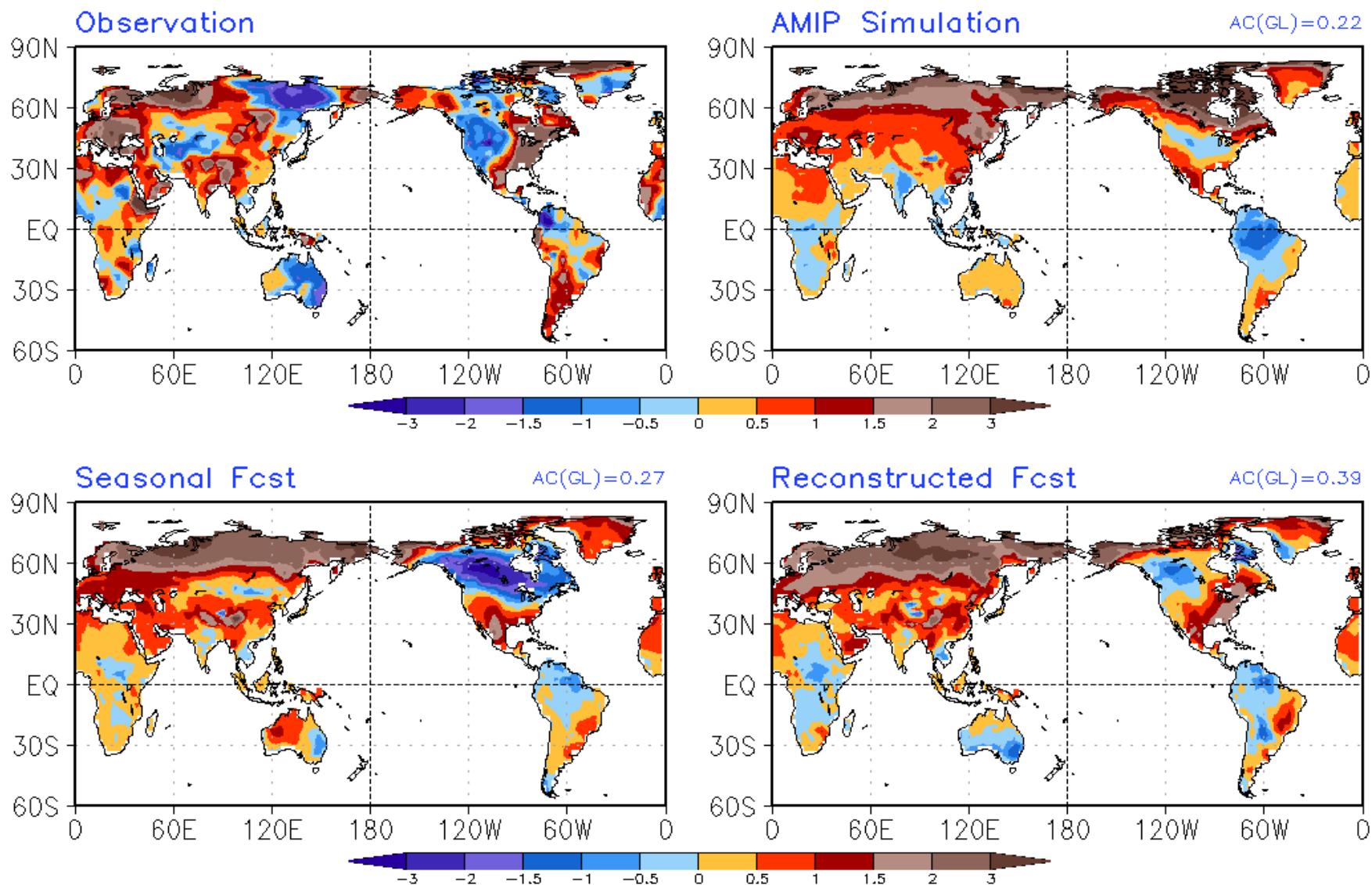
# DJF2022/2023 Observed & Model Simulated/Forecast Ensemble Average Anomalies Prec(mm/day)



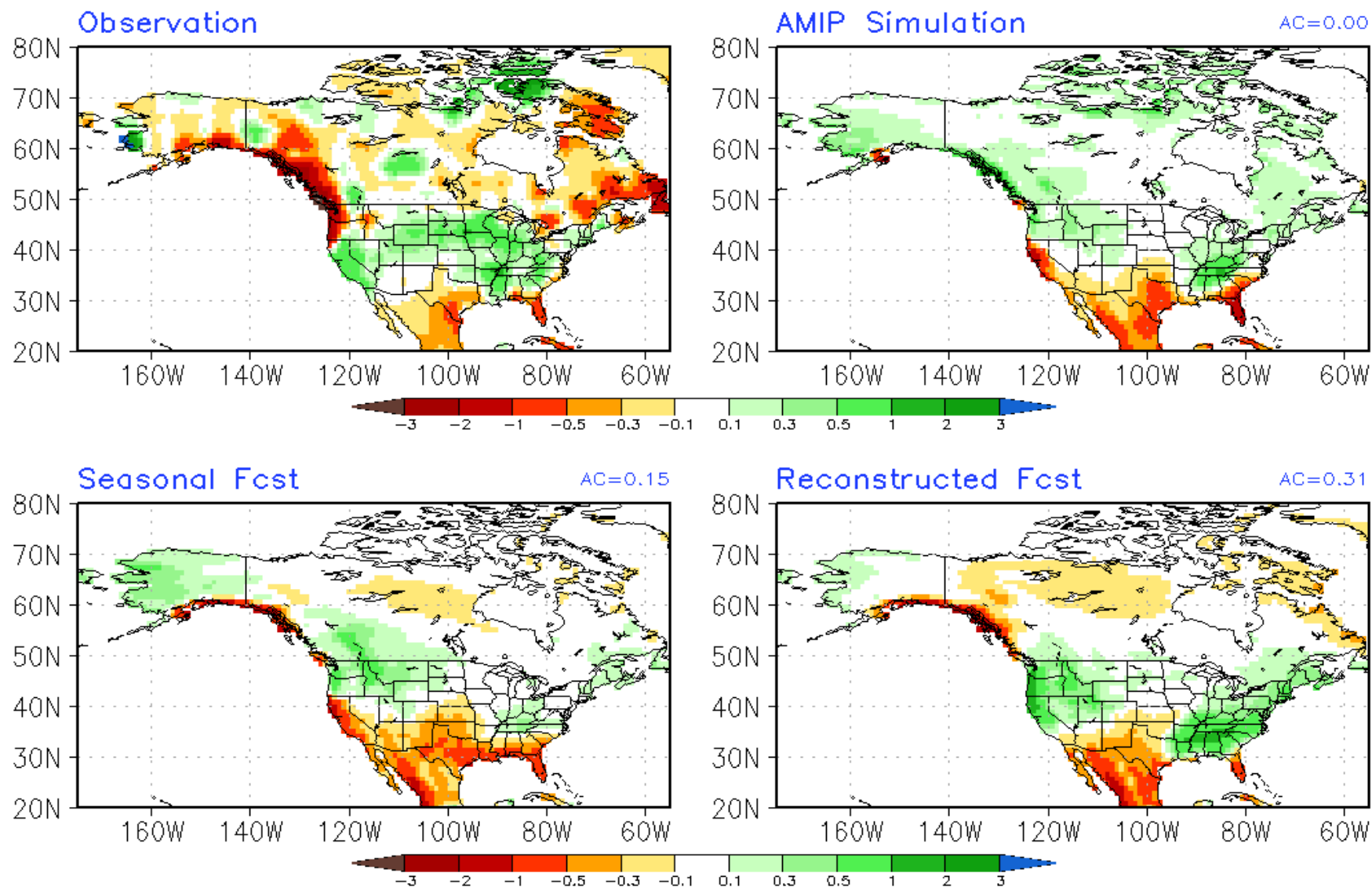
# DJF2022/2023 Observed & Model Simulated/Forecast Ensemble Average Anomalies z200(m)



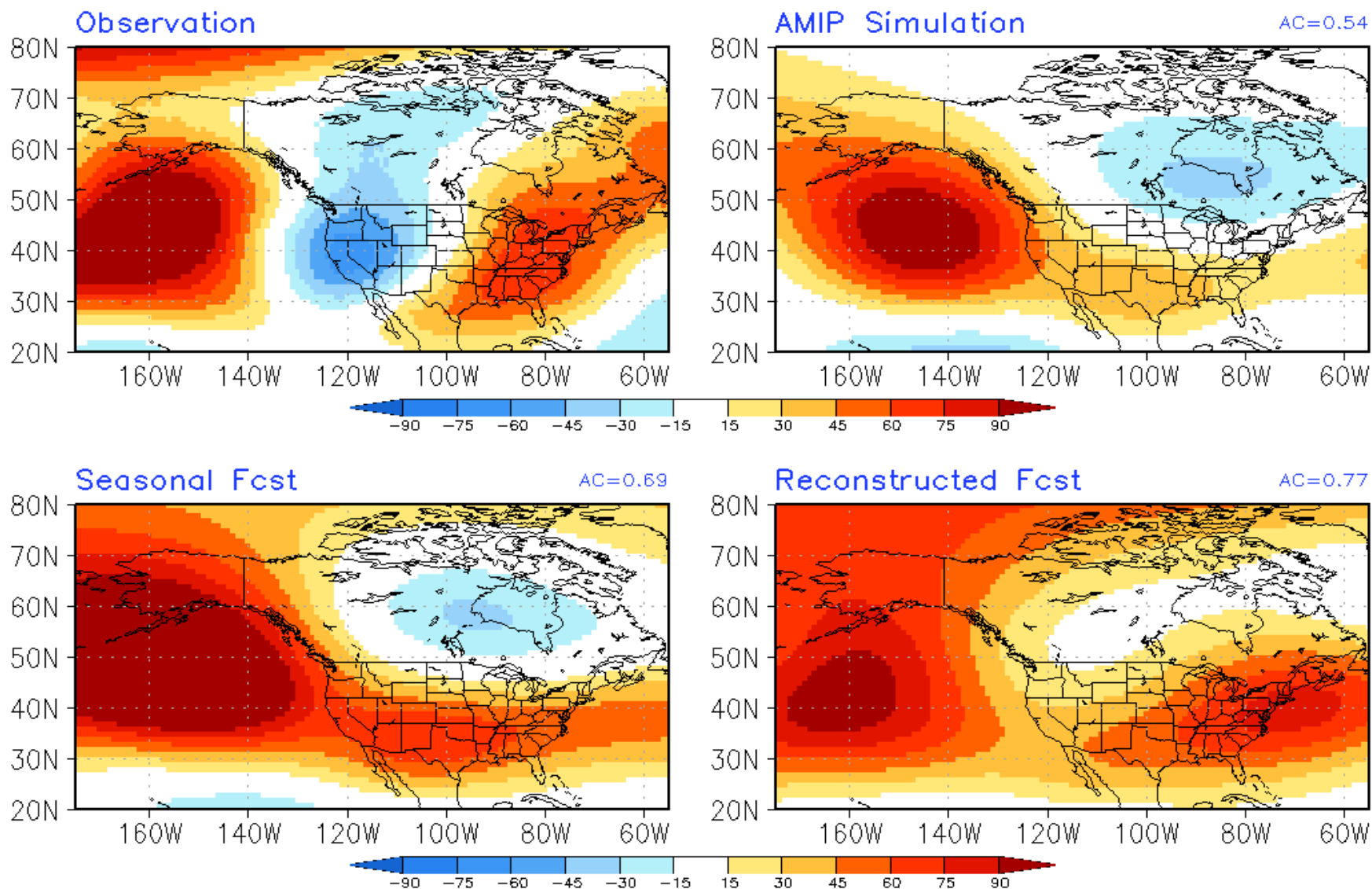
# DJF2022/2023 Observed & Model Simulated/Forecast Ensemble Average Anomalies T2m(K)



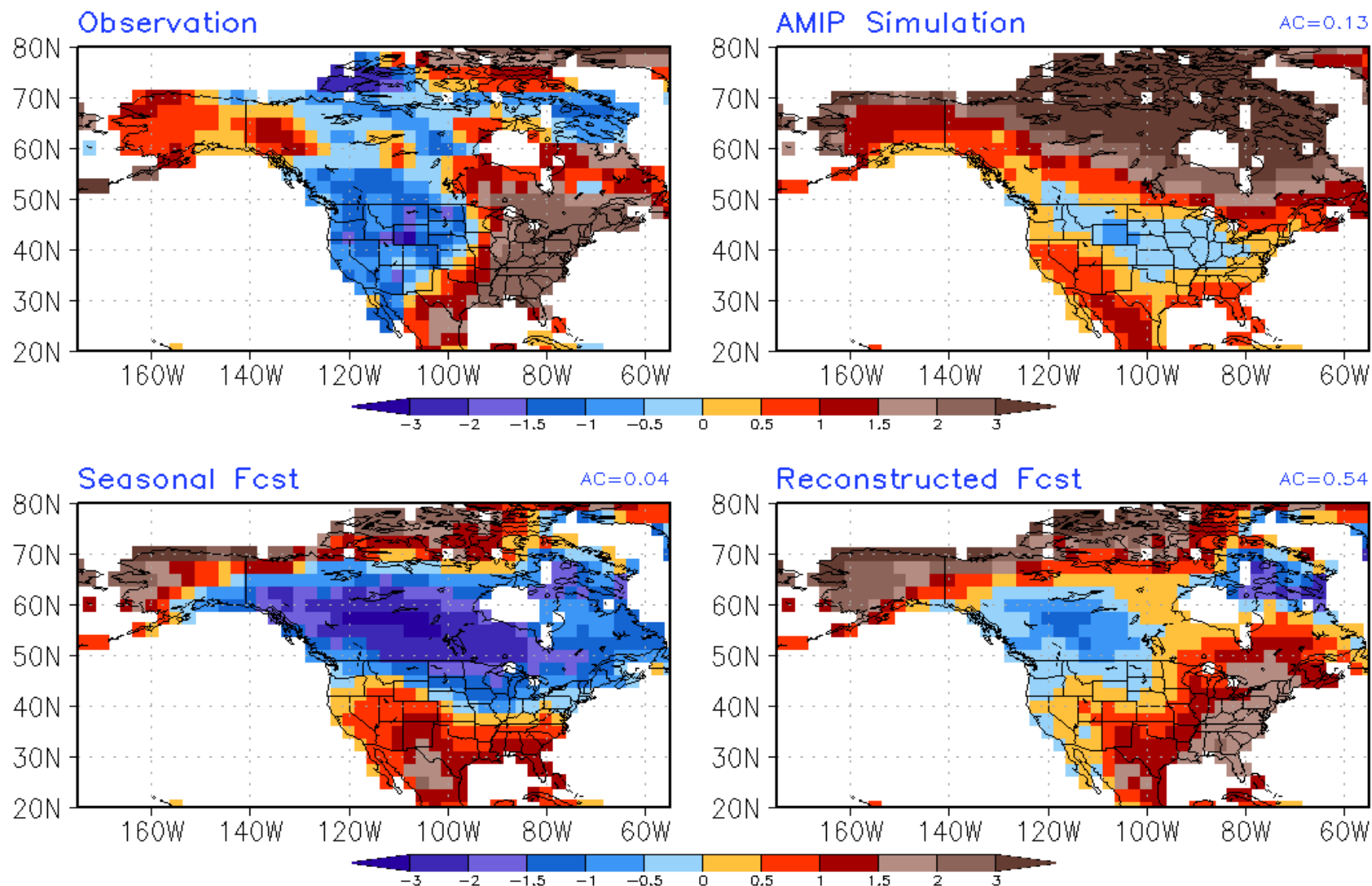
# DJF2022/2023 Observed & Model Simulated/Forecast Ensemble Average Anomalies Prec(mm/day)



# DJF2022/2023 Observed & Model Simulated/Forecast Ensemble Average Anomalies z200(m)



# DJF2022/2023 Observed & Model Simulated/Forecast Ensemble Average Anomalies T2m(K)



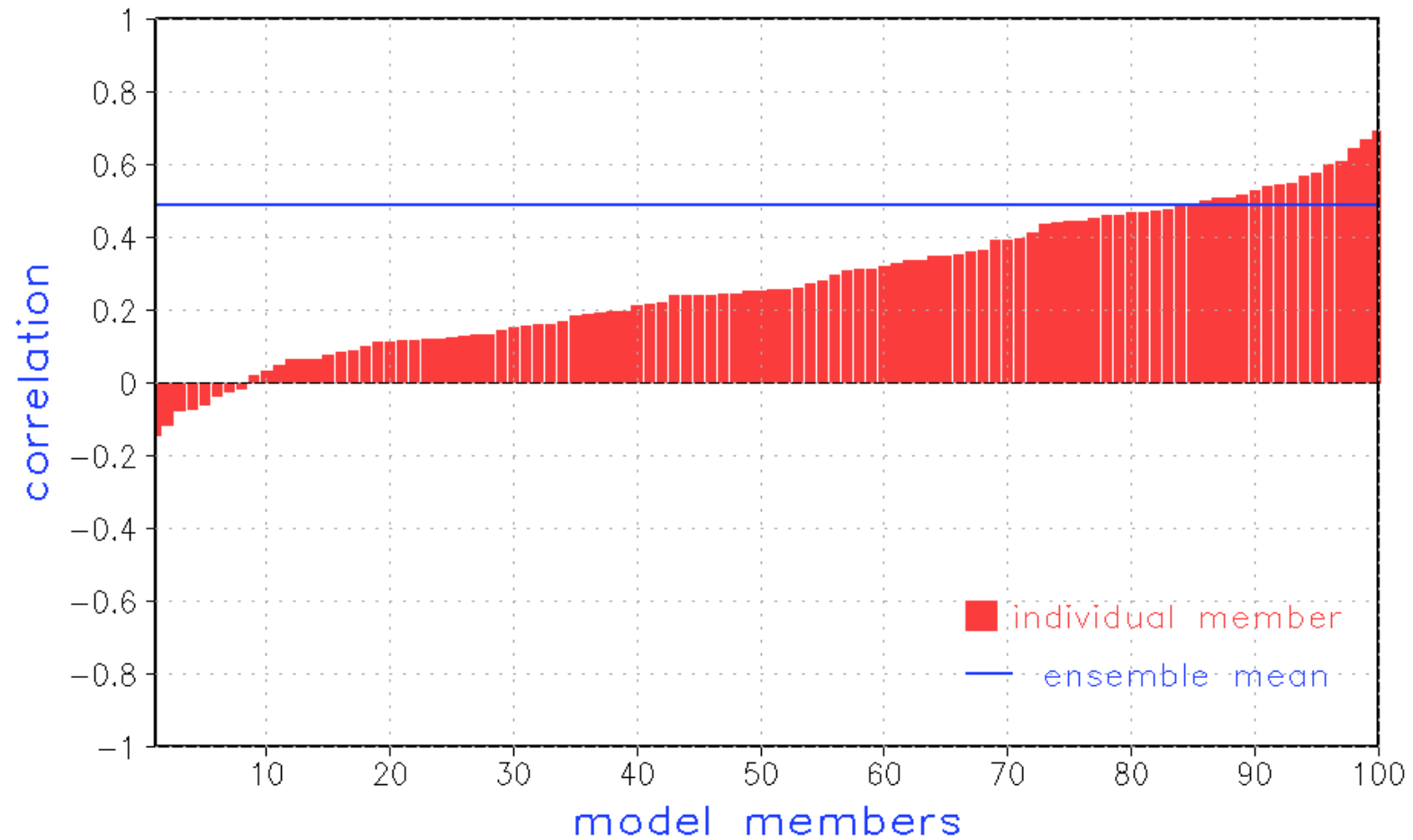


## Model Simulated/Forecast Anomalies: Individual Runs

## Model Simulated/Forecast Anomalies: Individual Runs

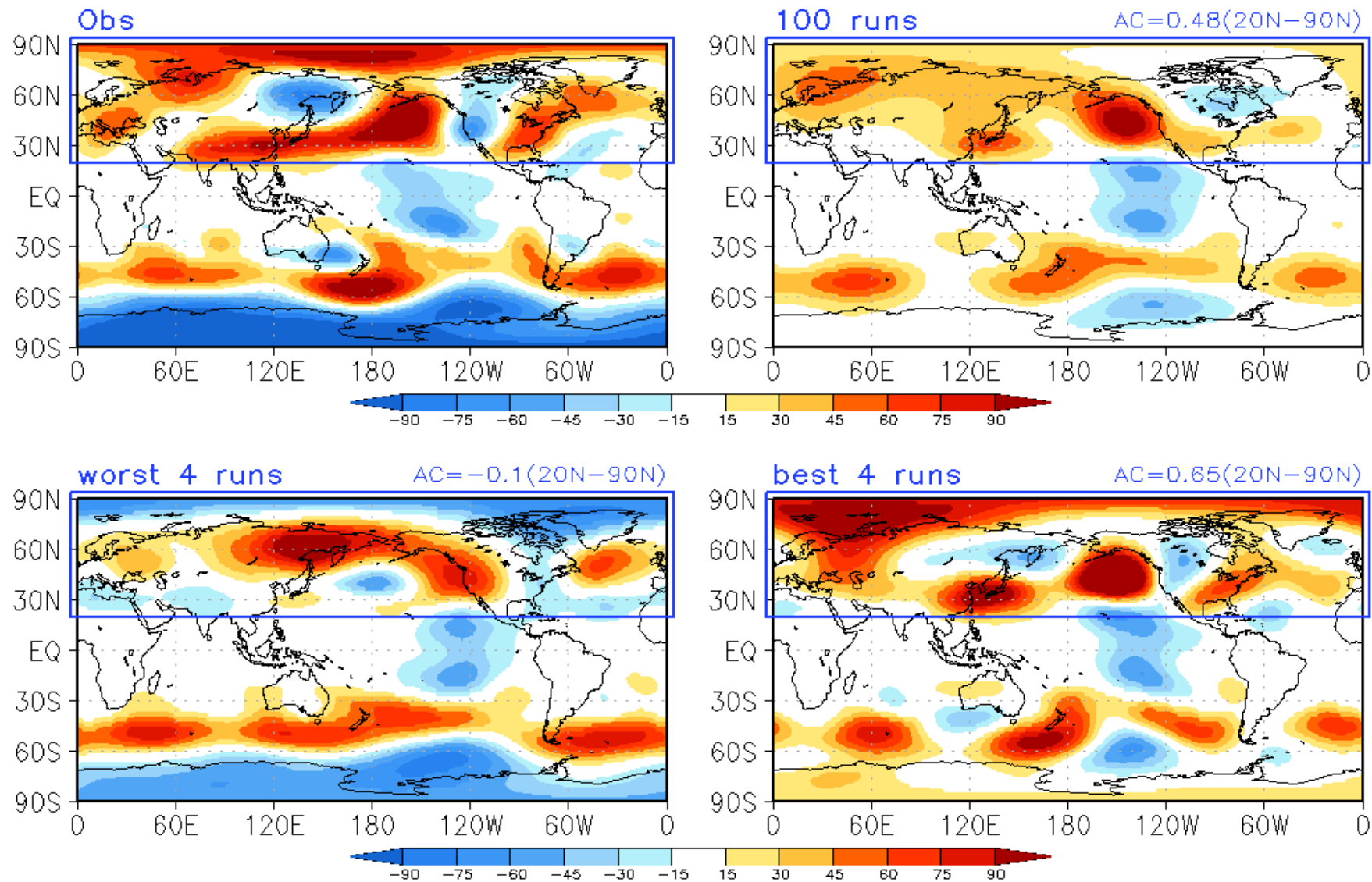
- In this analysis, anomalies from individual model runs are compared against the observed seasonal mean anomalies. The spatial resemblance between them is quantified based on anomaly correlation (AC).
- The distribution of AC across all model simulations is indicative of probability of observed anomalies 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).

# DJF2022/2023 Anomaly Correlation for Individual AMIP Simulation with Observation -- z200(20N-90N)

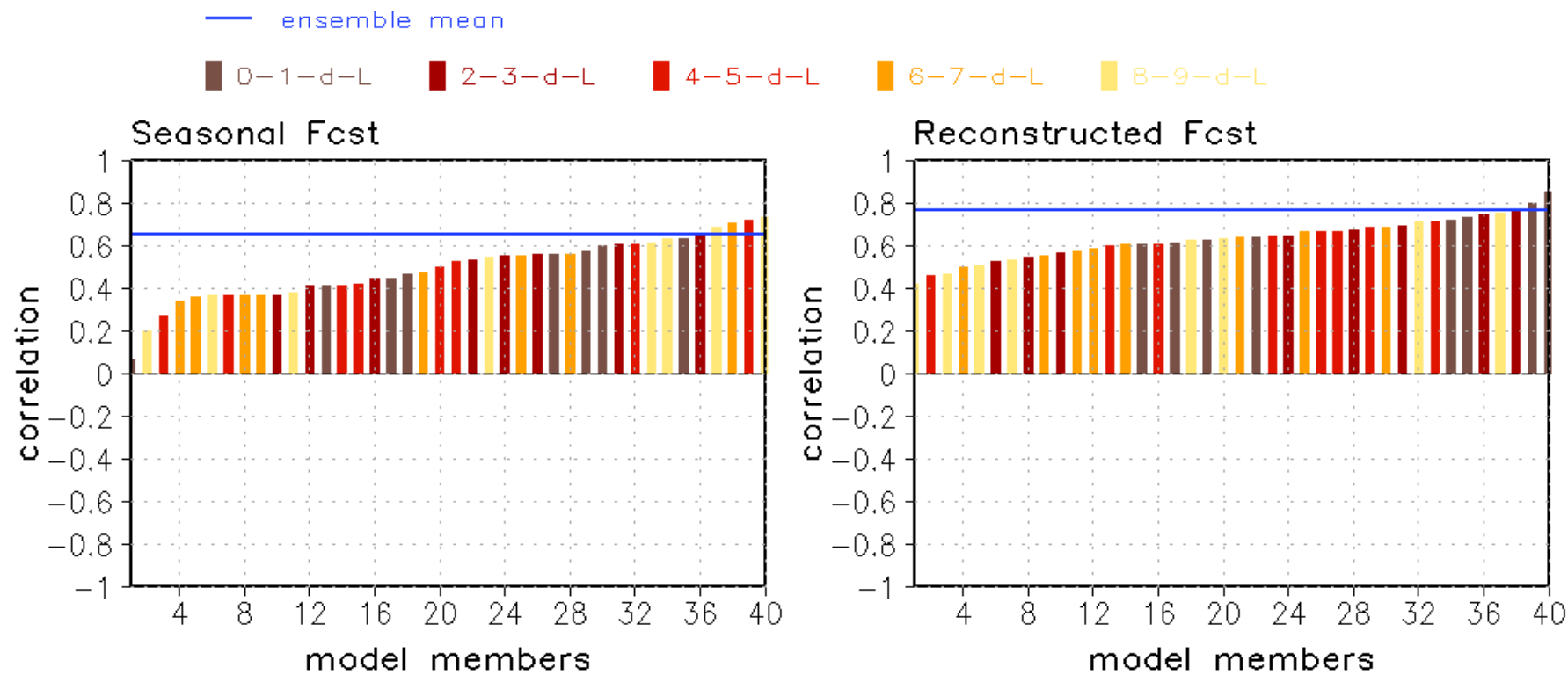


# Observed & AMIP Ensemble Mean Anomalies

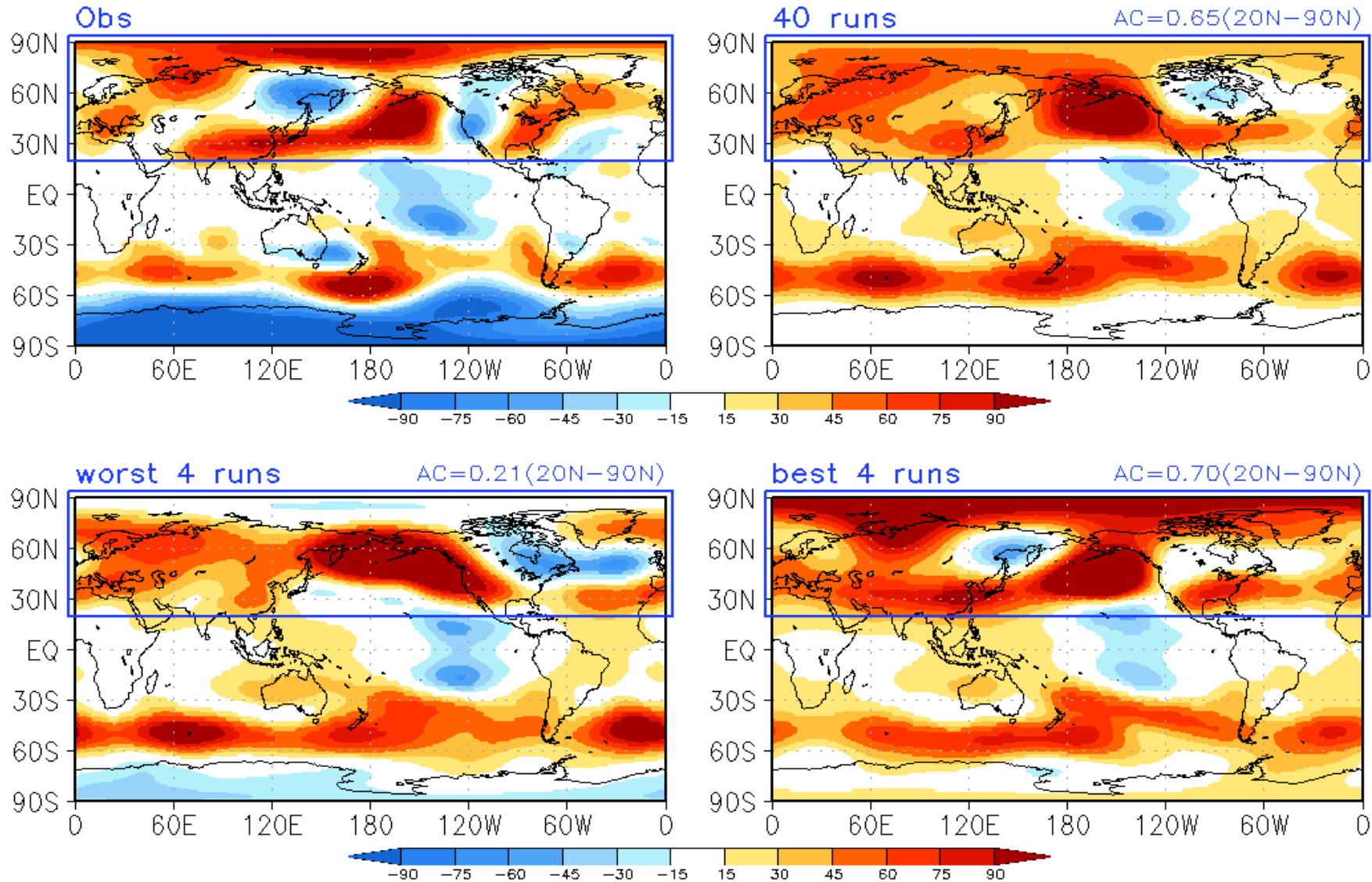
DJF2022/2023 z200(m) 100 runs/worst 4 runs/best 4 runs



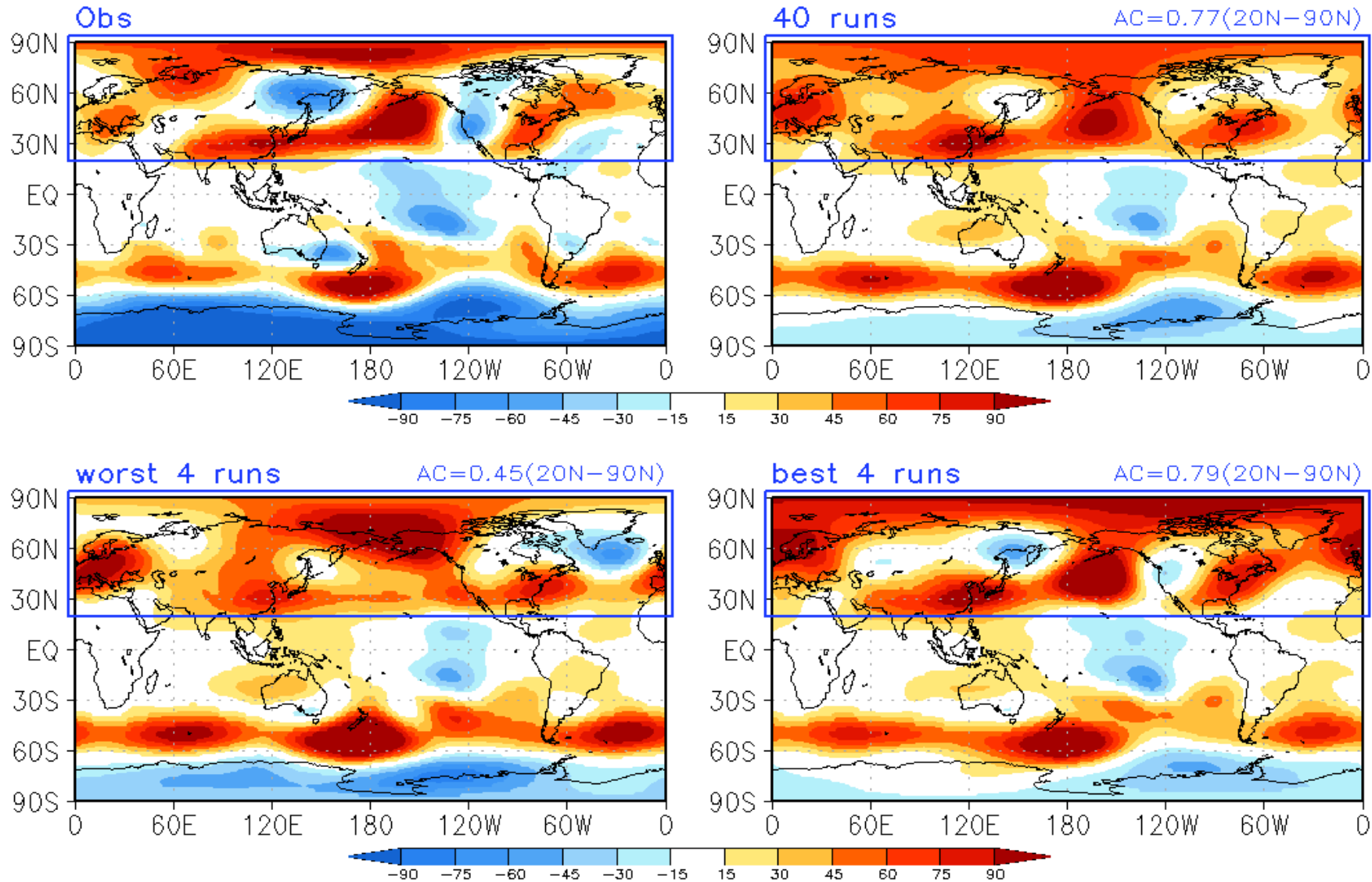
# DJF2022/2023 Anomaly Correlation for Individual CFSv2 Forecast with Observation -- z200 (20N-90N)



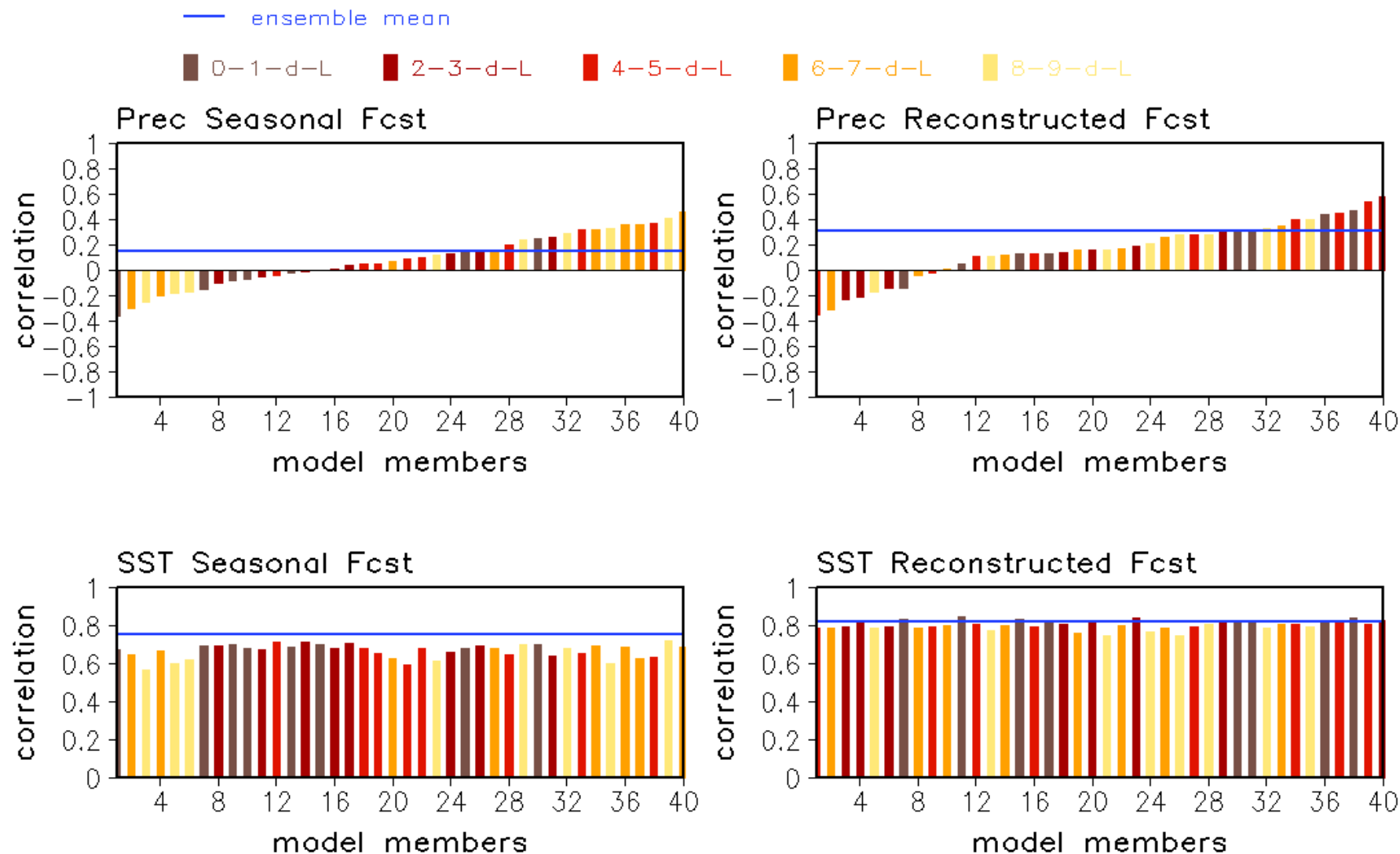
Observed & CFSv2 Forecast Ensemble Average Anomalies  
DJF2022/2023 z200(m) 40 runs/worst 4 runs/best 4 runs  
Seasonal Forecast



Observed & CFSv2 Forecast Ensemble Average Anomalies  
DJF2022/2023 z200(m) 40 runs/worst 4 runs/best 4 runs  
Reconstructed Forecast

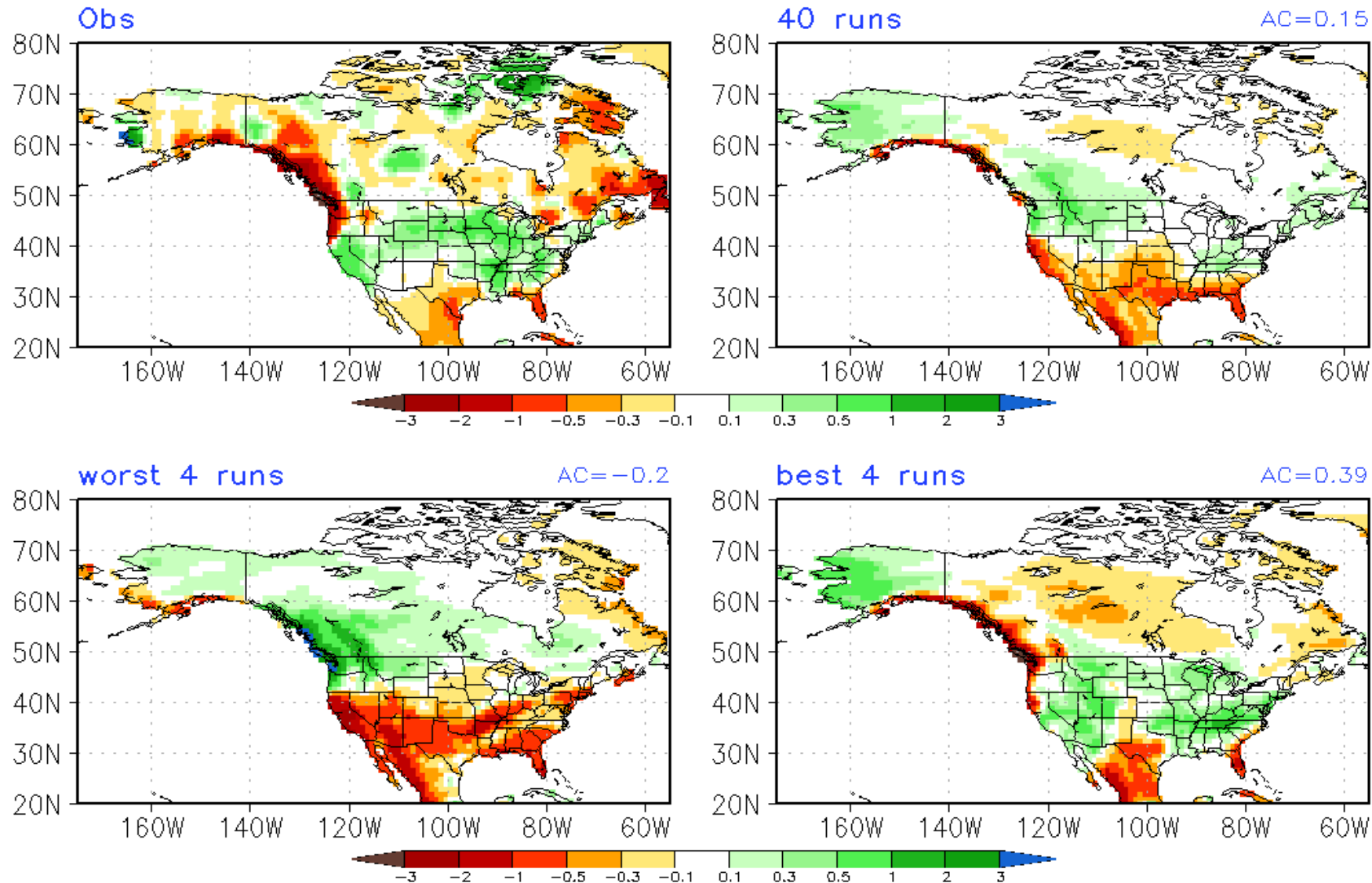


# DJF2022/2023 Anomaly Correlation for Individual CFSv2 Forecast with Observation -- Prec(NA)/SST(30S-30N)

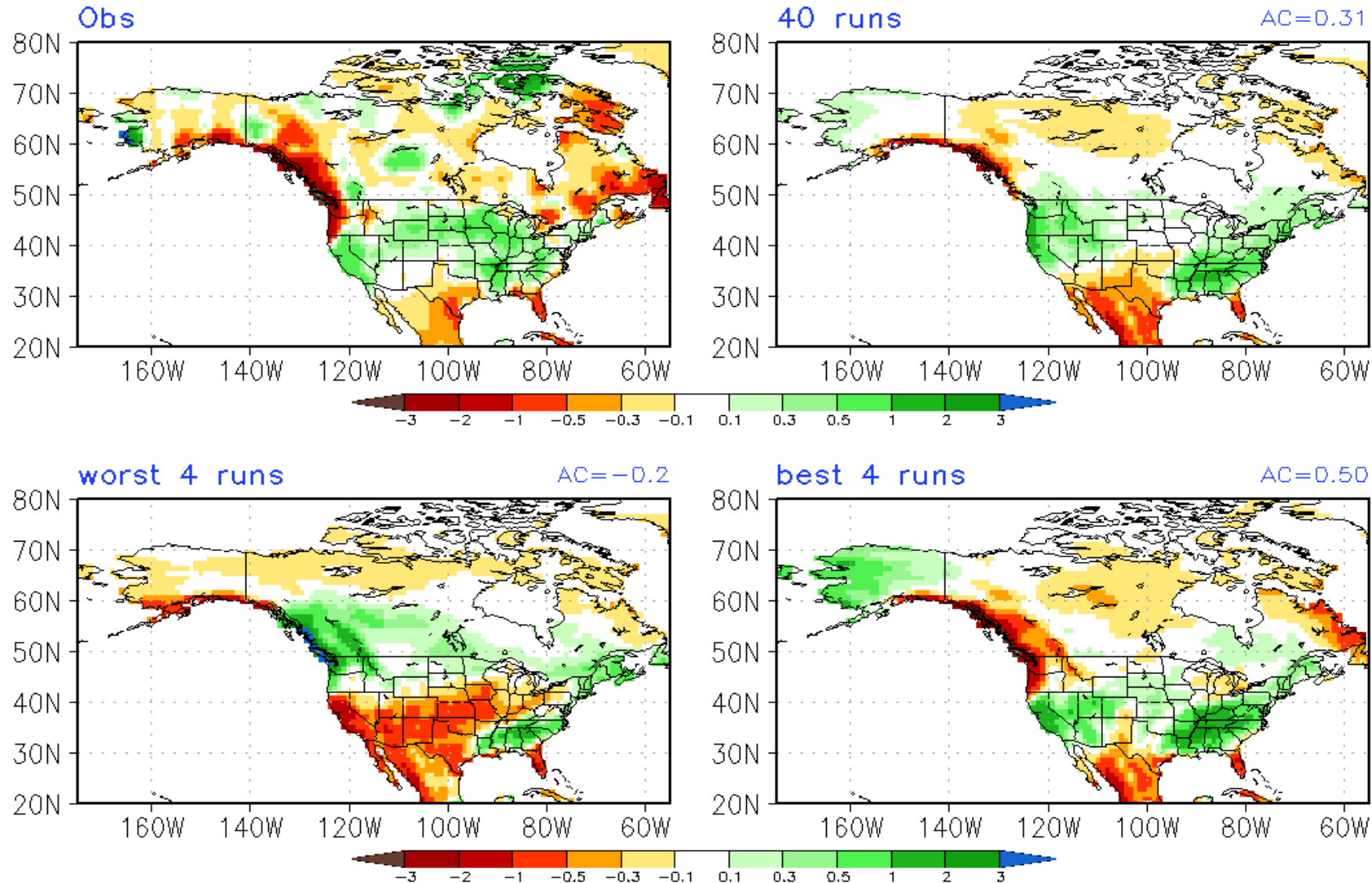




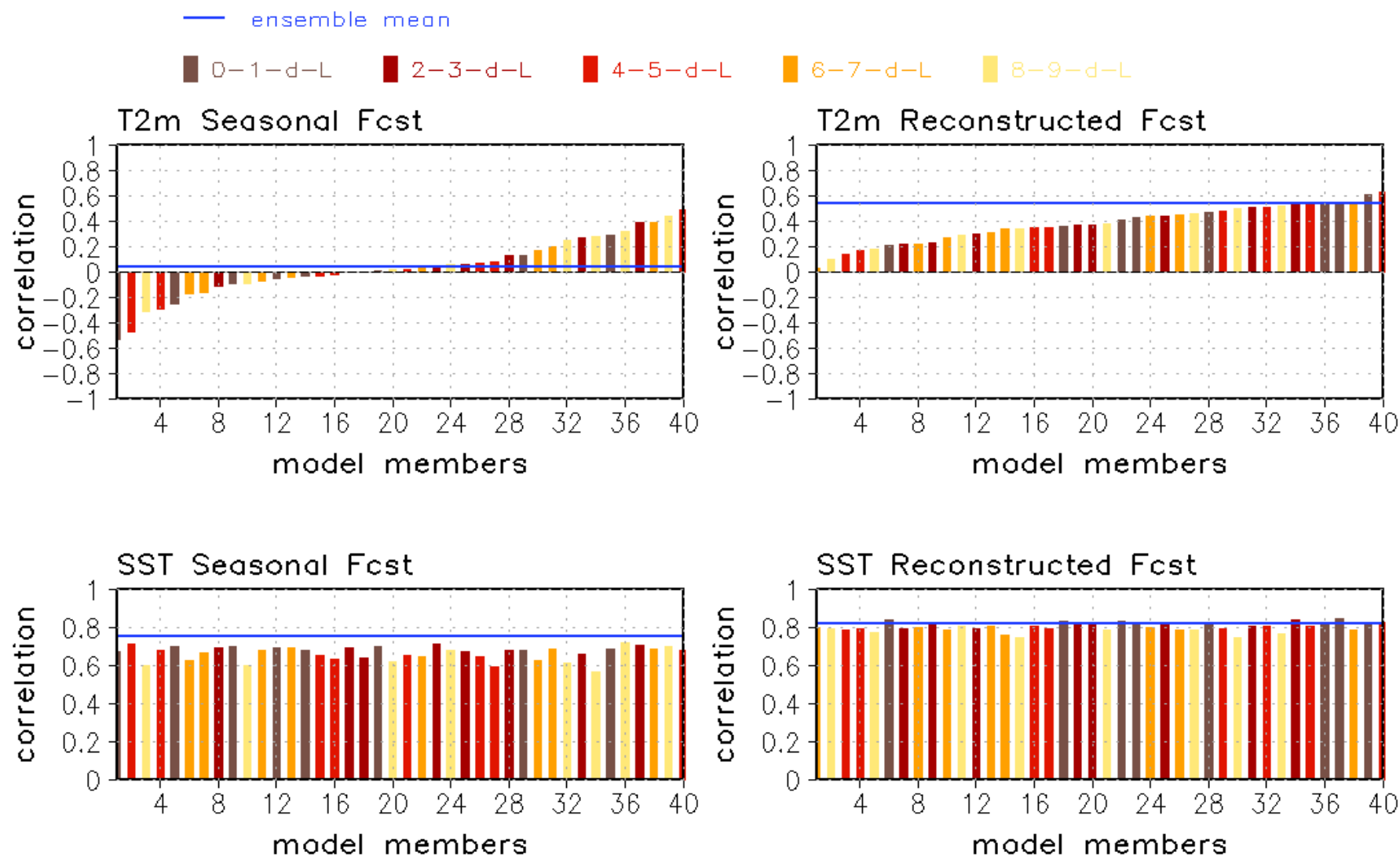
Observed & CFSv2 Forecast Ensemble Average Anomalies  
DJF2022/2023 Prec(mm/day) 40 runs/worst 4 runs/best 4 runs  
Seasonal Forecast



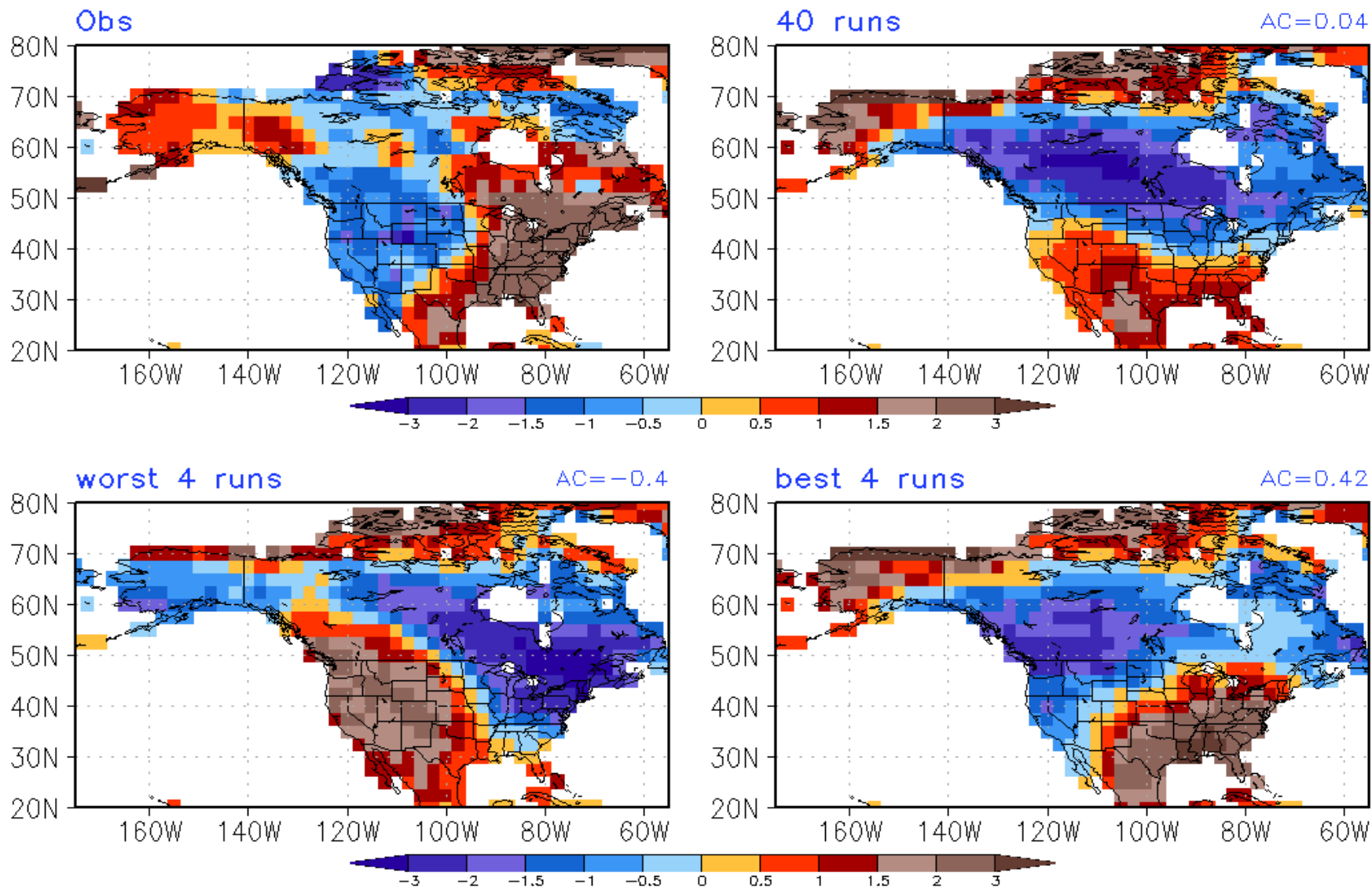
Observed & CFSv2 Forecast Ensemble Average Anomalies  
DJF2022/2023 Prec(mm/day) 40 runs/worst 4 runs/best 4 runs  
Reconstructed Forecast



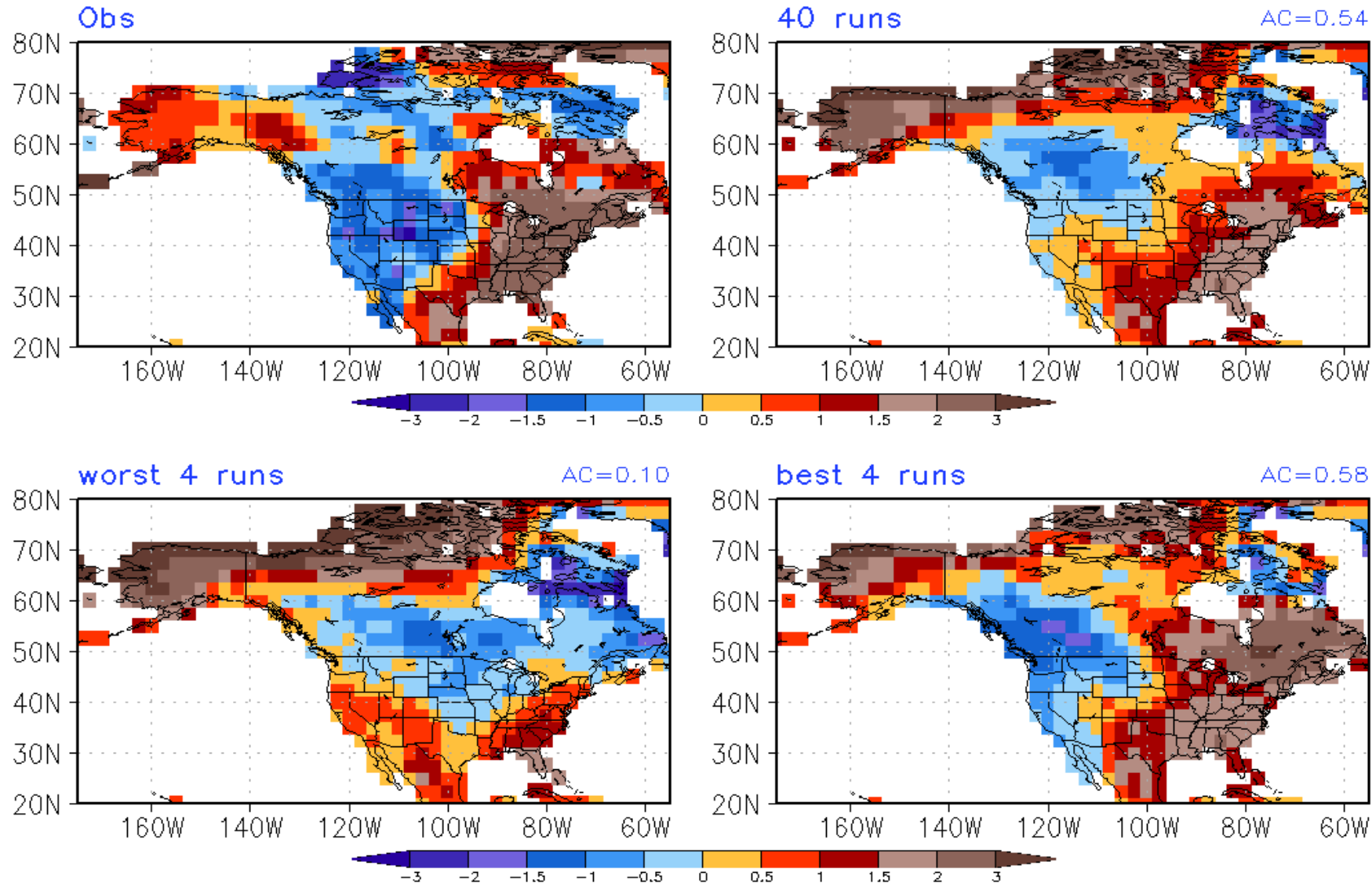
# DJF2022/2023 Anomaly Correlation for Individual CFSv2 Forecast with Observation -- T2m(NA)/SST(30S-30N)



Observed & CFSv2 Forecast Ensemble Average Anomalies  
DJF2022/2023 T2m(K) 40 runs/worst 4 runs/best 4 runs  
Seasonal Forecast

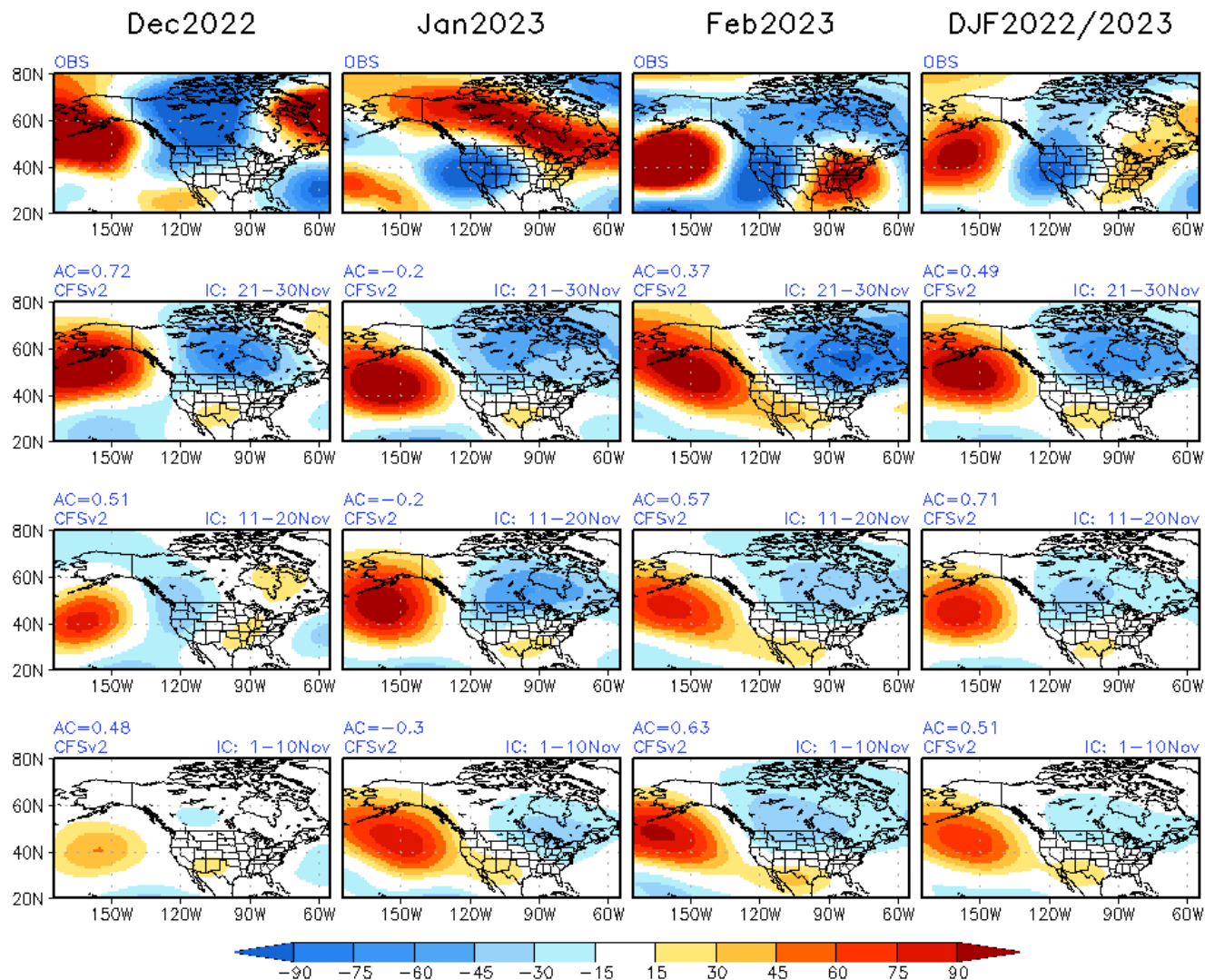


Observed & CFSv2 Forecast Ensemble Average Anomalies  
DJF2022/2023 T2m(K) 40 runs/worst 4 runs/best 4 runs  
Reconstructed Forecast



# z200(m) Monthly Means from Seasonal Forecast

Monthly Means from Seasonal Fcst (40ensm) DJF2022/2023 z200(m) eddy & Obs



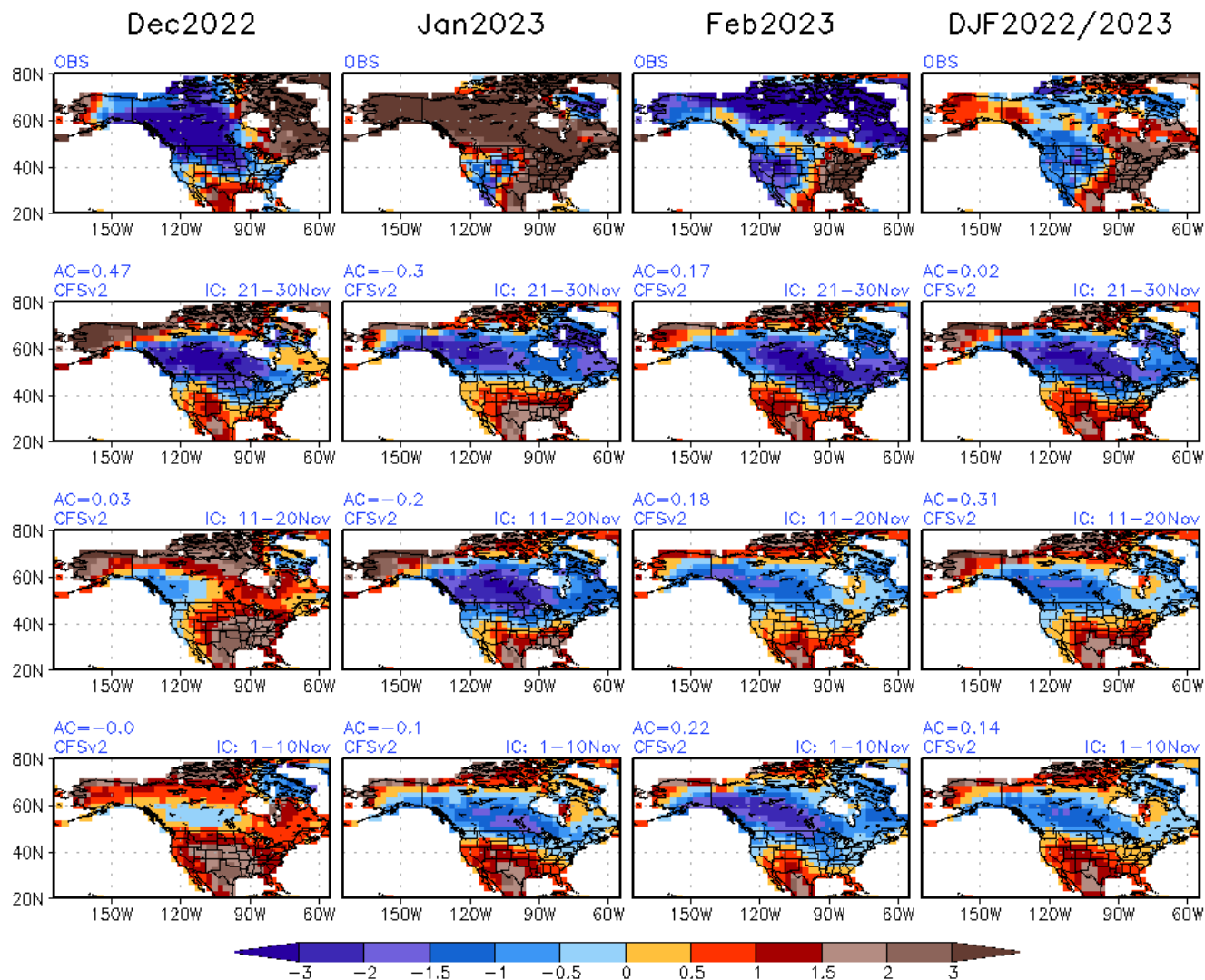
Top row: Observed anomaly.

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) DJF2022/2023 T2m(K) & Obs



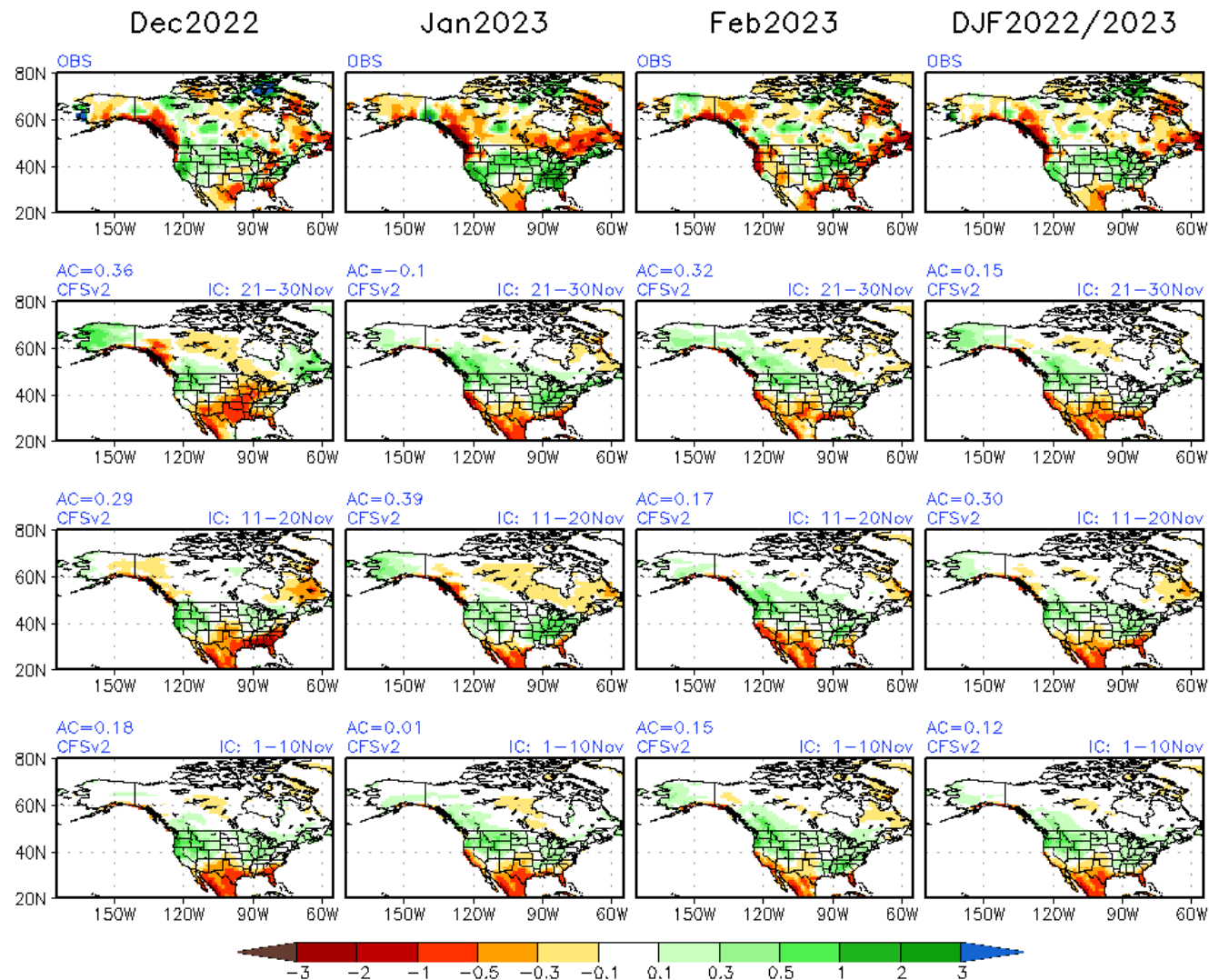
Top row: Observed anomaly.

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

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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) DJF2022/2023 Prec(mm/day) & Obs



Top row: Observed anomaly.

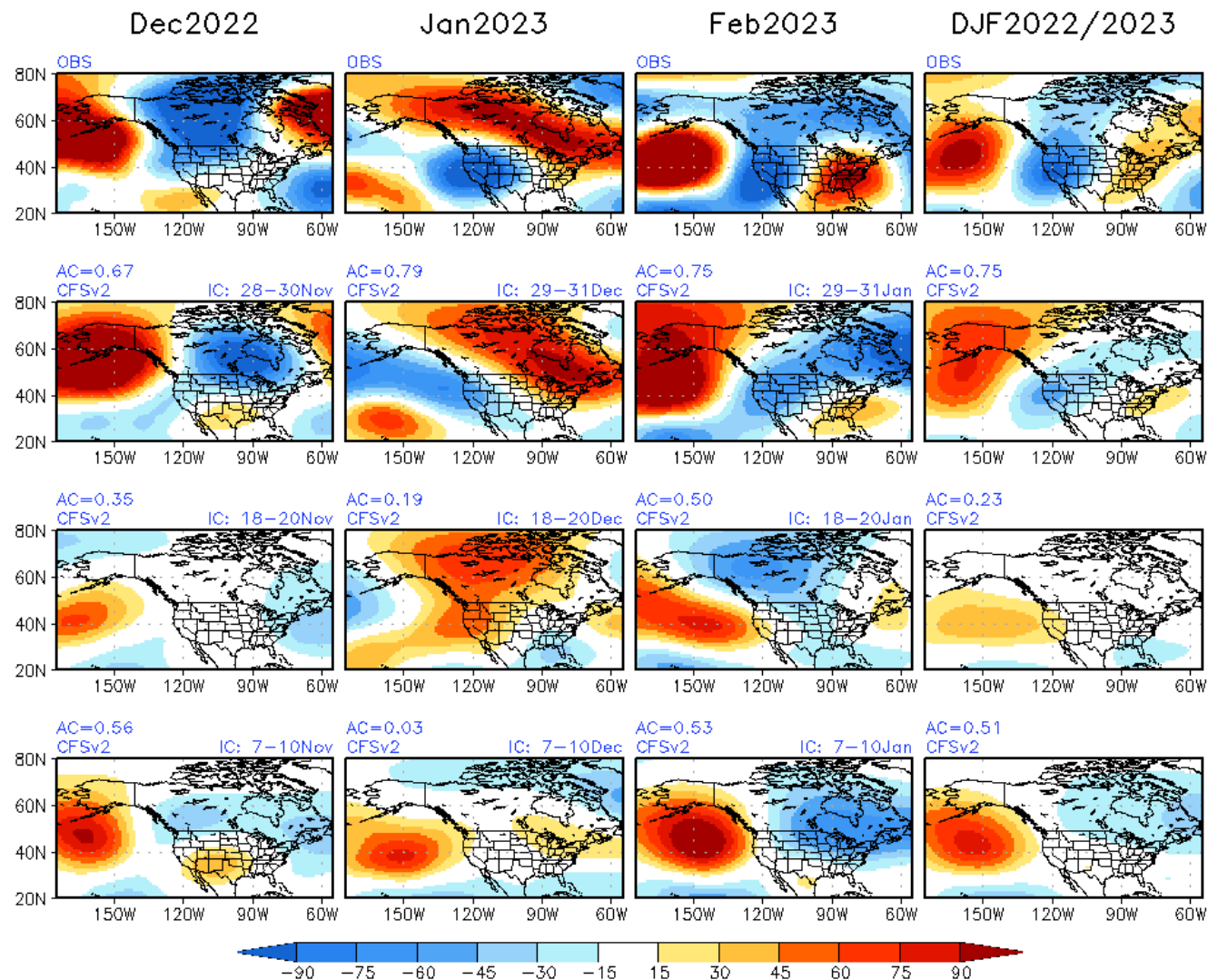
CFSv2 seasonal forecasts from different initial conditions in the month prior to the target season:

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



# z200(m) Monthly Means from Monthly Forecast

Monthly Means from Monthly Fcst DJF2022/2023 z200(m) eddy & Obs



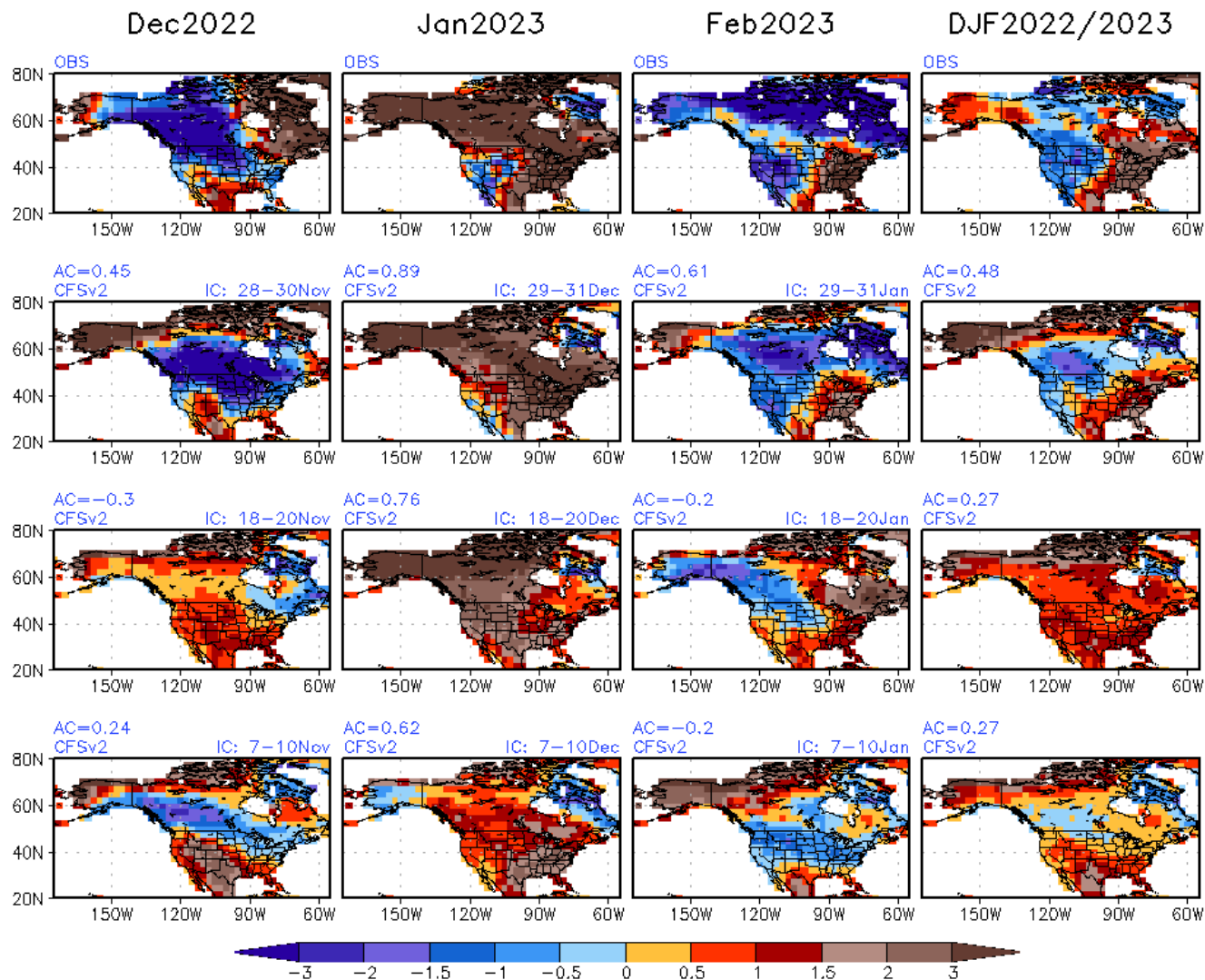
Top row: Observed anomaly.

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.

# T2m(k) Monthly Means from Monthly Forecast

Monthly Means from Monthly Fcst DJF2022/2023 T2m(K) & Obs



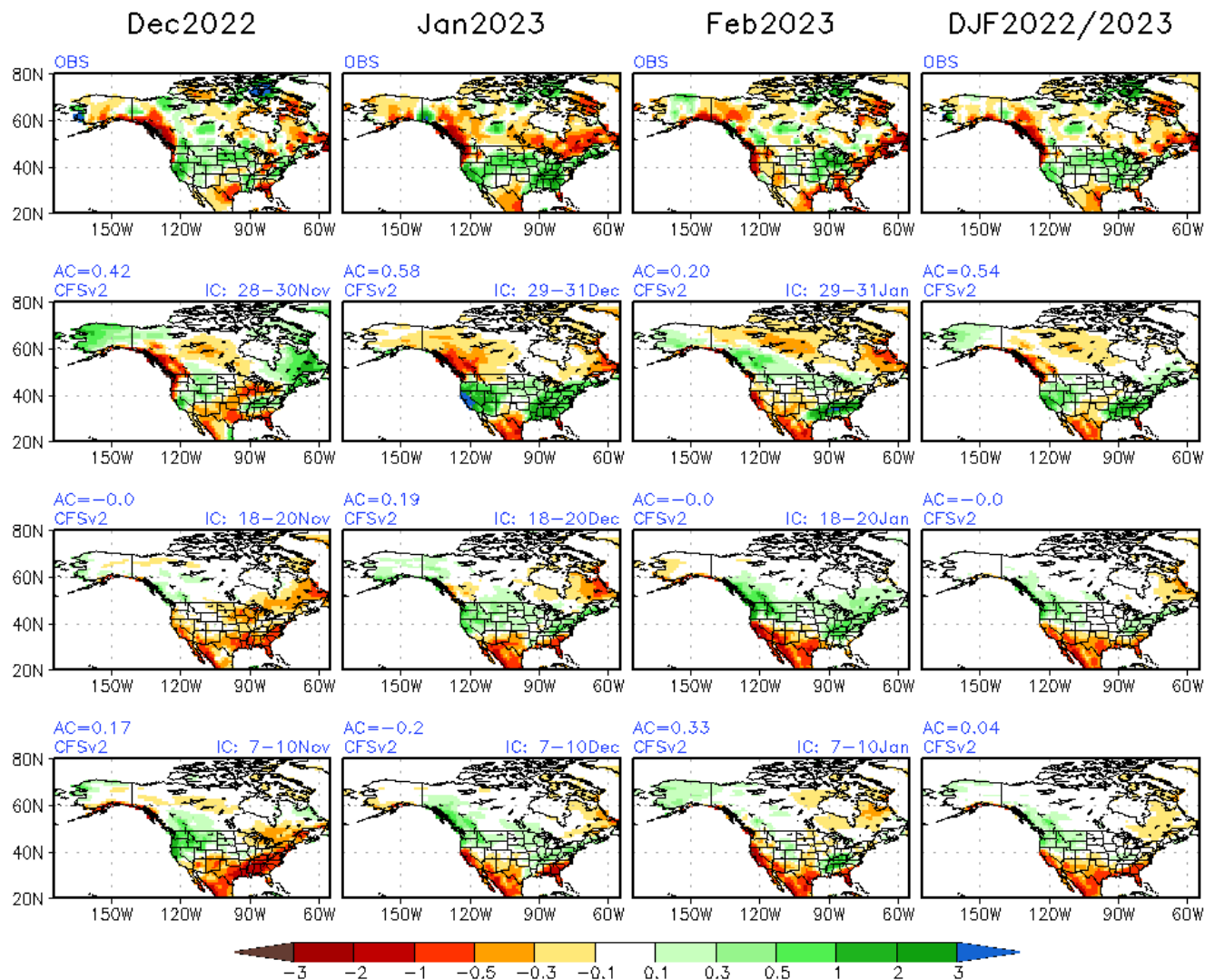
Top row: Observed anomaly.

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

Monthly Means from Monthly Fcst DJF2022/2023 Prec(mm/day) & 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.
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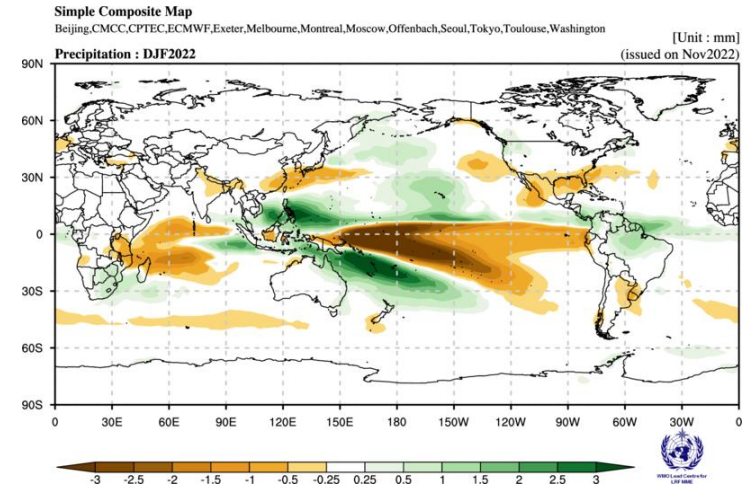
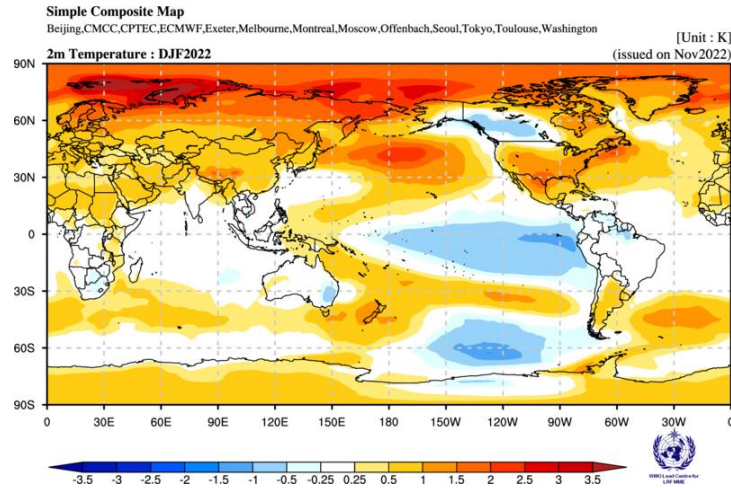
## Seasonal Forecasts from Multi-Model Ensemble Systems

- WMO Lead Center for Long-Range Forecast Multi-Model Ensemble (LC-LRFMME).  
<https://www.wmolc.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/>

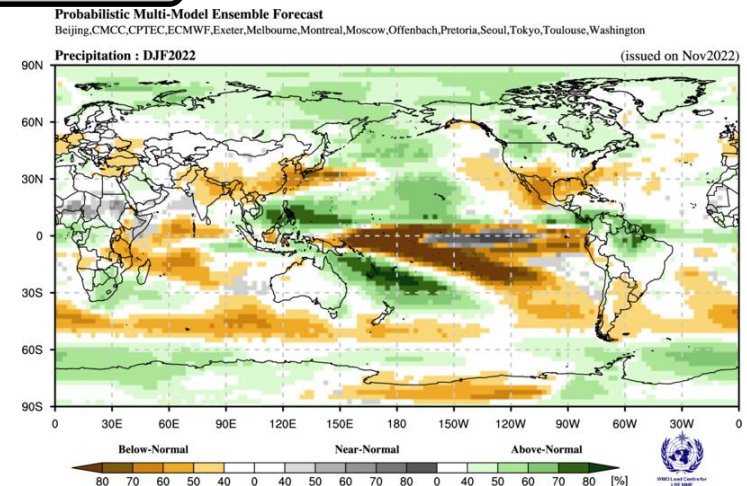
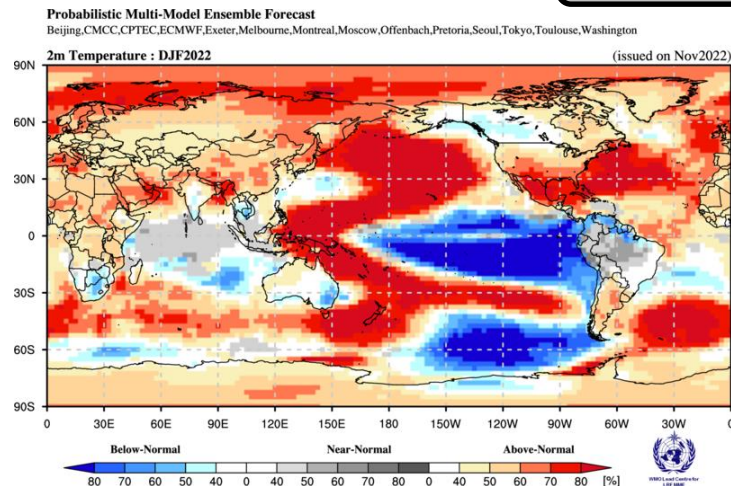
# LC-LRFMM Seasonal Forecasts

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

## Ensemble means



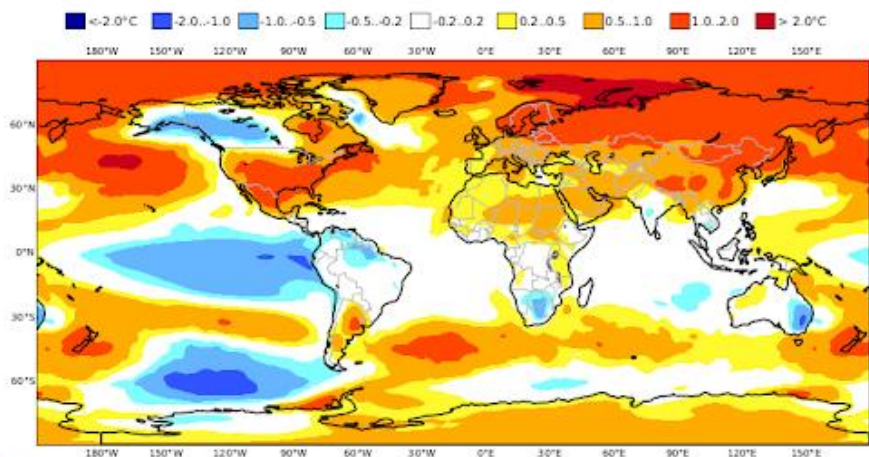
## Probabilities



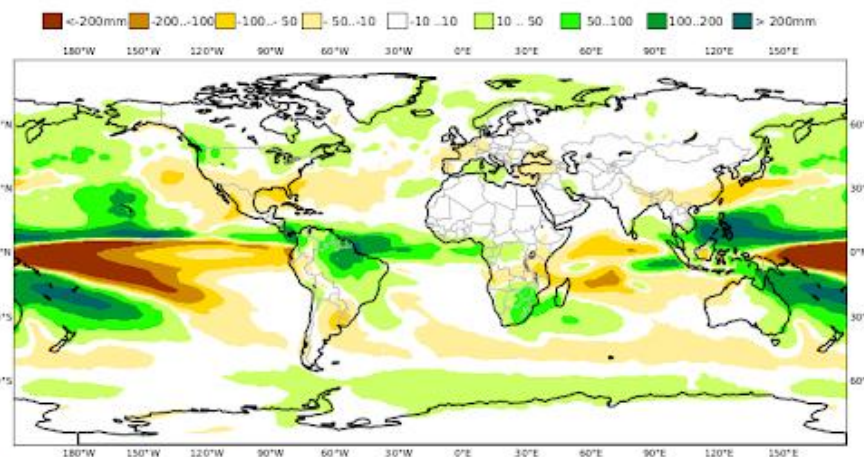
# C3S Seasonal Forecast

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

C3S multi-system seasonal forecast  
Mean 2m temperature anomaly  
Nominal forecast start: 01/11/22  
Variance-standardized mean  
ECMWF/Met Office/Météo-France/CMCC/DWD/NCEP/JMA/ECCC  
DJF 2022/23

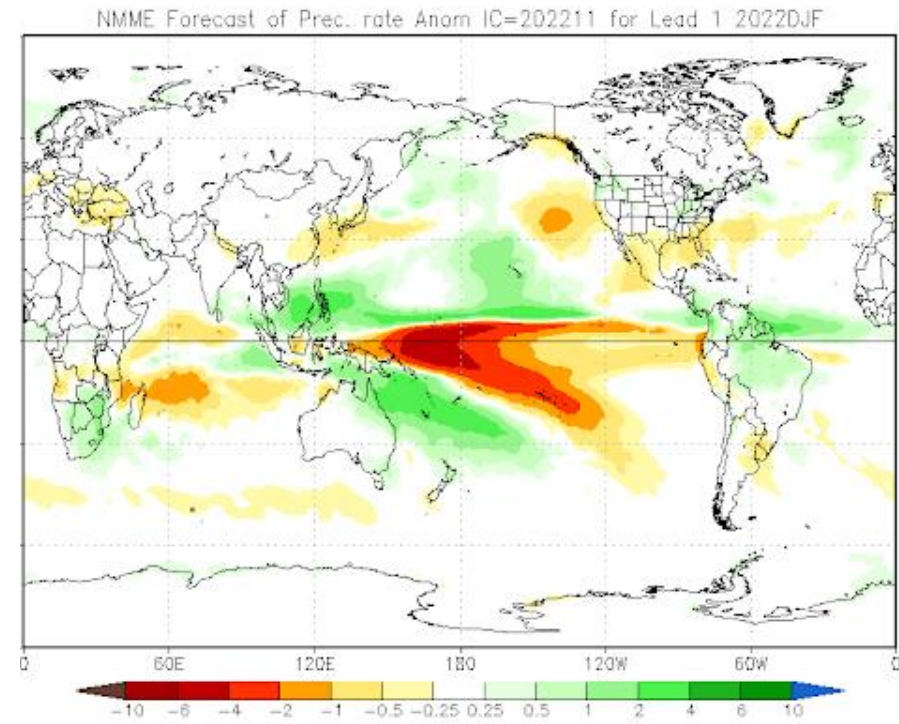
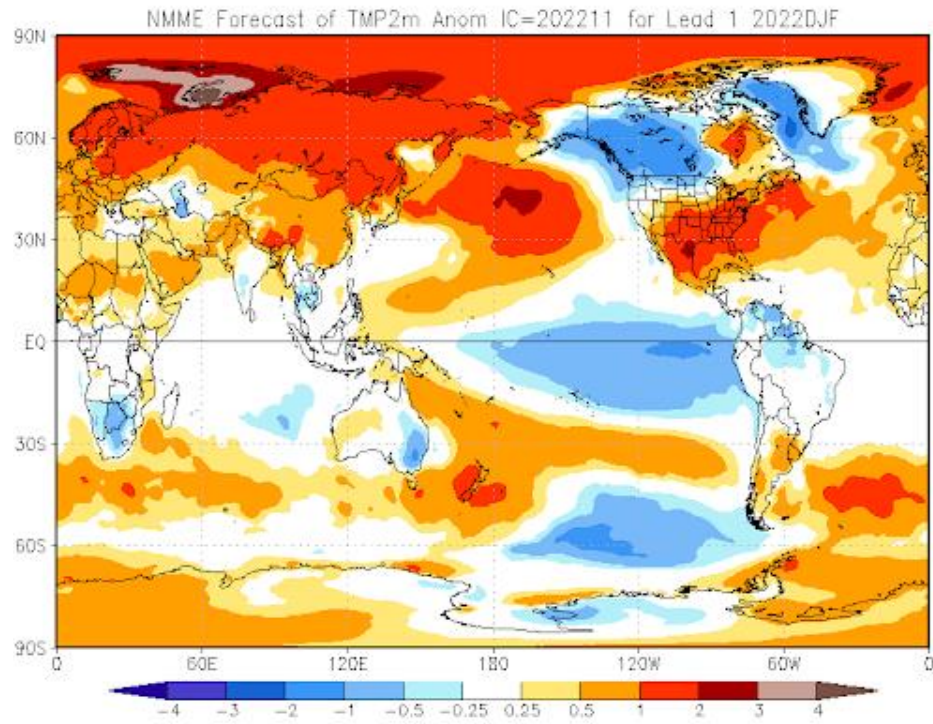


C3S multi-system seasonal forecast  
Mean precipitation anomaly  
Nominal forecast start: 01/11/22  
Variance-standardized mean  
ECMWF/Met Office/Météo-France/CMCC/DWD/NCEP/JMA/ECCC  
DJF 2022/23



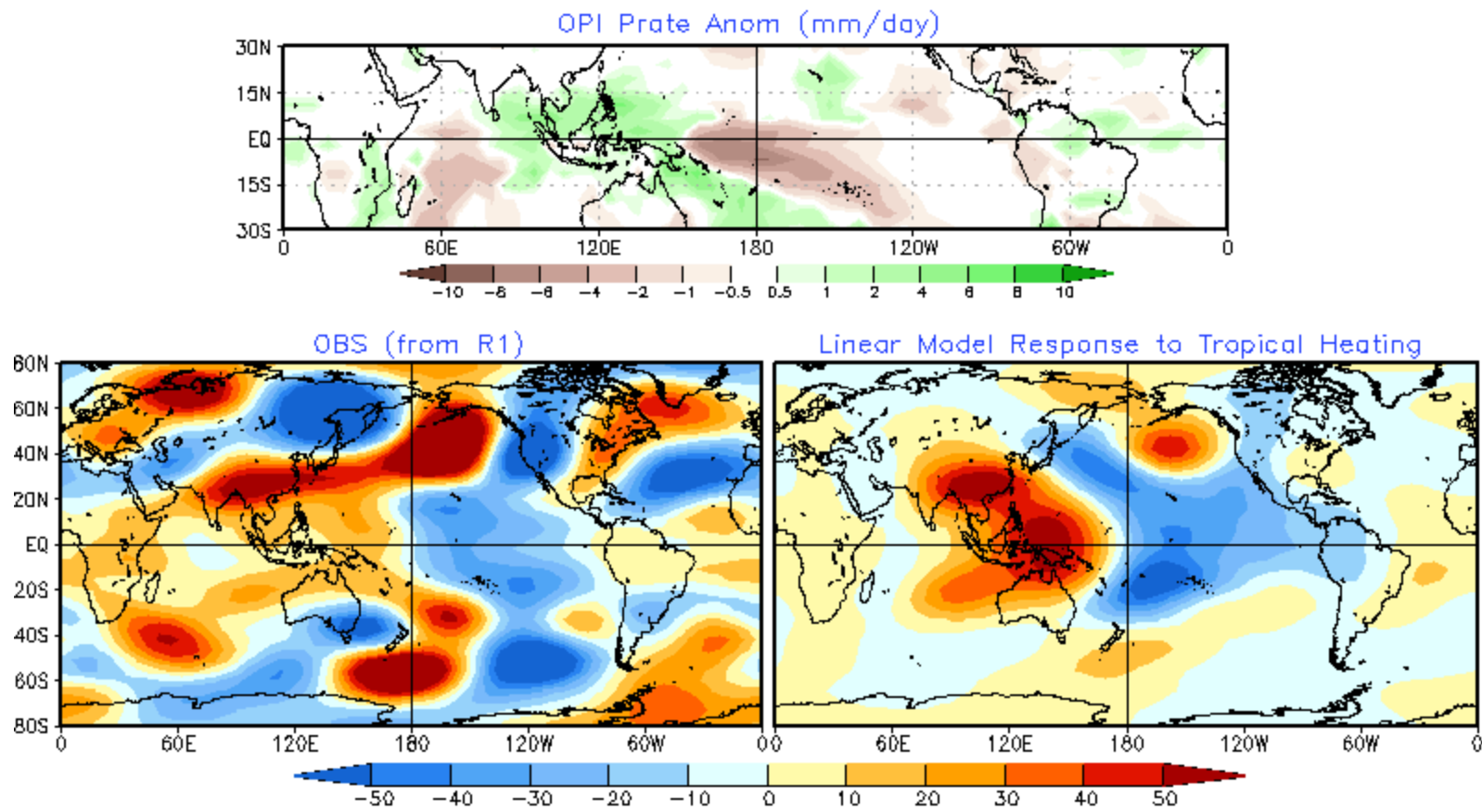
# North American Multi-Model Ensemble Seasonal Forecast

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



# 200mb Height from Linear Model

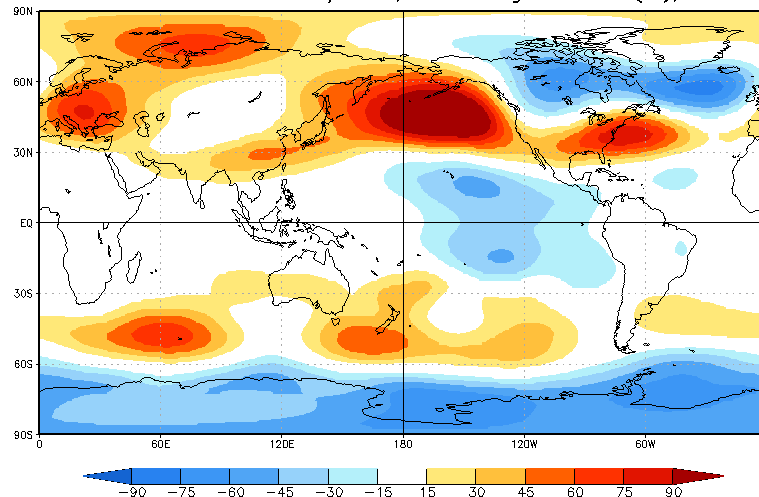
DJF2022-23 200mb Eddy HGT(m)  
OBS vs. Linear Model Response to Tropical Heating  
Heating is converted from Prate in 15S-15N





# Seasonal Forecasts from the Constructed Analog Model

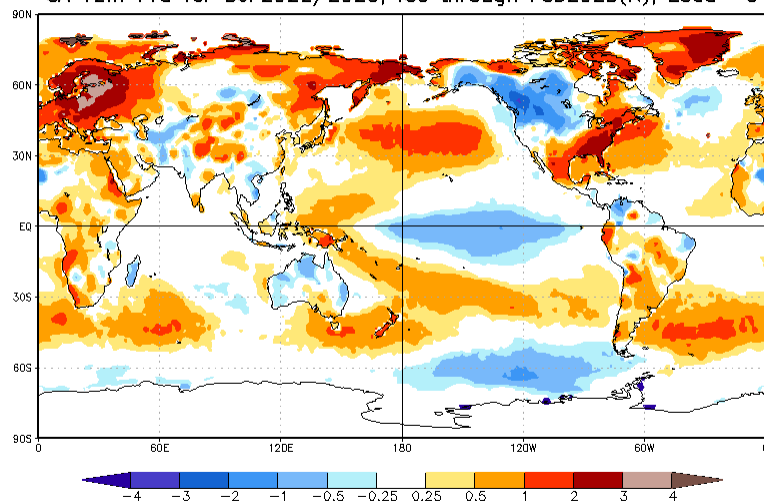
CA HGT200 Prd for DJF2022/2023, ICs through Feb2023(m), Lead -3



Peitao Peng CPC/NCEP/NWS/NOAA

Base Period 1991-2020

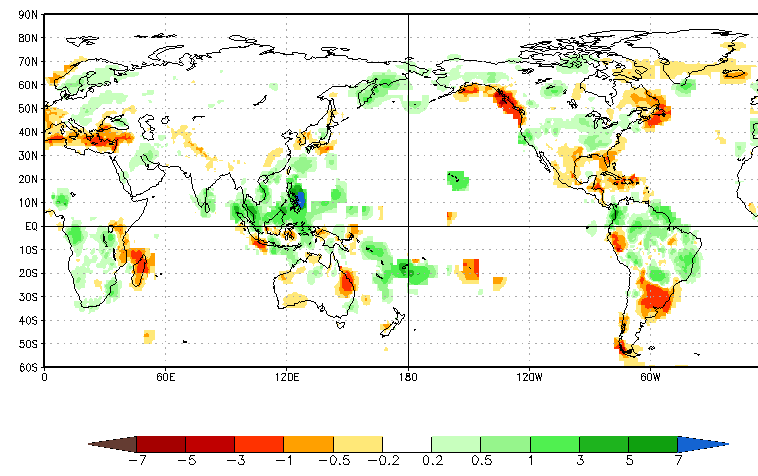
CA T2m Prd for DJF2022/2023, ICs through Feb2023(K), Lead -3



Peitao Peng CPC/NCEP/NWS/NOAA

Base Period 1991-2020

CA Prec Prd for DJF2022/2023, ICs through Feb2023(mm/day), Lead -3



Peitao Peng CPC/NCEP/NWS/NOAA

Base Period 1991-2020

## 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)