Attribution of Seasonal Climate Anomalies

December-January-February 2016/2017

Attribution of Seasonal Climate Anomalies

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

Outline

- Methodology
- Data description
- Observed seasonal anomalies
- Ensemble average seasonal mean anomalies from AGCM simulations and initialized forecasts
- Seasonal mean anomalies from the individual AGCM simulations and initialized forecasts
- Summary
- References

Methodology - 1

- Compare observed seasonal mean anomalies with those from model simulations and forecasts.
- Ensemble averaged of 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 average anomalies.
- The relative magnitude of ensemble averaged seasonal mean anomalies to the deviations of seasonal mean anomalies in the individual model runs 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 are attributable (Kumar et al. 2013).

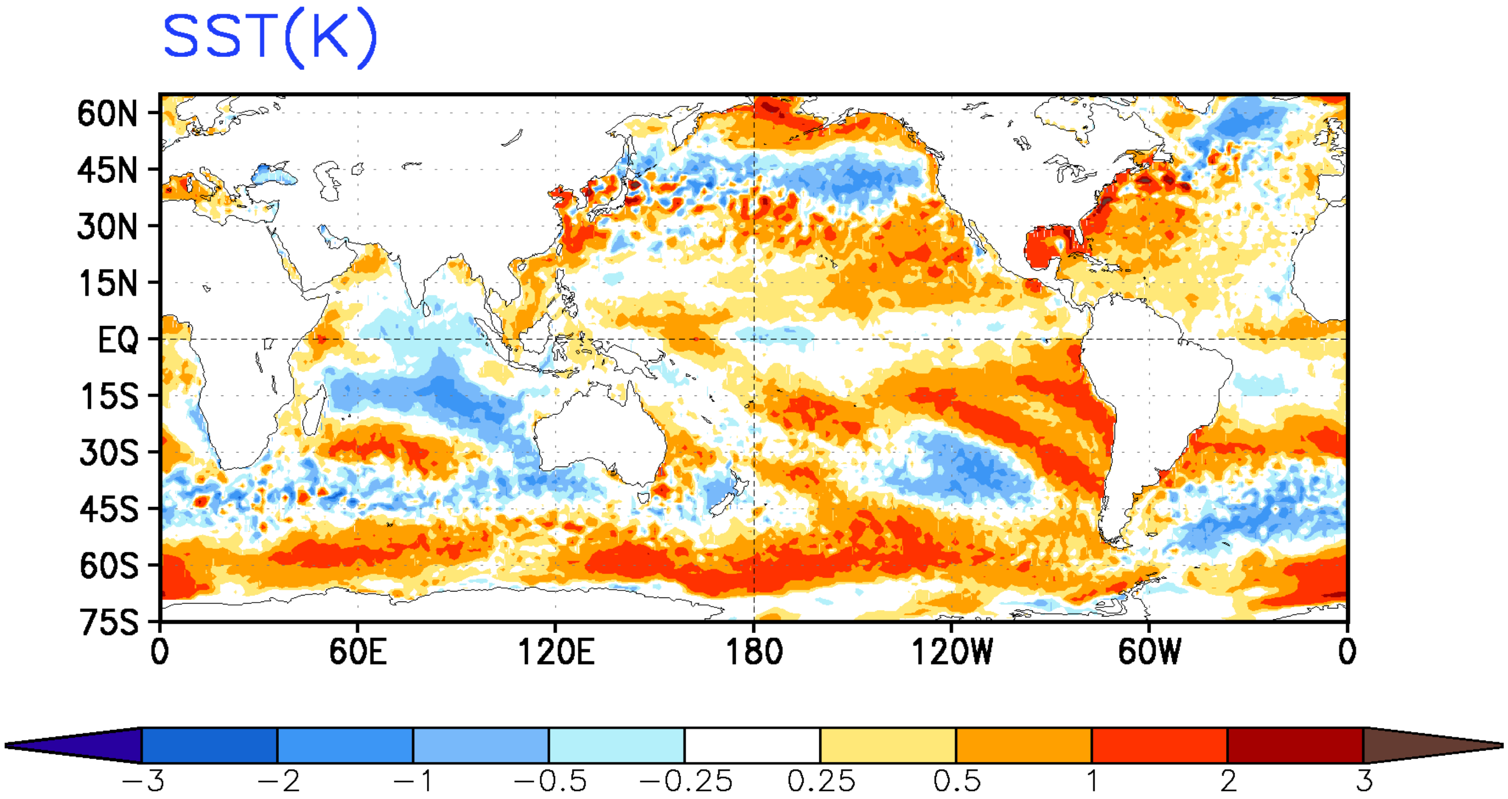
Data

- Observations
  - SST: NCDC daily OI 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)
  - 0-month-lead: the seasonal mean forecasts based on 40 members from the latest 10 days before the target season;
  - 0-month-lead-monthly: 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 from CFSv2 (provided by Dr. Bhaskar Jha)
  - 18 members
- All above seasonal mean anomalies are based on 1999-2010 climatology.
- z200 responses to tropical heating in linear model (provided by Dr. Peitao Peng)
- Seasonal mean anomalies of z200, T2m, and Prec forecasted from the Constructed Analog Model (provided by Dr. Peitao Peng)

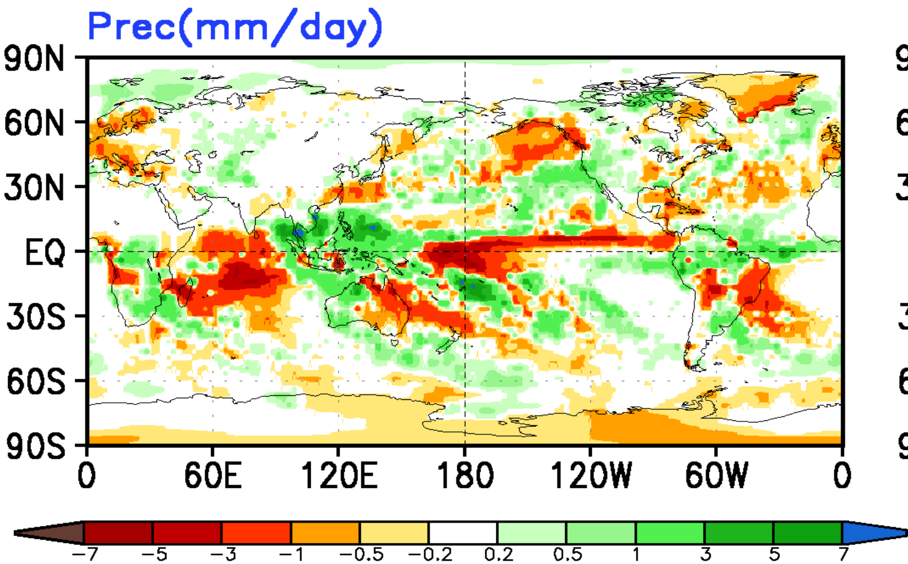
Observed Seasonal Anomalies

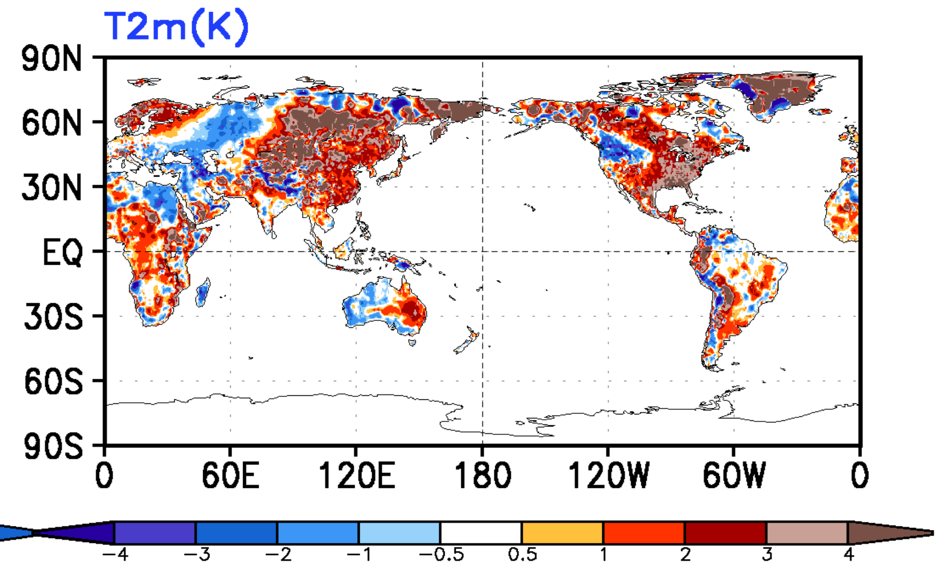
Global and North America

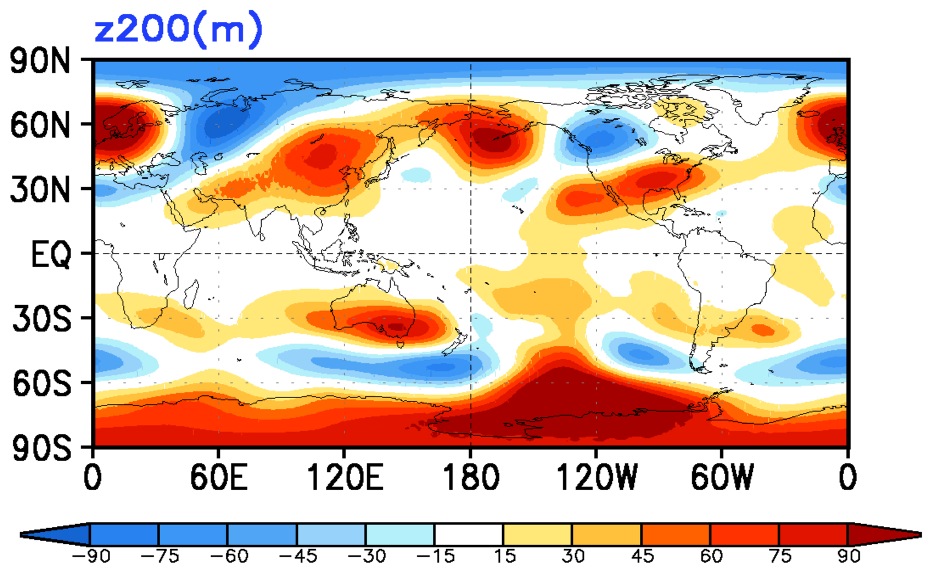
Observed Anomaly DJF2016/2017



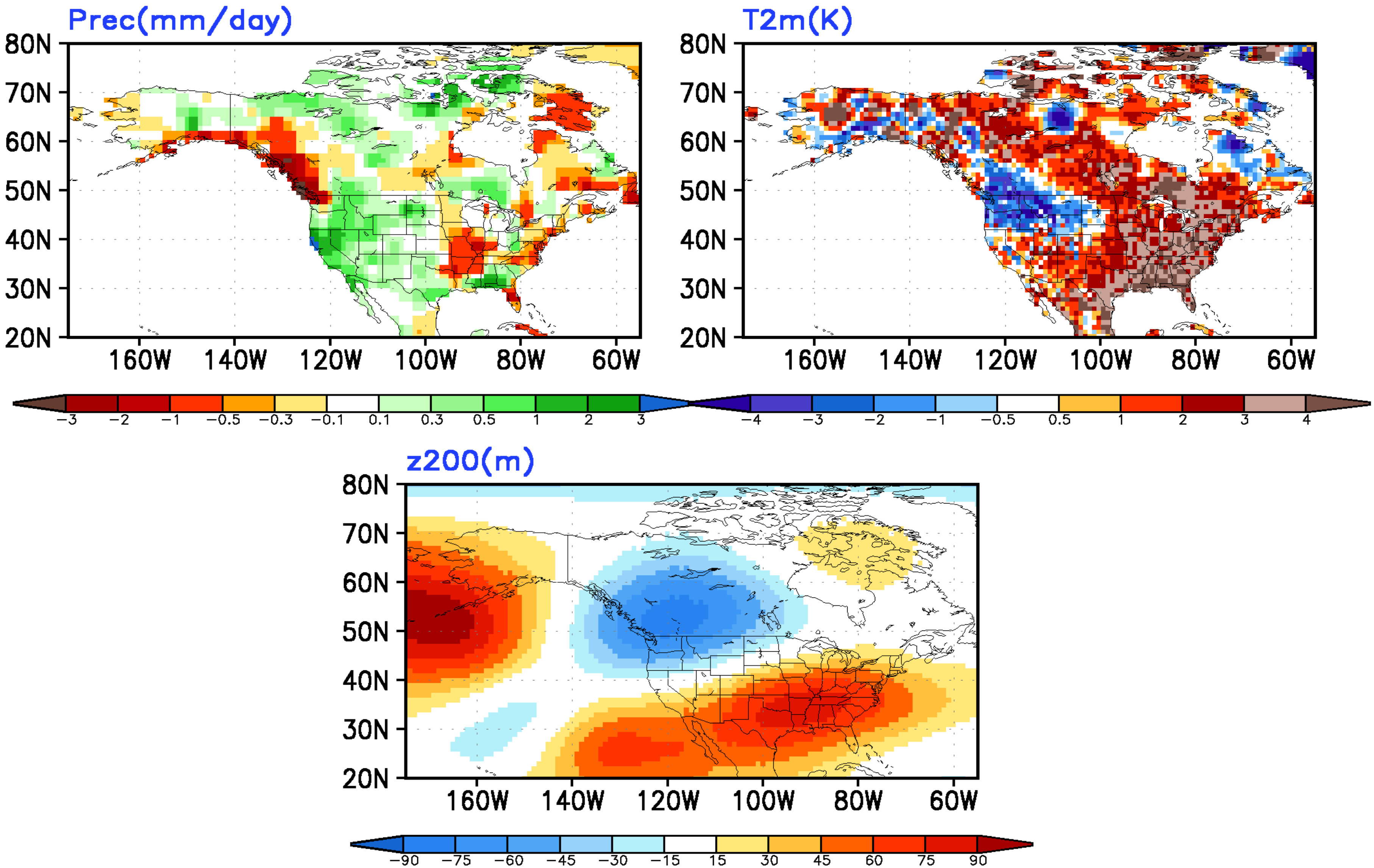
Observed Anomaly DJF2016/2017







Observed Anomaly DJF2016/2017

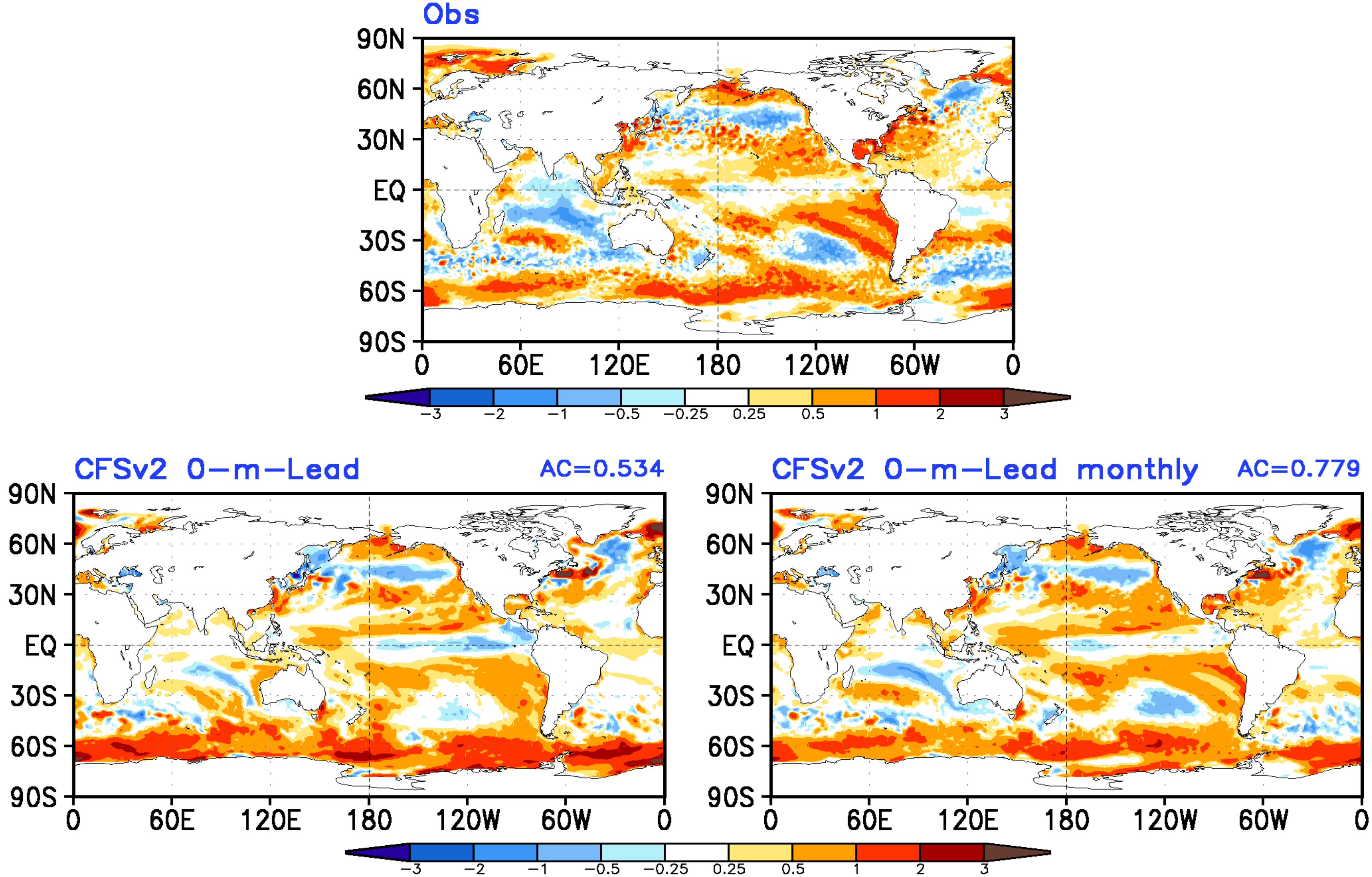


Model Simulated/Forecast Ensemble Average Anomalies

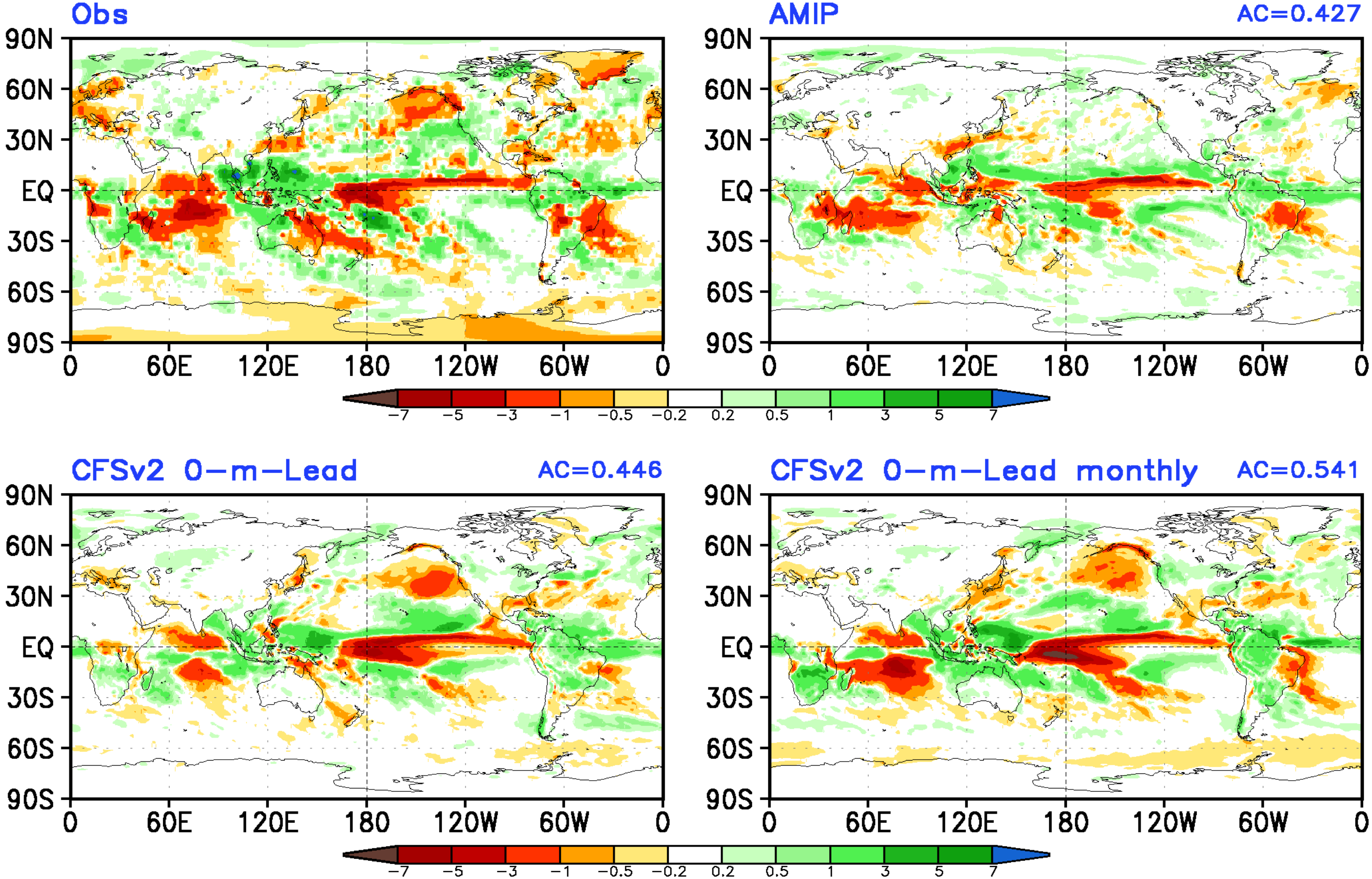
Model Simulated/Forecast Ensemble Average Anomalies

- CFS AMIP simulations forced with observed sea surface temperatures (18 members ensemble)
- CFSv2 real time operational forecasts
  - 0-month-lead: the seasonal mean forecasts based on 40 members from the latest 10 days before the target season. For example, 2016AMJ seasonal mean forecasts are 40 members from 22-31 March2016 initial conditions.
  - 0-month-lead-monthly: 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).

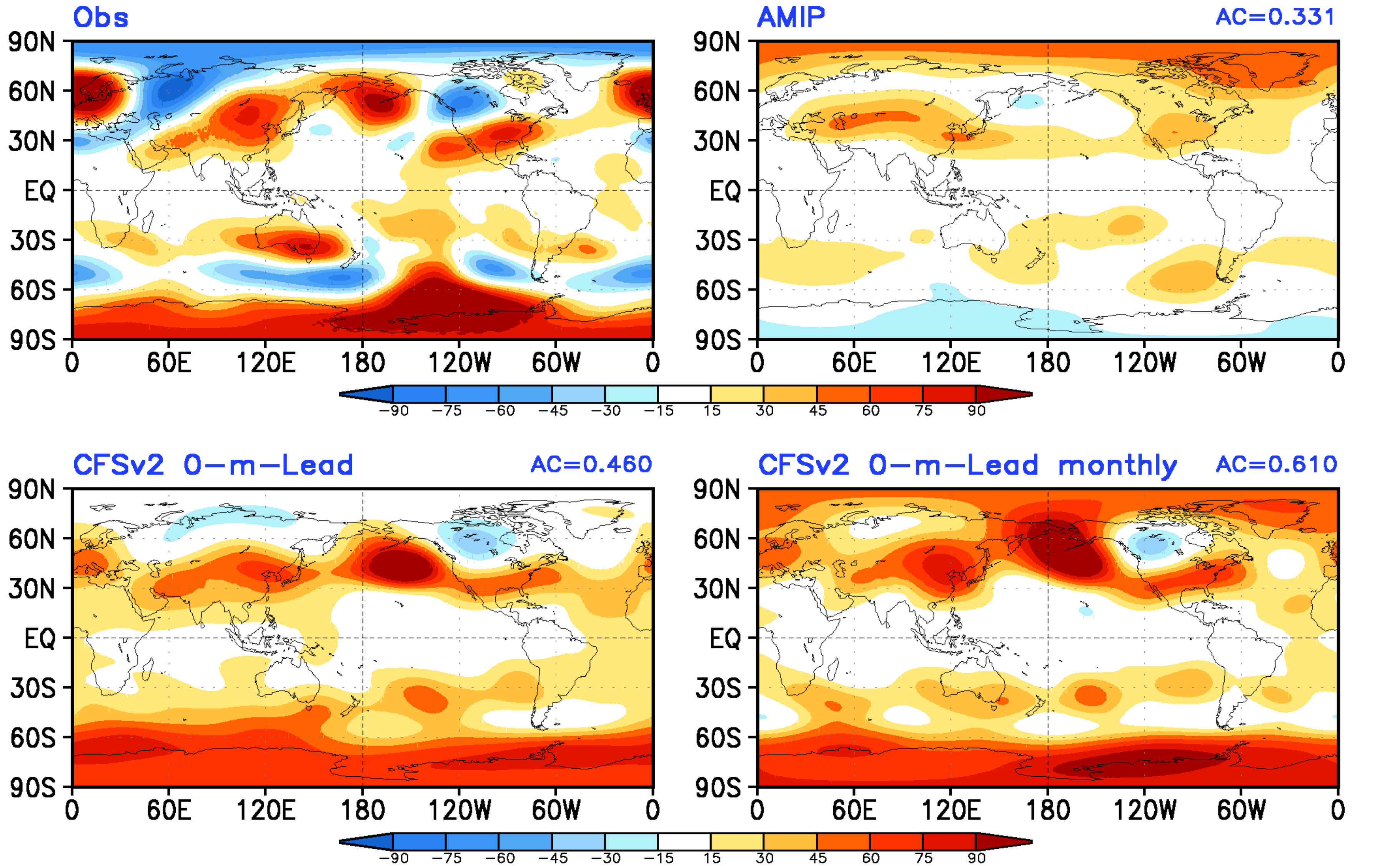
DJF2016/2017 Observed & Model Simulated/Forecas
Ensemble Average Anomalies SST(K)



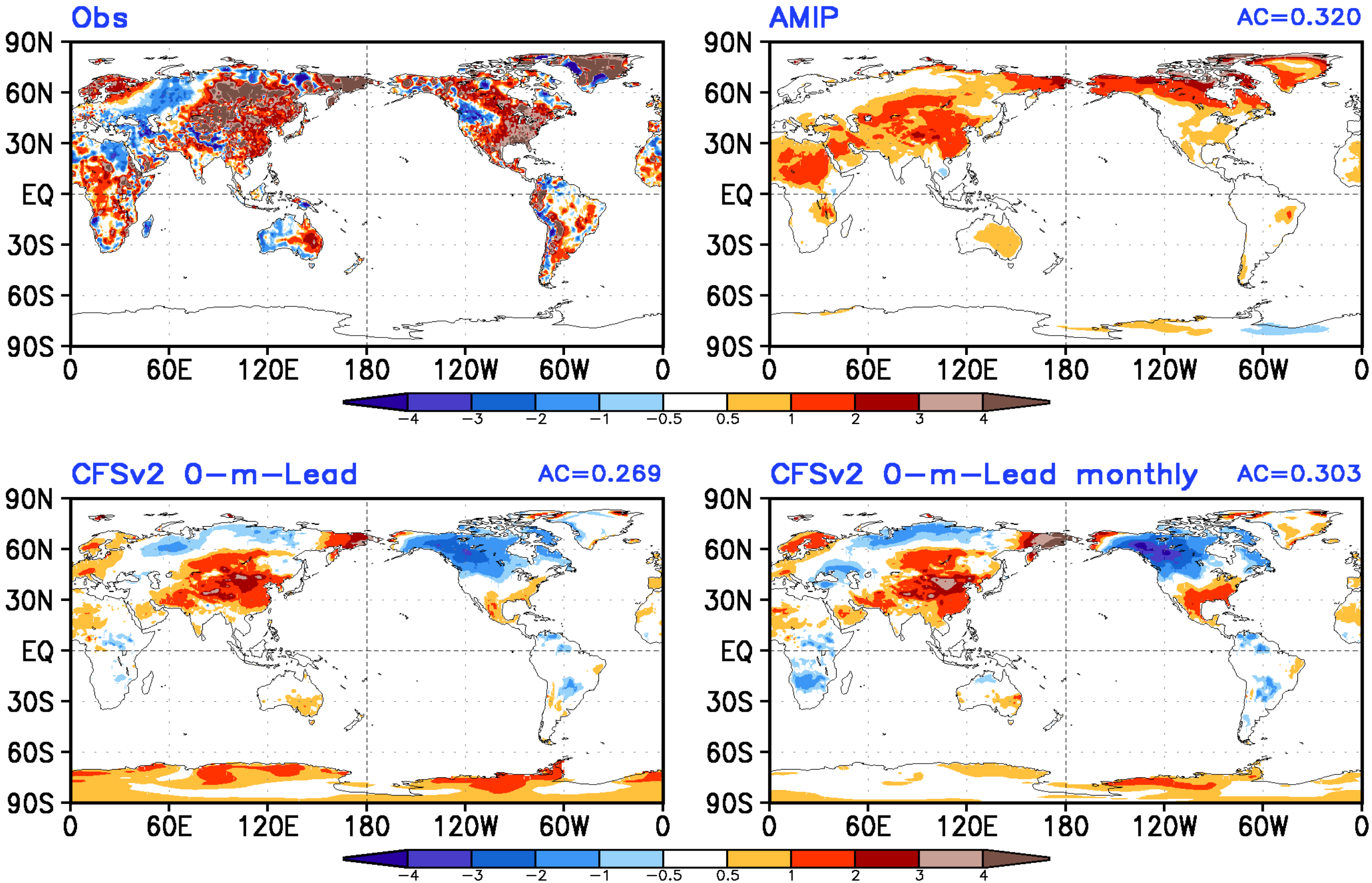
DJF2016/2017 Observed & Model Simulated/Forecas Ensemble Average Anomalies Prec(mm/day)



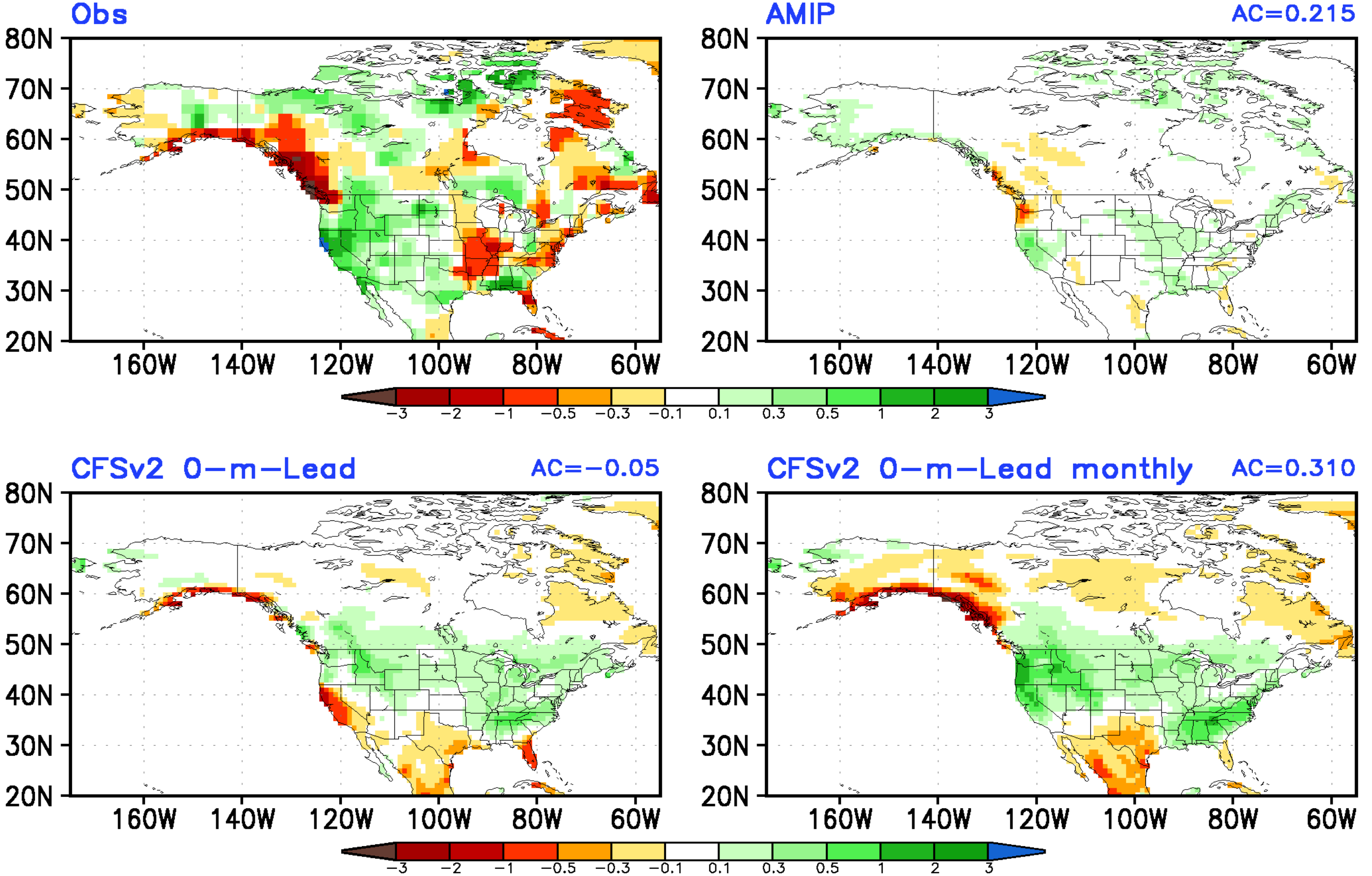
DJF2016/2017 Observed & Model Simulated/Forecas
Ensemble Average Anomalies z200(m)



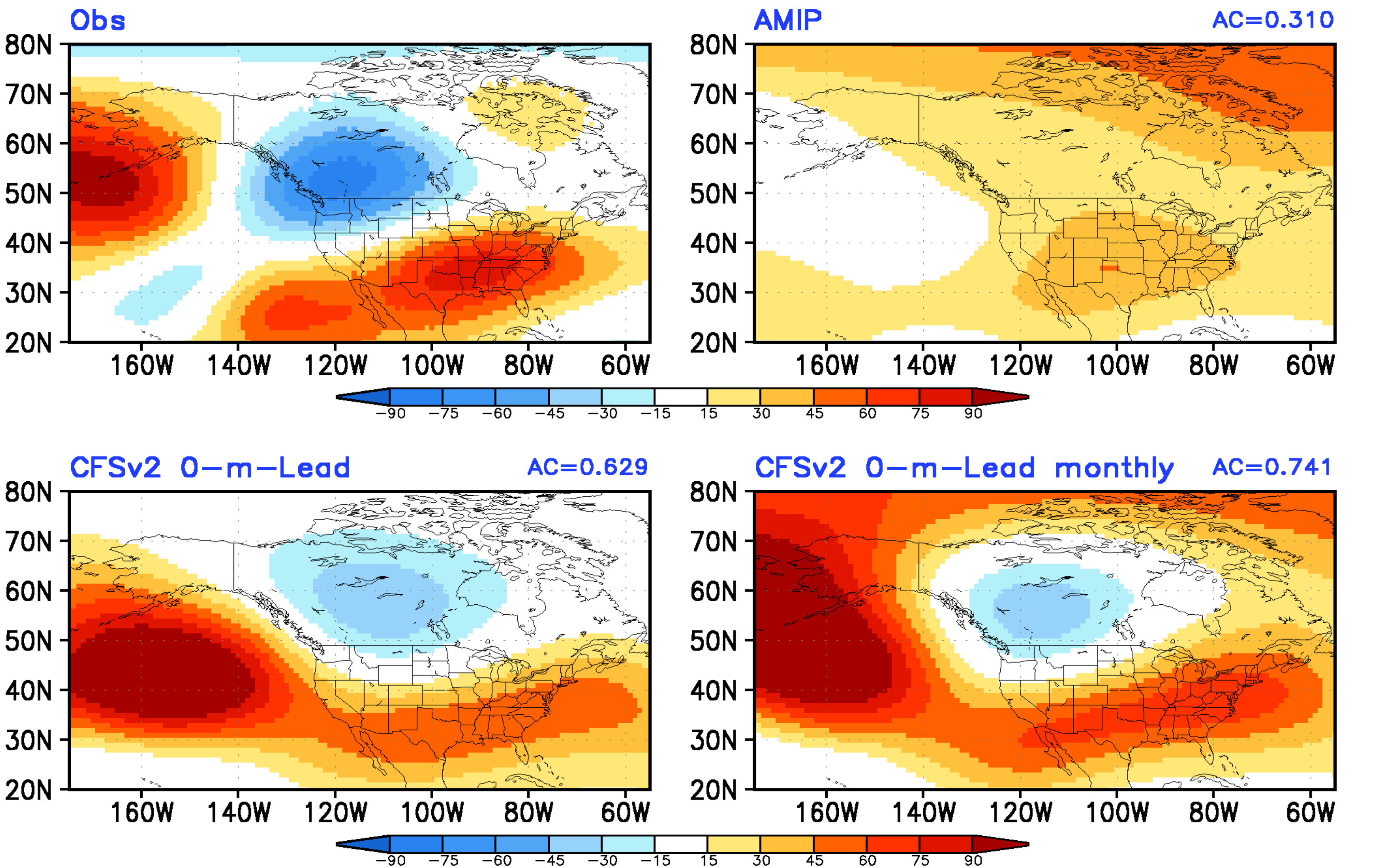
DJF2016/2017 Observed & Model Simulated/Forecas
Ensemble Average Anomalies T2m(K)



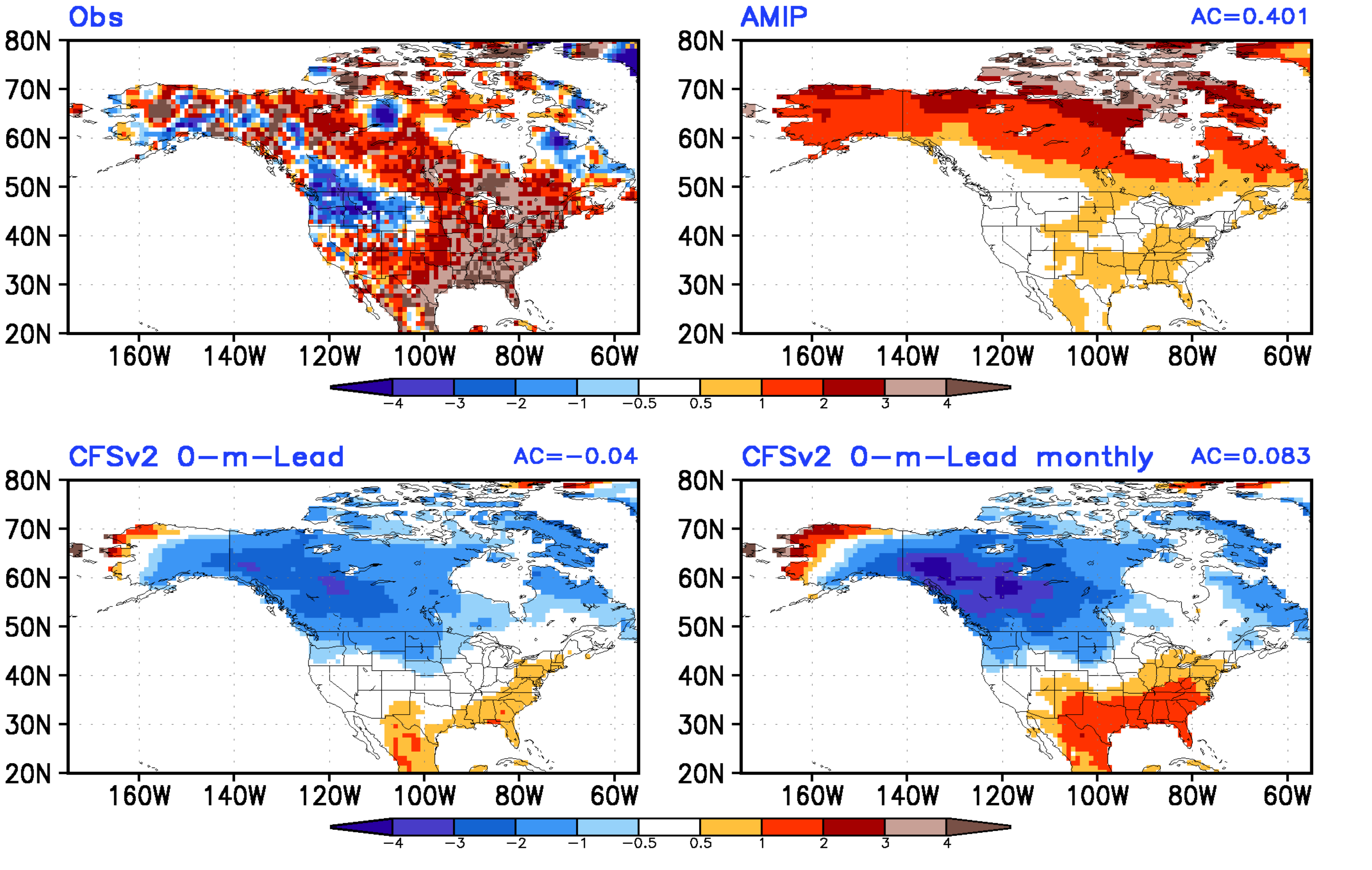
DJF2016/2017 Observed & Model Simulated/Forecas
Ensemble Average Anomalies Prec(mm/day)



DJF2016/2017 Observed & Model Simulated/Forecas
Ensemble Average Anomalies z200(m)



DJF2016/2017 Observed & Model Simulated/Forecas
Ensemble Average Anomalies T2m(K)

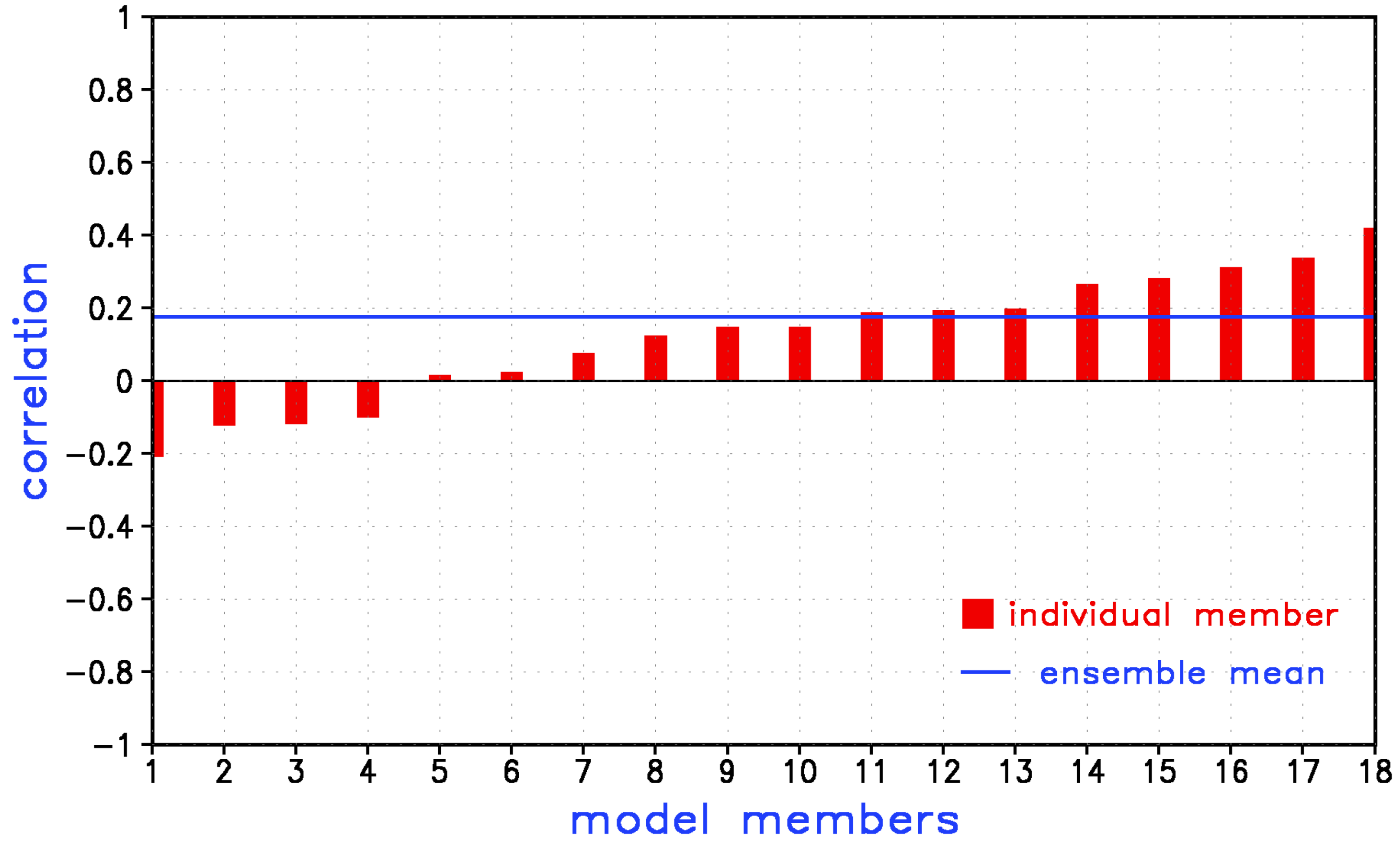


Model Simulated/Forecast Anomalies: Individual Runs

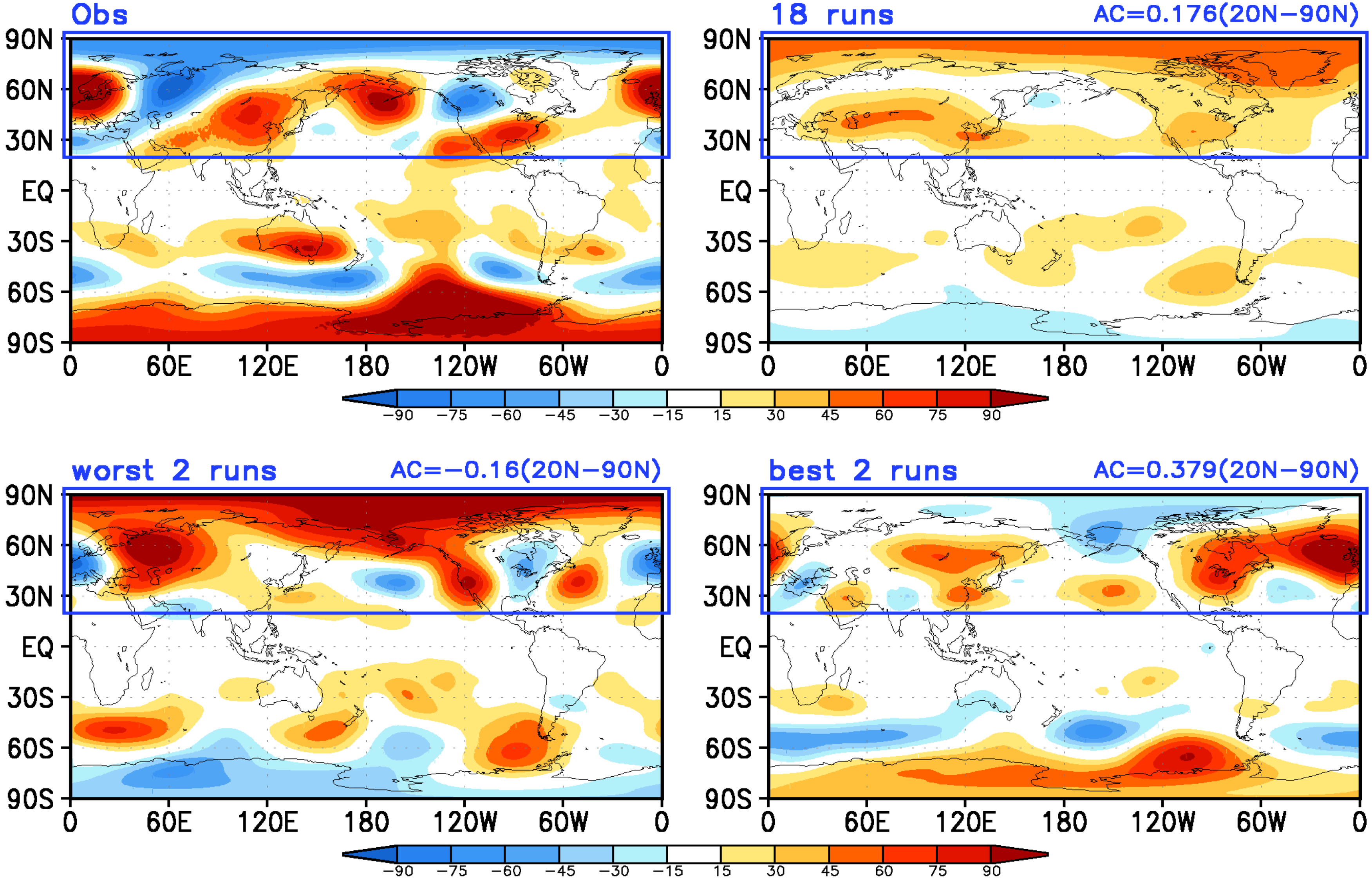
Model Simulated/Forecast Anomalies: Individual Runs

- 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 outcomes.

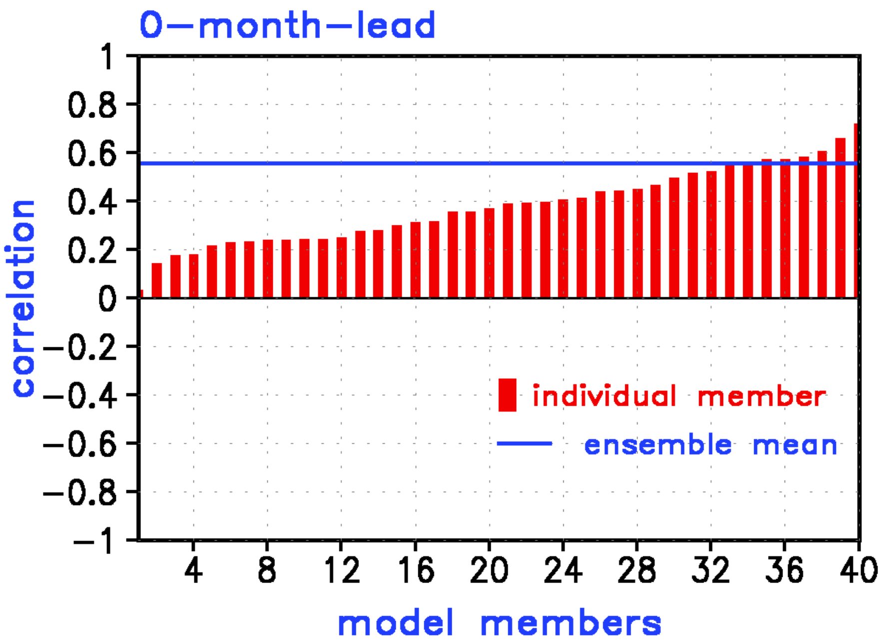
DJF2016/2017 Anomaly Correlation for Individual AMIP Simulation with Observation -- z200(20N-90N)

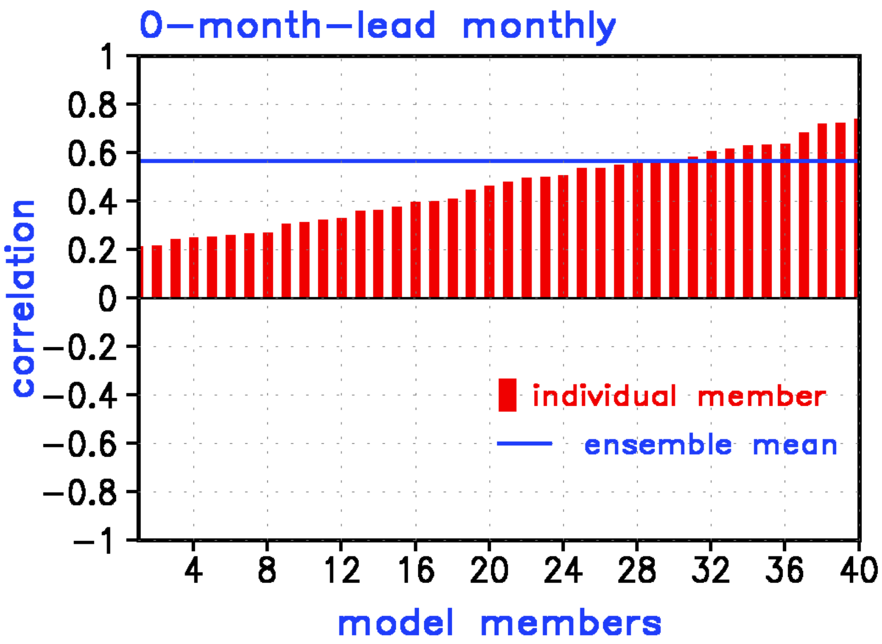


Observed & AMIP Ensemble Average Anomalies
DJF2016/2017 z200(m) 18 runs/worst 2 runs/best 2 runs

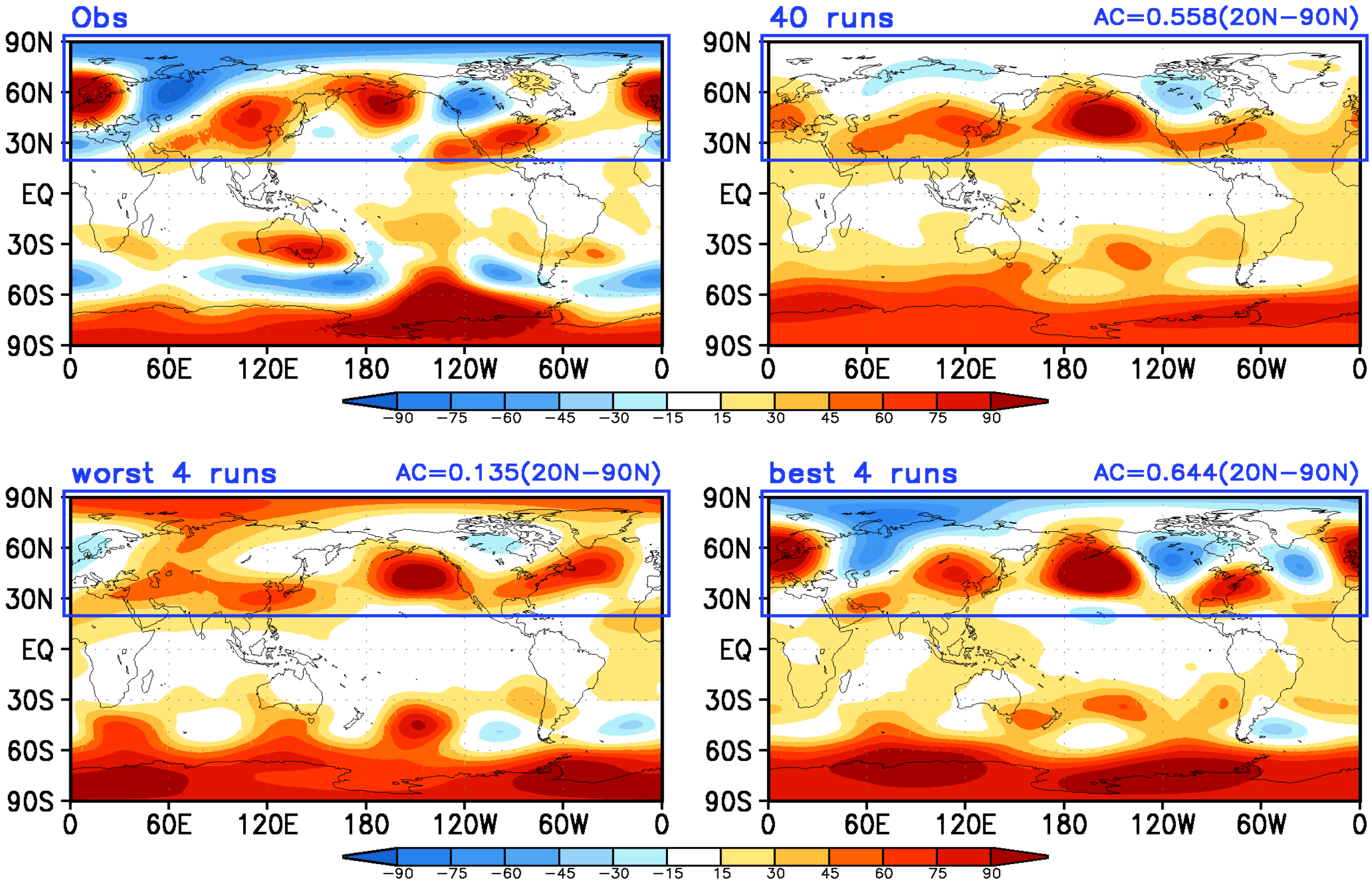


DJF2016/2017 Anomaly Correlation for Individual CFSv2 Forecast with Observation -- z200 (20N-90N)

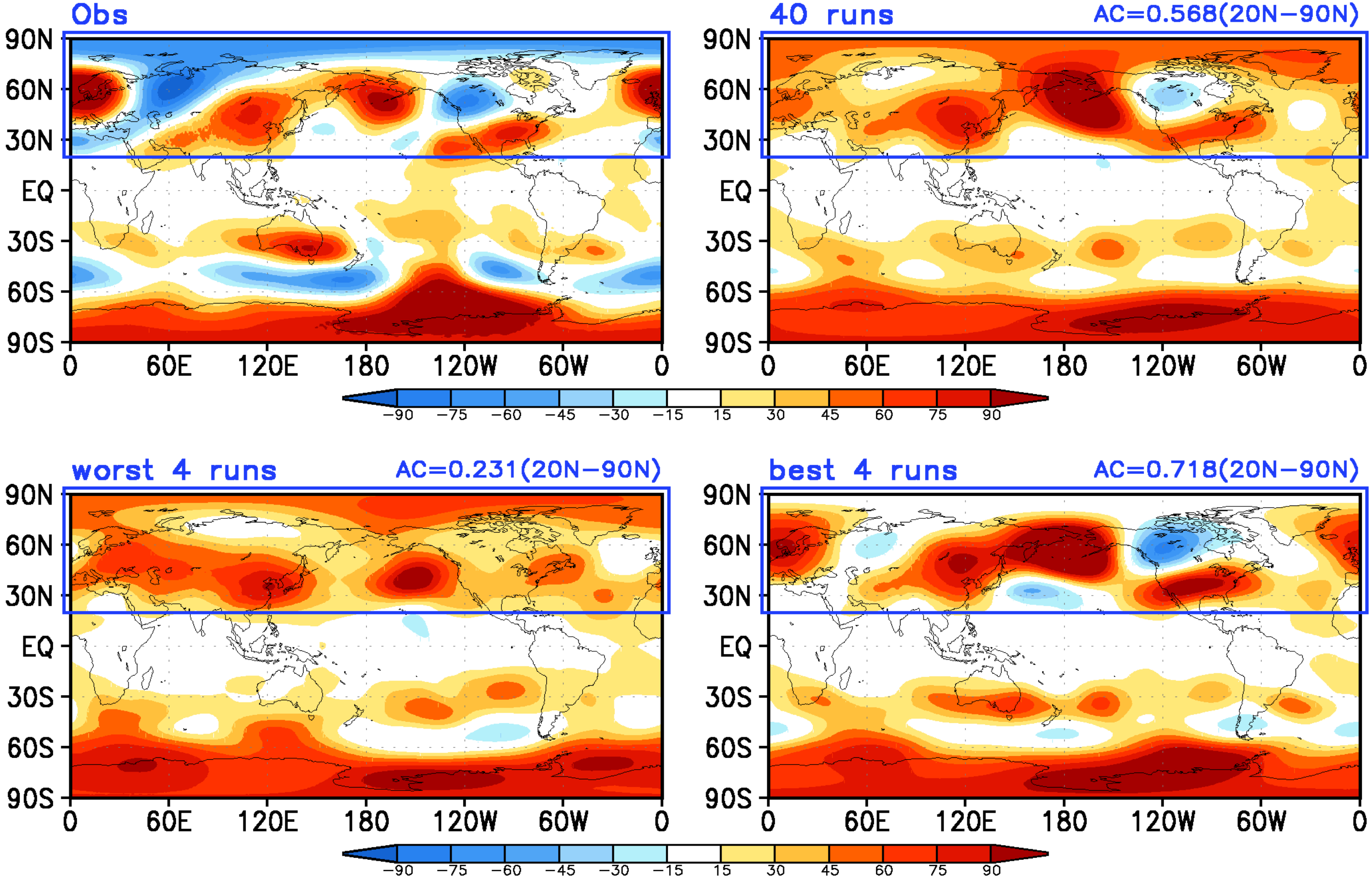




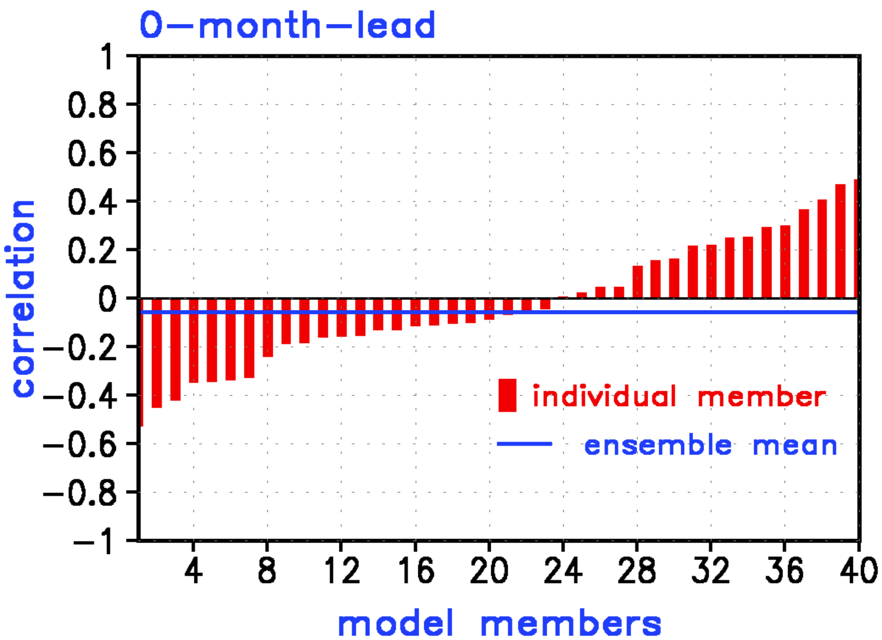
Observed & CFSv2 Forecast Ensemble Average Anomalies
DJF2016/2017 z200(m) 40 runs/worst 4 runs/best 4 runs
0-month-lead

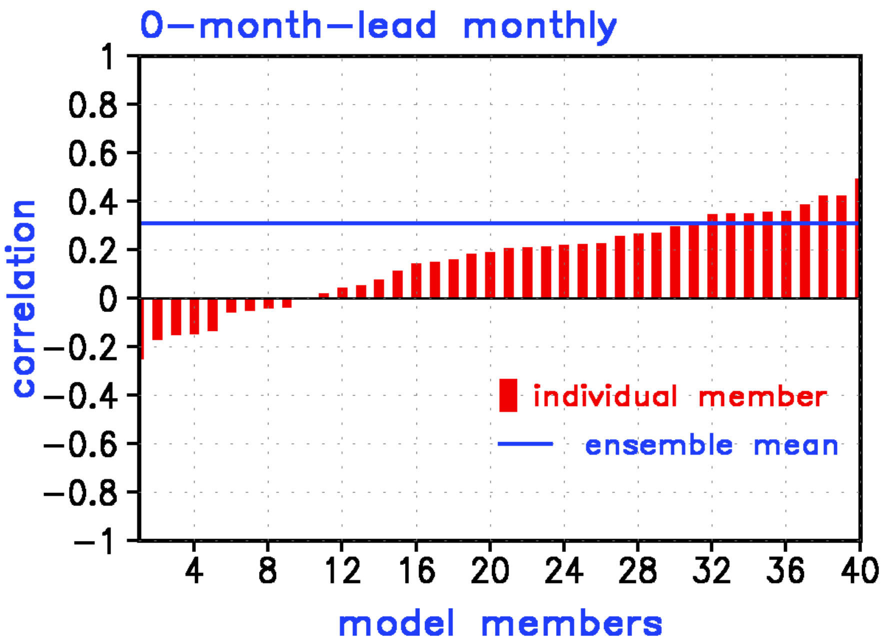


Observed & CFSv2 Forecast Ensemble Average Anomalies
DJF2016/2017 z200(m) 40 runs/worst 4 runs/best 4 runs
0-month-lead monthly

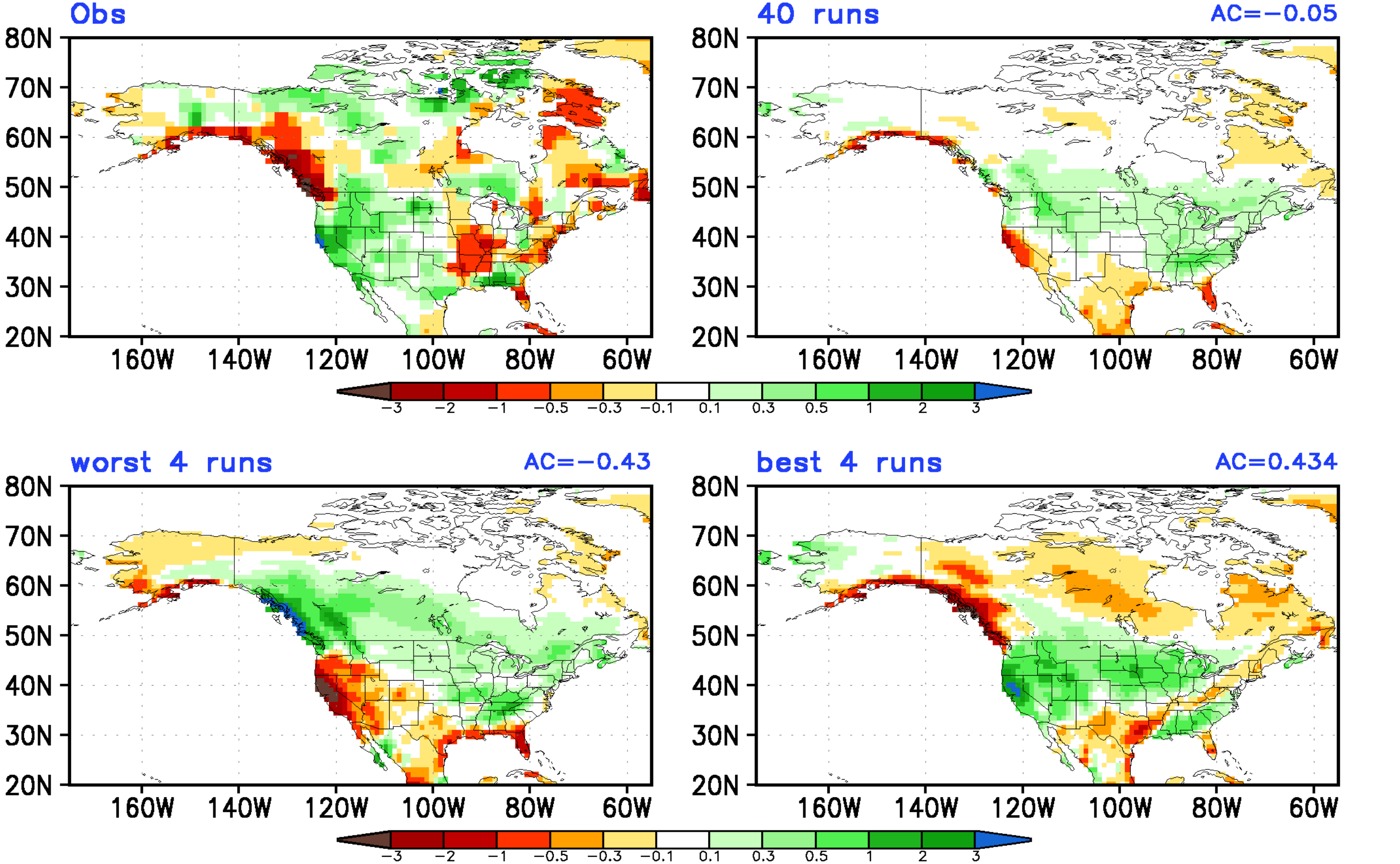


DJF2016/2017 Anomaly Correlation for Individual CFSv2 Forecast with Observation -- Prec (NA)

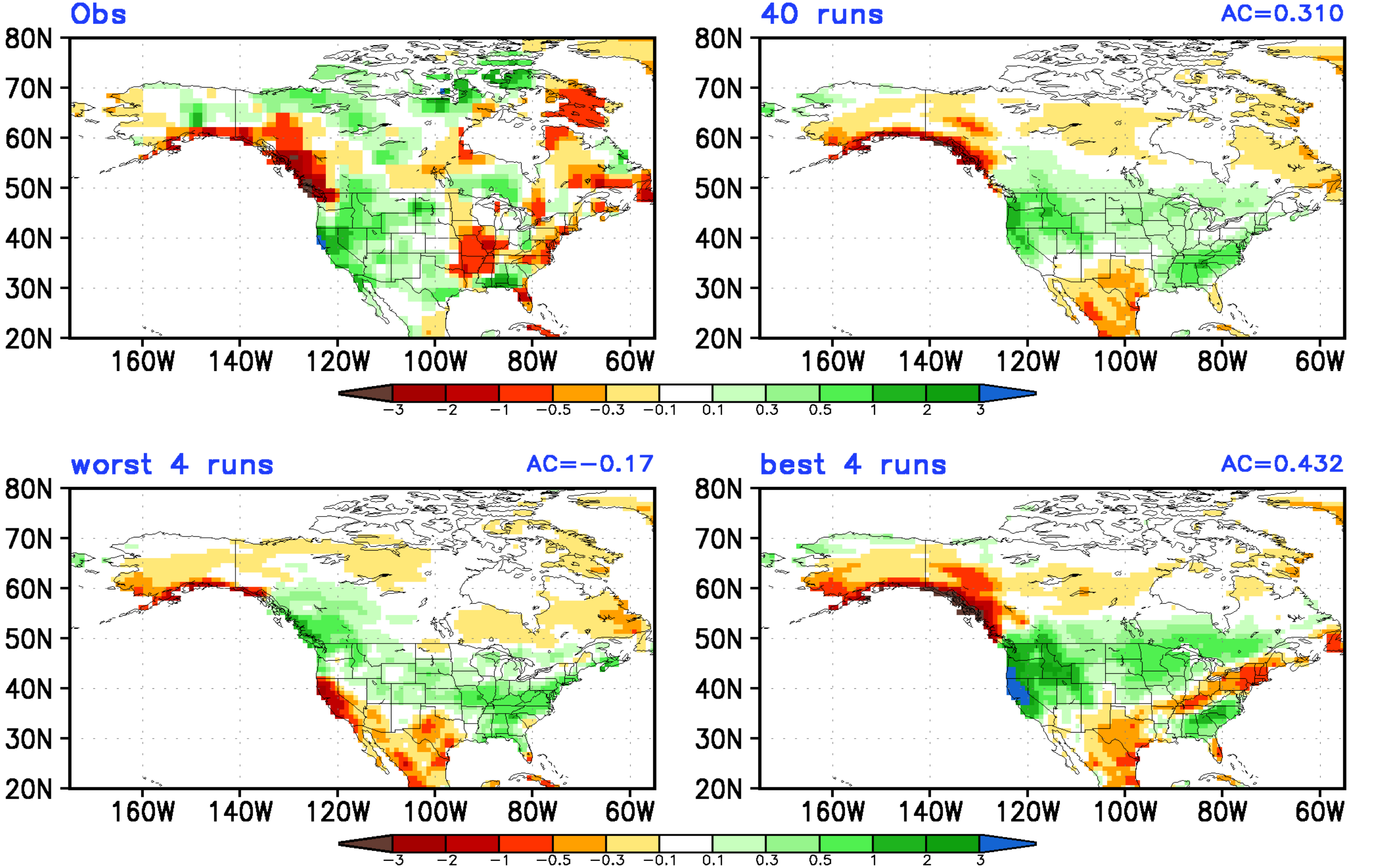




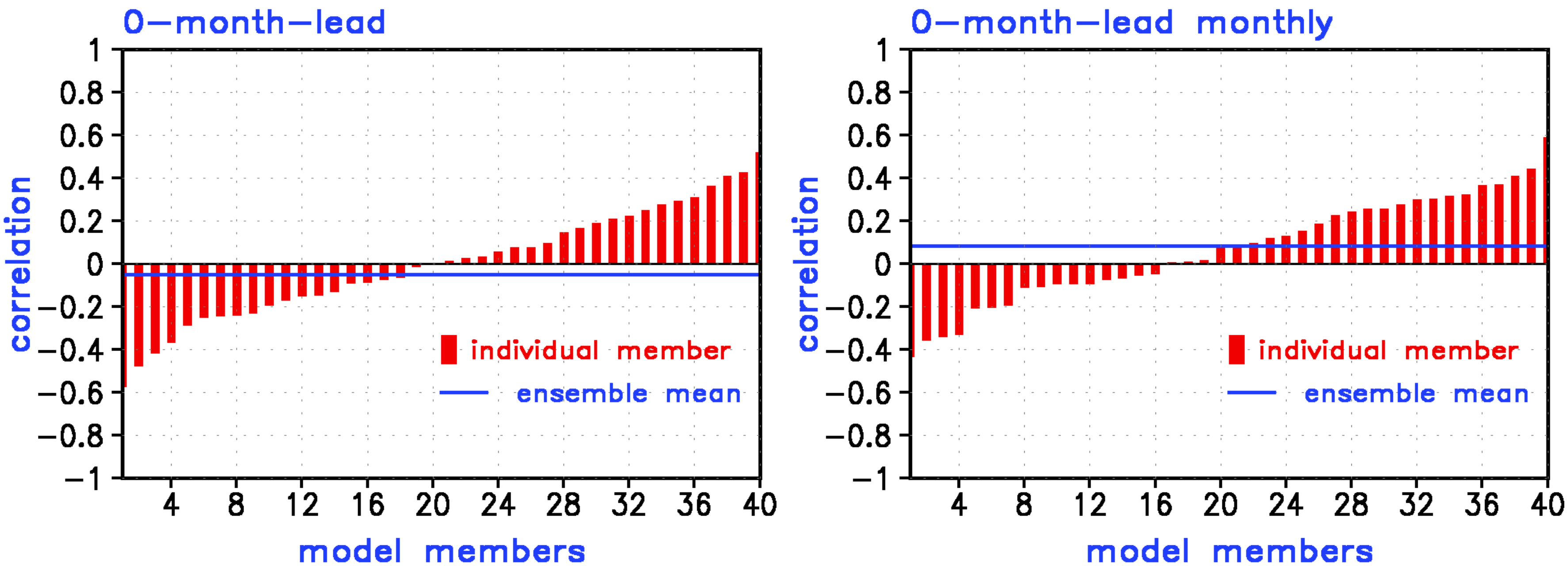
Observed & CFSv2 Forecast Ensemble Average Anomalies
DJF2016/2017 Prec(mm/day) 40 runs/worst 4 runs/best 4 runs
0-month-lead



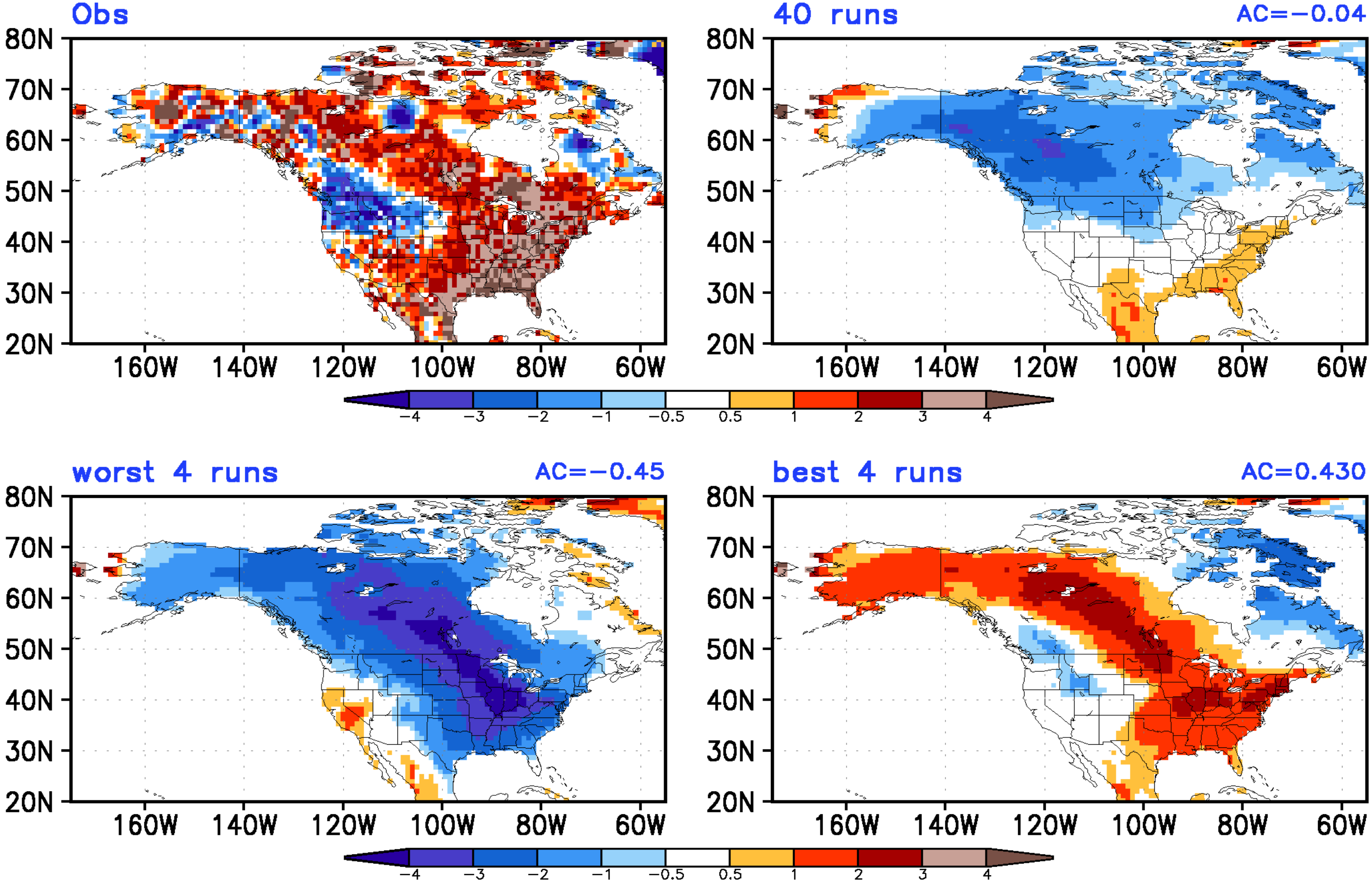
Observed & CFSv2 Forecast Ensemble Average Anomalies
DJF2016/2017 Prec(mm/day) 40 runs/worst 4 runs/best 4 runs
0-month-lead monthly

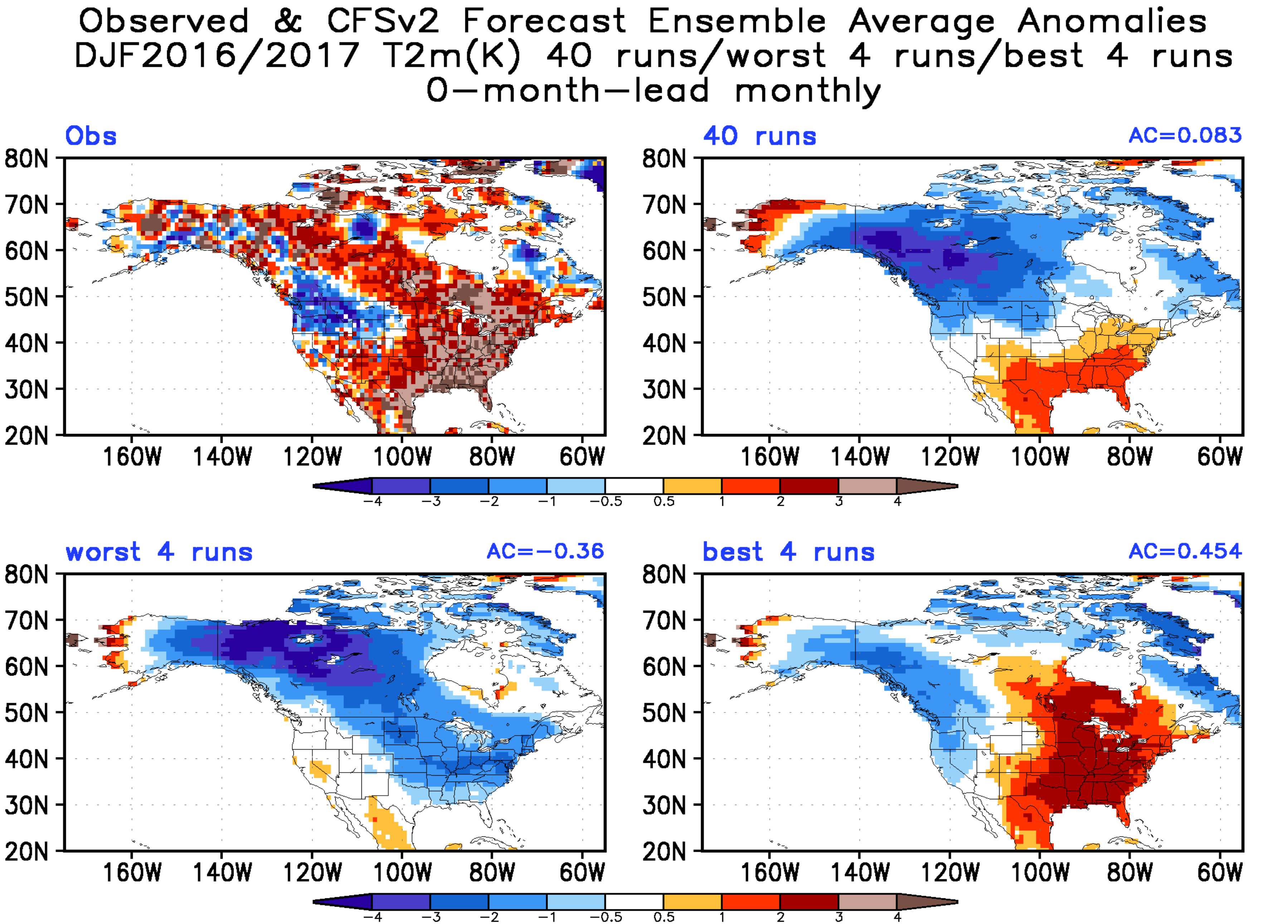


DJF2016/2017 Anomaly Correlation for Individual CFSv2 Forecast with Observation -- T2m (NA)



Observed & CFSv2 Forecast Ensemble Average Anomalies
DJF2016/2017 T2m(K) 40 runs/worst 4 runs/best 4 runs
0-month-lead

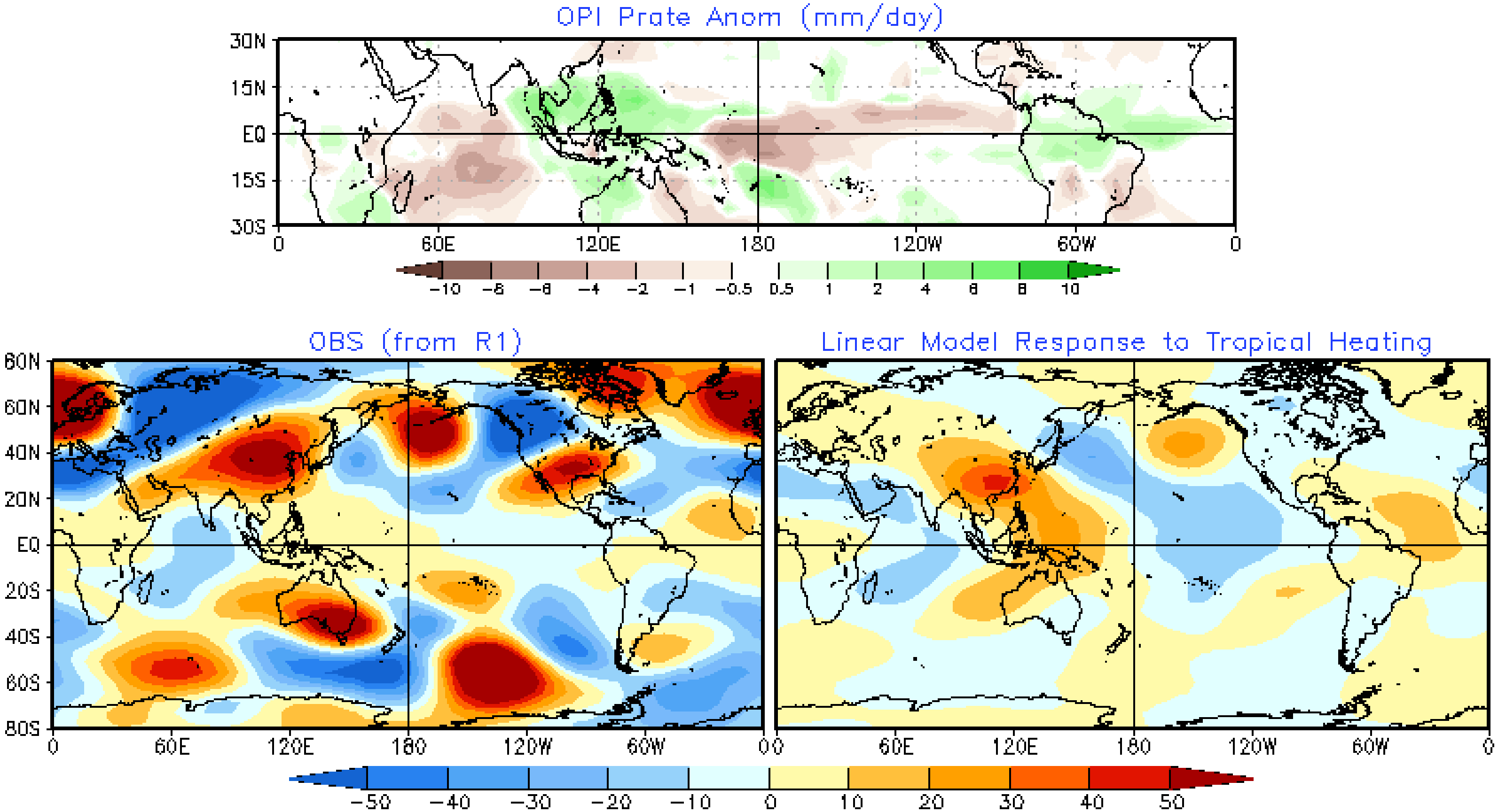




Observed & CFSv2 Forecast Ensemble Average Anomalies
DJF2016/2017 T2m(K) 40 runs/worst 4 runs/best 4 runs
0-month-lead monthly
Obs
40 runs
AC=0.083
worst 4 runs
AC=-0.36
best 4 runs
AC=0.454
80N 70N 60N 50N 40N 30N 20N
160W 140W 120W 100W 80W 60W
-4 -3 -2 -1 -0.5 0.5 1 2 3 4

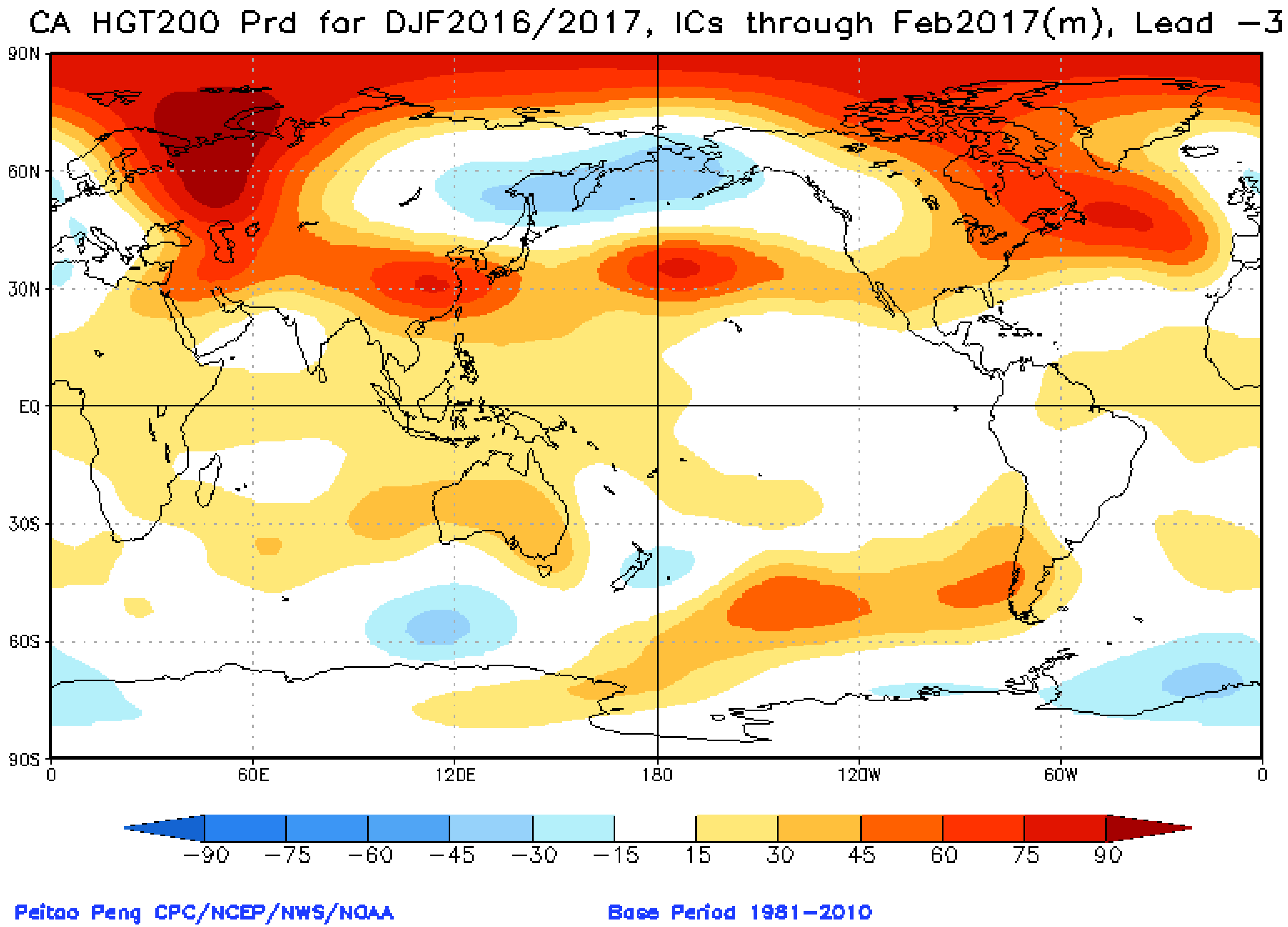
200mb Height from Linear Model

DJF2016-17 200mb Eddy HGT(m)
OBS vs. Linear Model Response to Tropical Heating
Heating is converted from Prate in 15S-15N

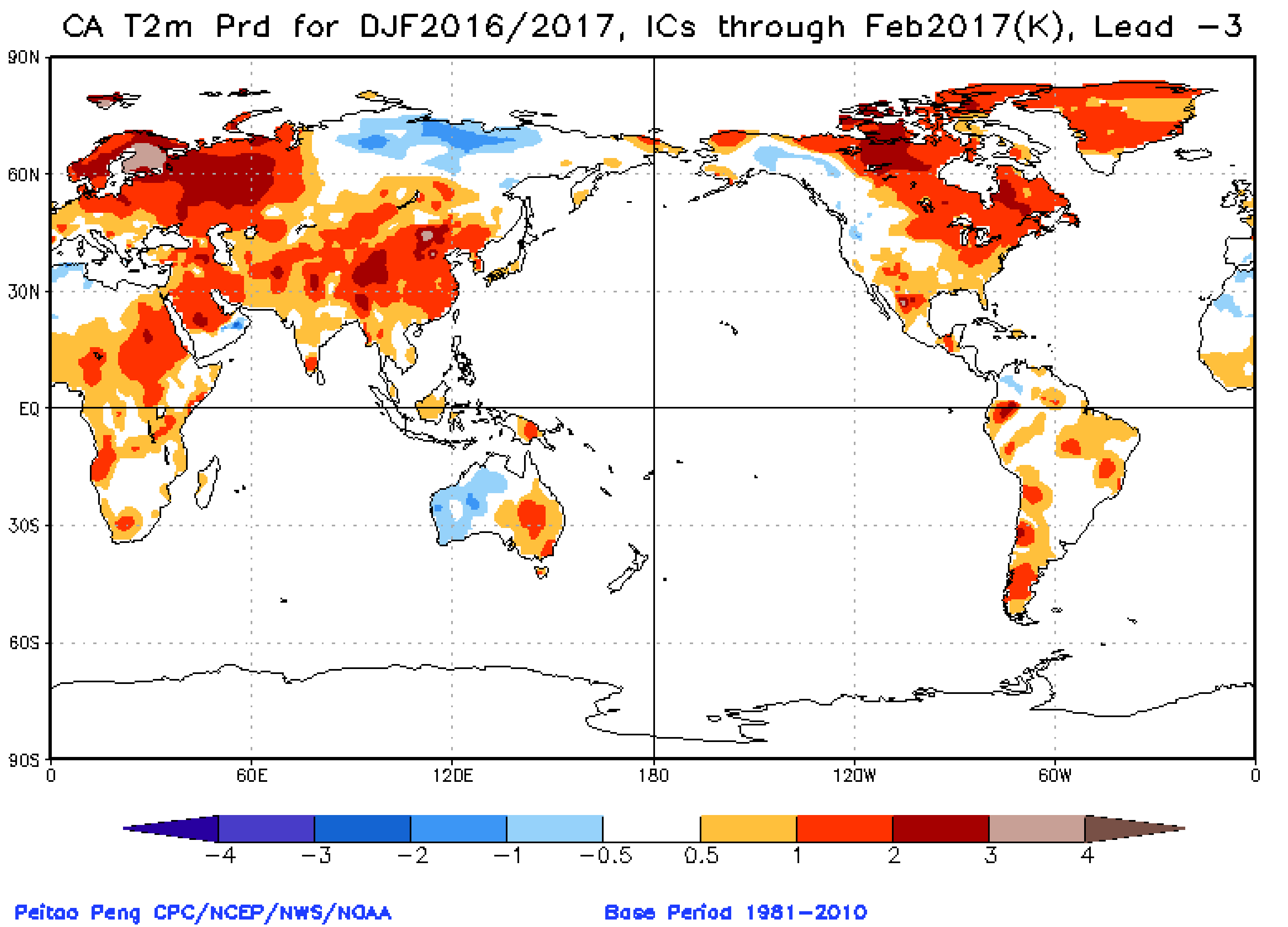


Pattern COR: global=0.22, tropics(30S-30N)=0.40

Seasonal Forecasts from the Constructed Analog Model

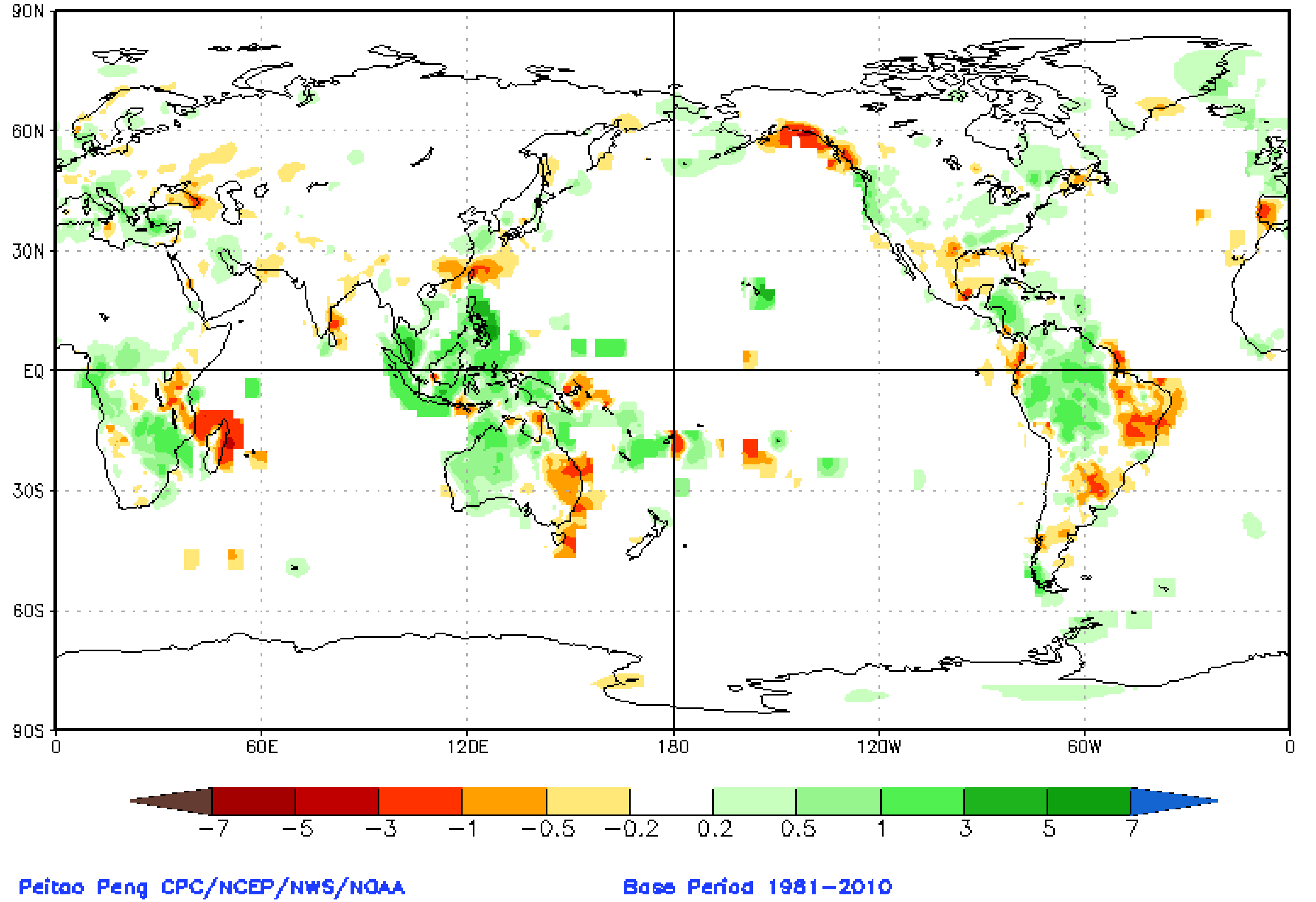


CA HGT200 Prd for DJF2016/2017, ICs through Feb2017(m), Lead -3
90N
60N
30N
EQ
30S
60S
90S
0
60E
120E
180
120W
60W
0
-90 -75 -60 -45 -30 -15 15 30 45 60 75 90
Peitao Peng CPC/NCEP/NWS/NOAA
Base Period 1981-2010



CA T2m Prd for DJF2016/2017, ICs through Feb2017(K), Lead -3
90N
60N
30N
EQ
30S
60S
90S
0
60E
120E
180
120W
60W
0
-4
-3
-2
-1
-0.5
0.5
1
2
3
4
Peitao Peng CPC/NCEP/NWS/NOAA
Base Period 1981-2010

CA Prec Prd for DJF2016/2017, ICs through Feb2017(mm/day), Lead -3



Summary

- The observed tropical SST DJF2016/17 anomalies were weak; the wave train pattern of z200 response to the tropical heating in the linear model originated from western Pacific-Maritime Continent to west and east N-Pacific, with very weak signal over N. America, and the centers of highs and lows in linear response pattern is very different from that in observation.
- The SST anomalies over the tropics were forecasted reasonably well in CFSv2, especially for the constructed monthly-seasonal mean forecasts.
- For the ensemble means, both the AMIP runs and initialized forecasts captured the major large scale La Niña pattern of Prec anomalies over tropical Pacific; but they didn’t forecast well the PNA height anomalies, and the NA Prec and T2m.
- For the individual members, the NA Prec and T2m correlation skills have large variations between members, almost half of 40 members show negative skills.
- The Constructed Analog model didn’t forecast well NA anomalies of z200 and Prec neither.

References

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