Attribution of Seasonal Climate Anomalies January-February-March 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).

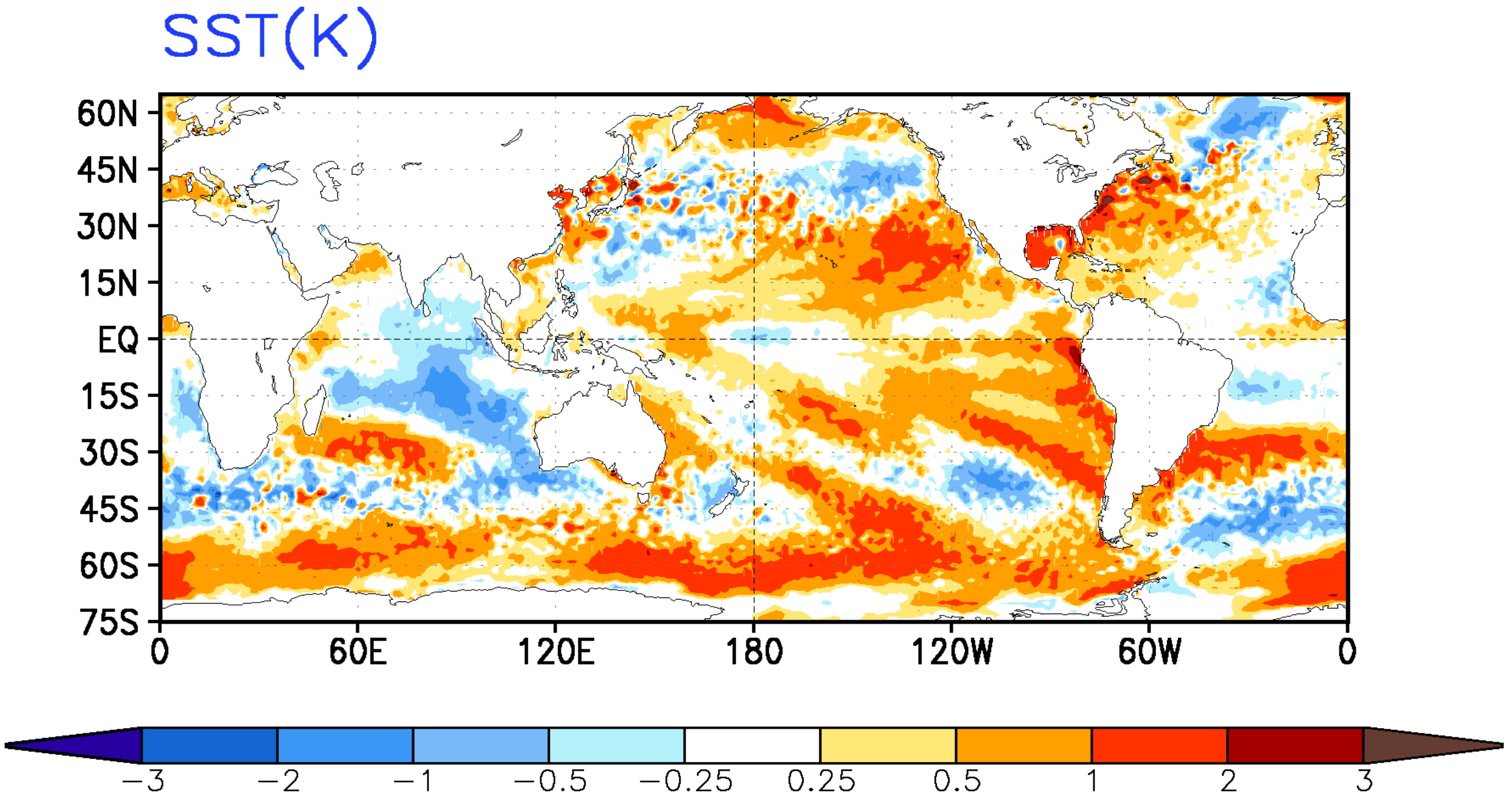
Data

- 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)

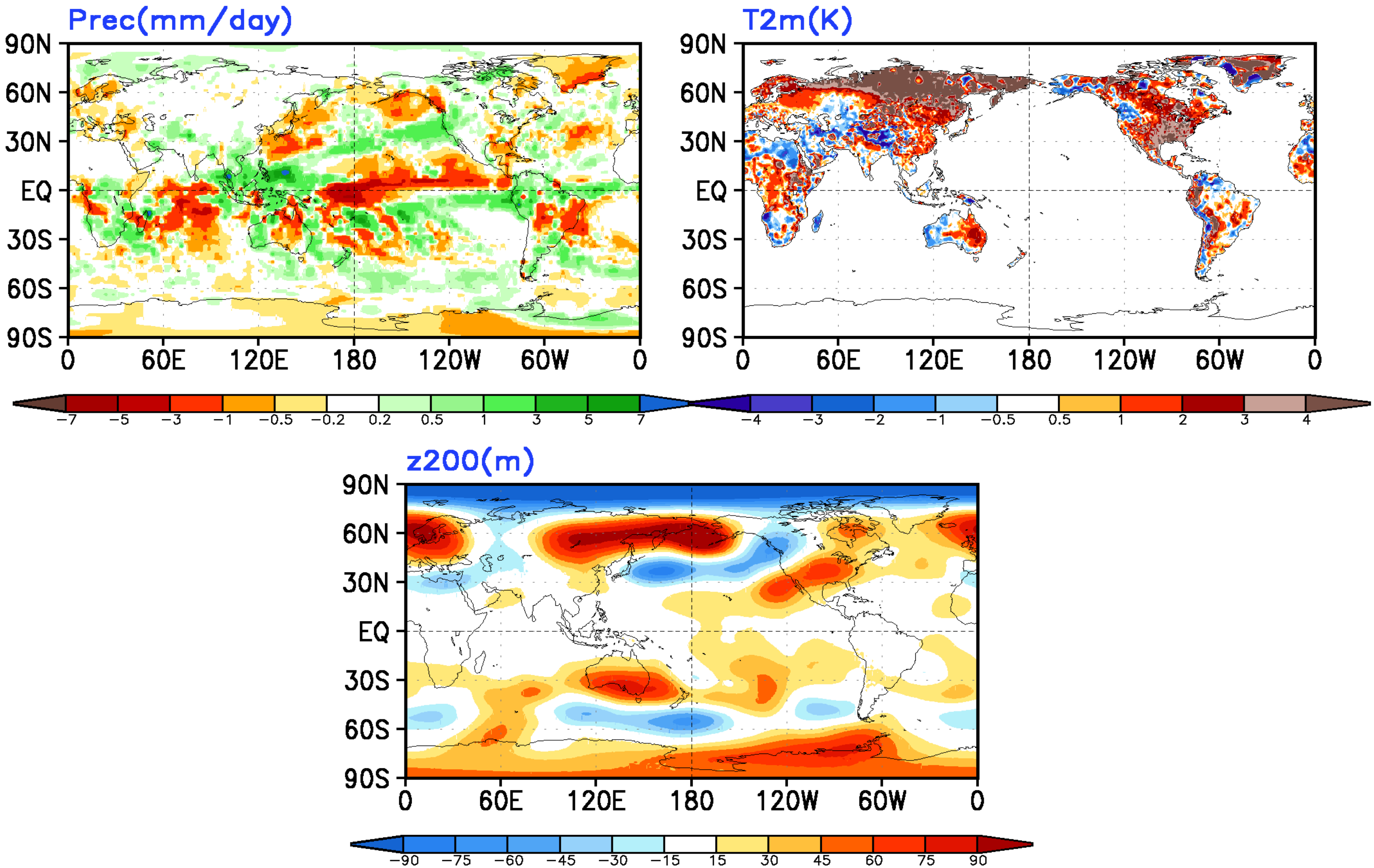
Observed Seasonal Anomalies

Global and North America

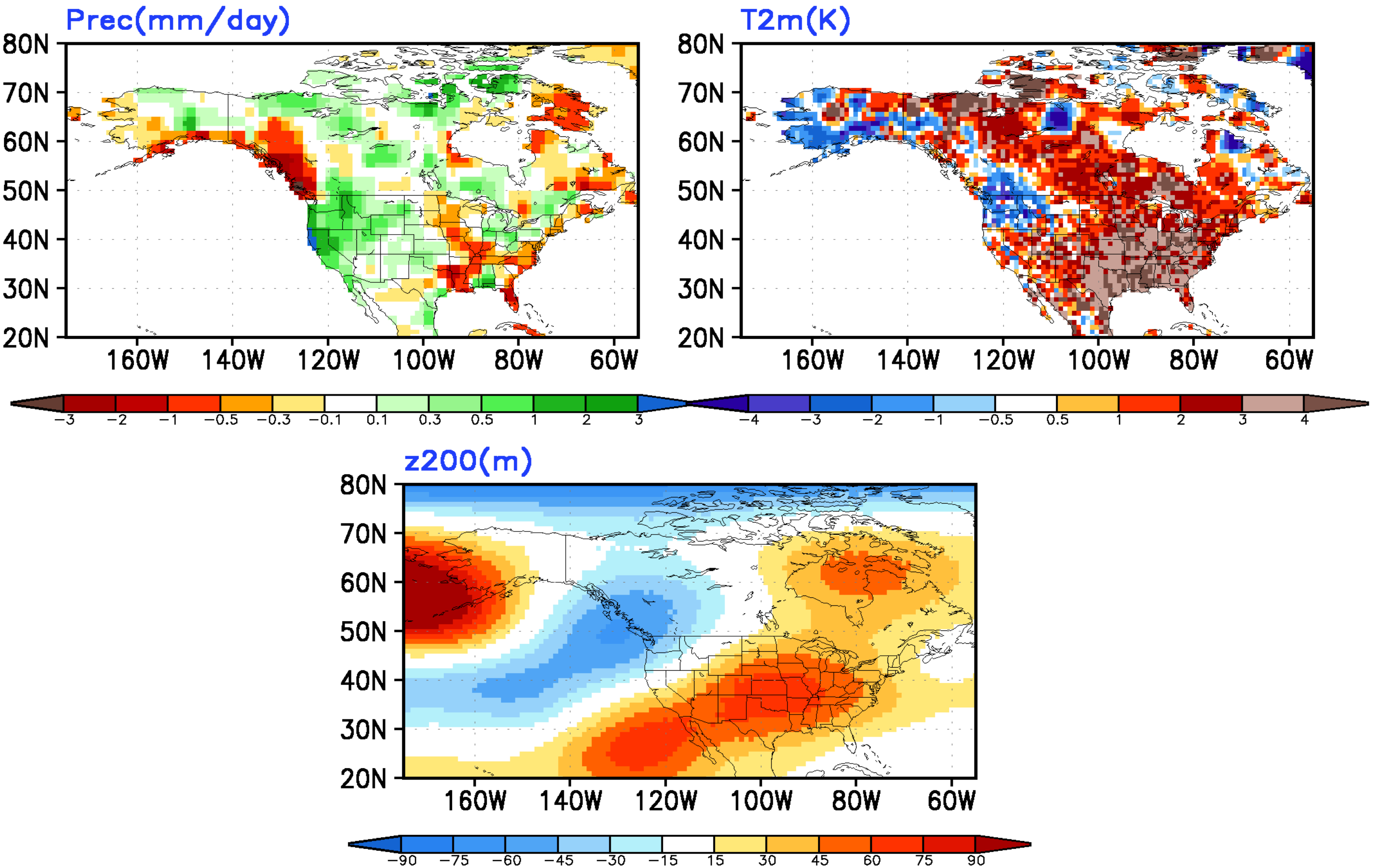
Observed Anomaly JFM2017



Observed Anomaly JFM2017



Observed Anomaly JFM2017

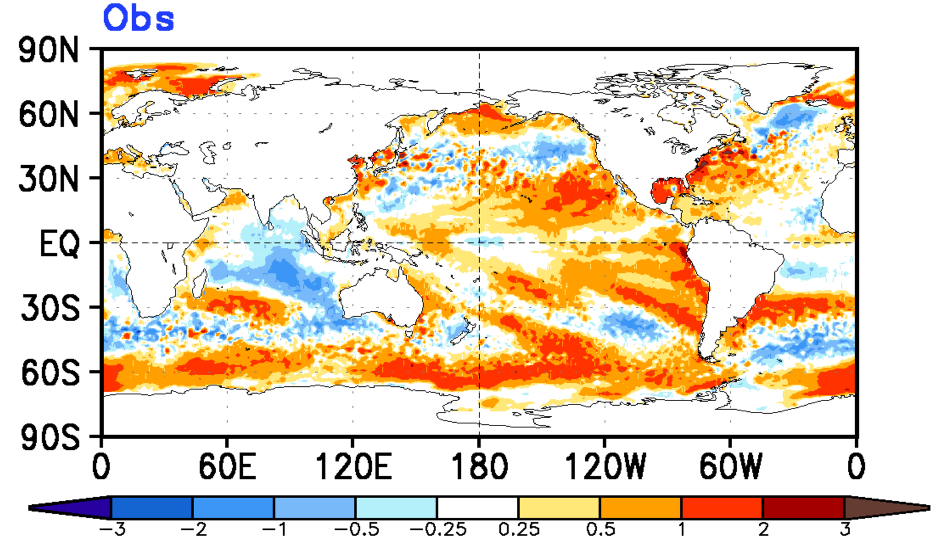


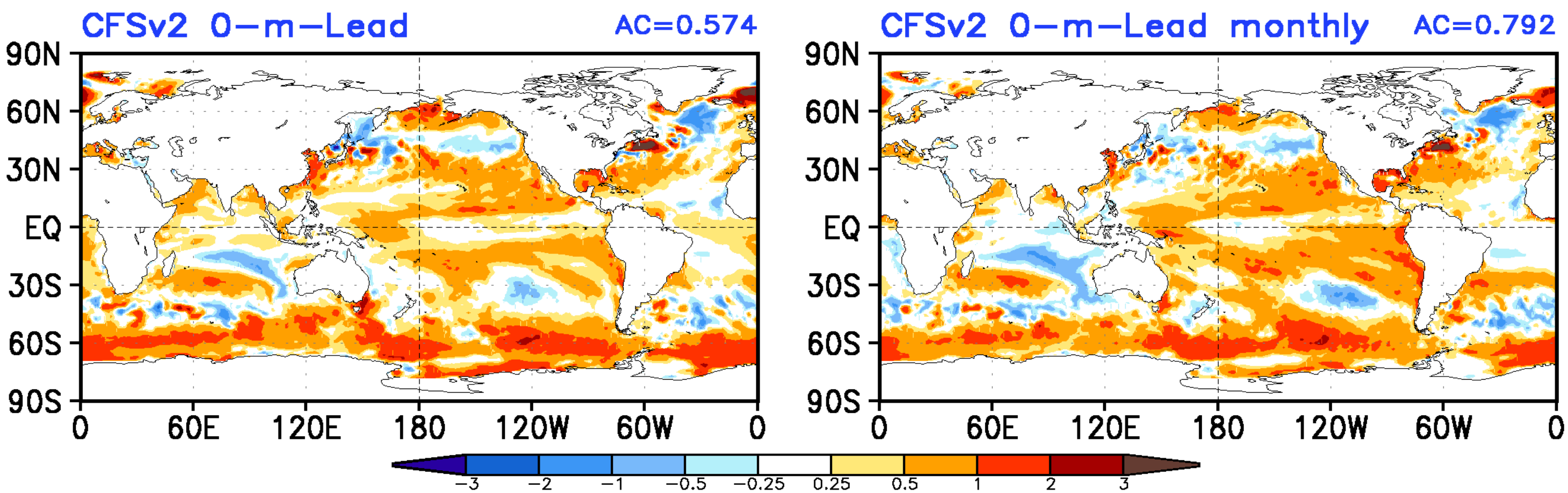
Model Simulated/Forecast Ensemble Average Anomalies

Model Simulated/Forecast Ensemble Average Anomalies

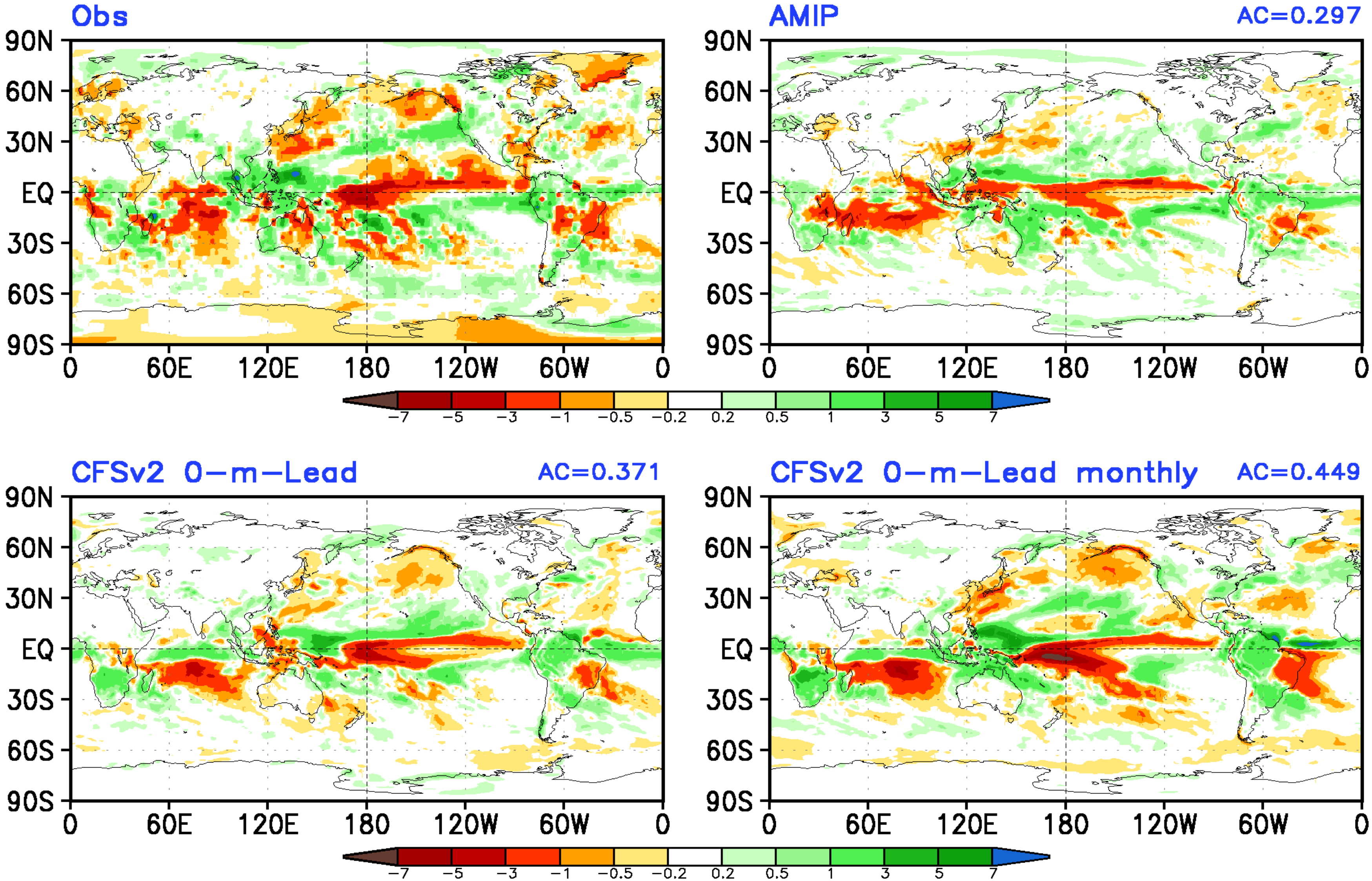
- CFS AMIP simulations forced with observed sea surface temperatures (18 members ensemble)
- CFSv2 real time operational forecasts
  - 0-month-lead: the seasonal mean forecasts based on 40 members from the latest 10 days before the target season. For example, 2016AMJ seasonal mean forecasts are 40 members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

JFM2017 Observed & Model Simulated/Forecast Ensemble Average Anomalies SST(K)

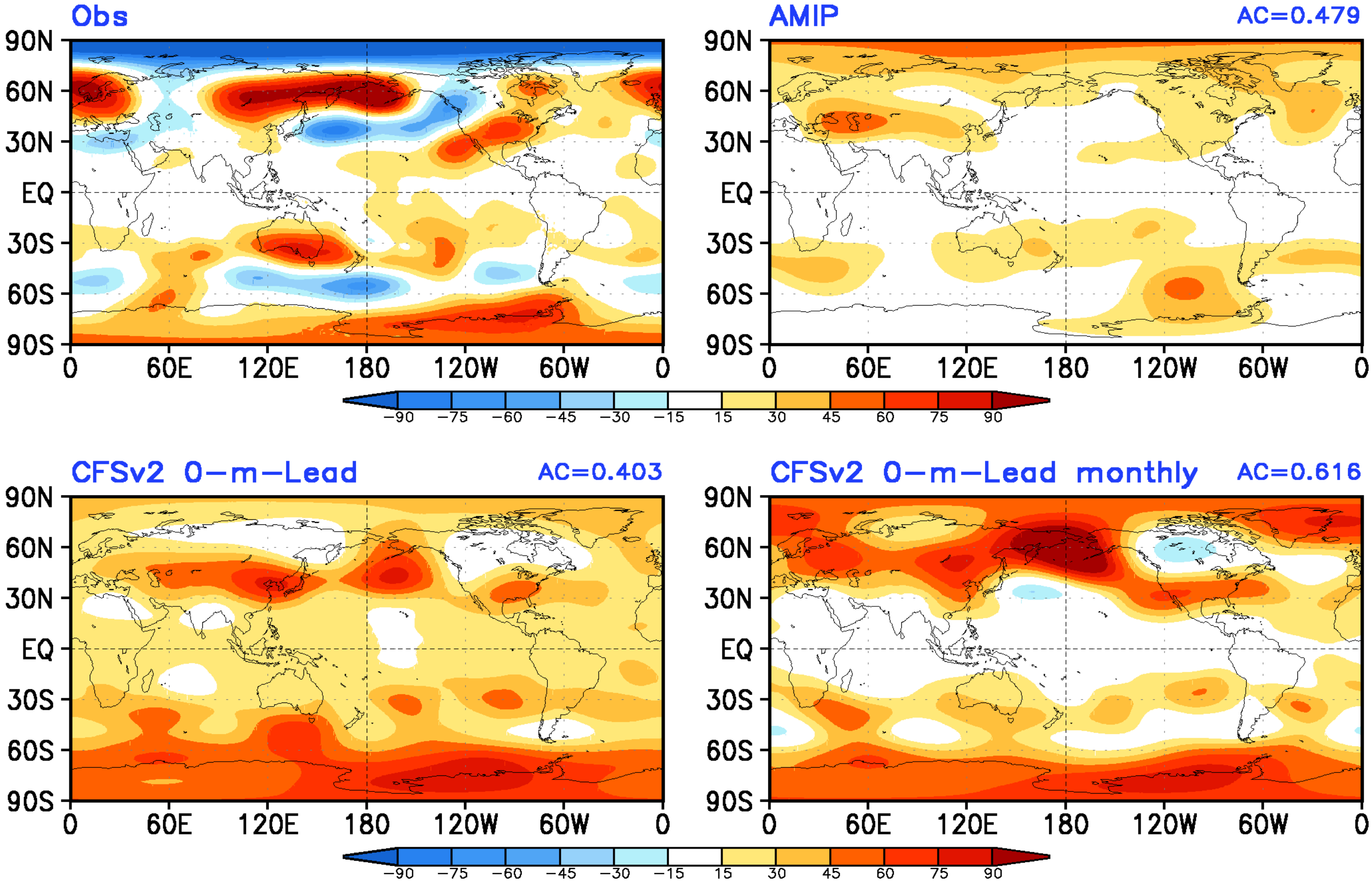




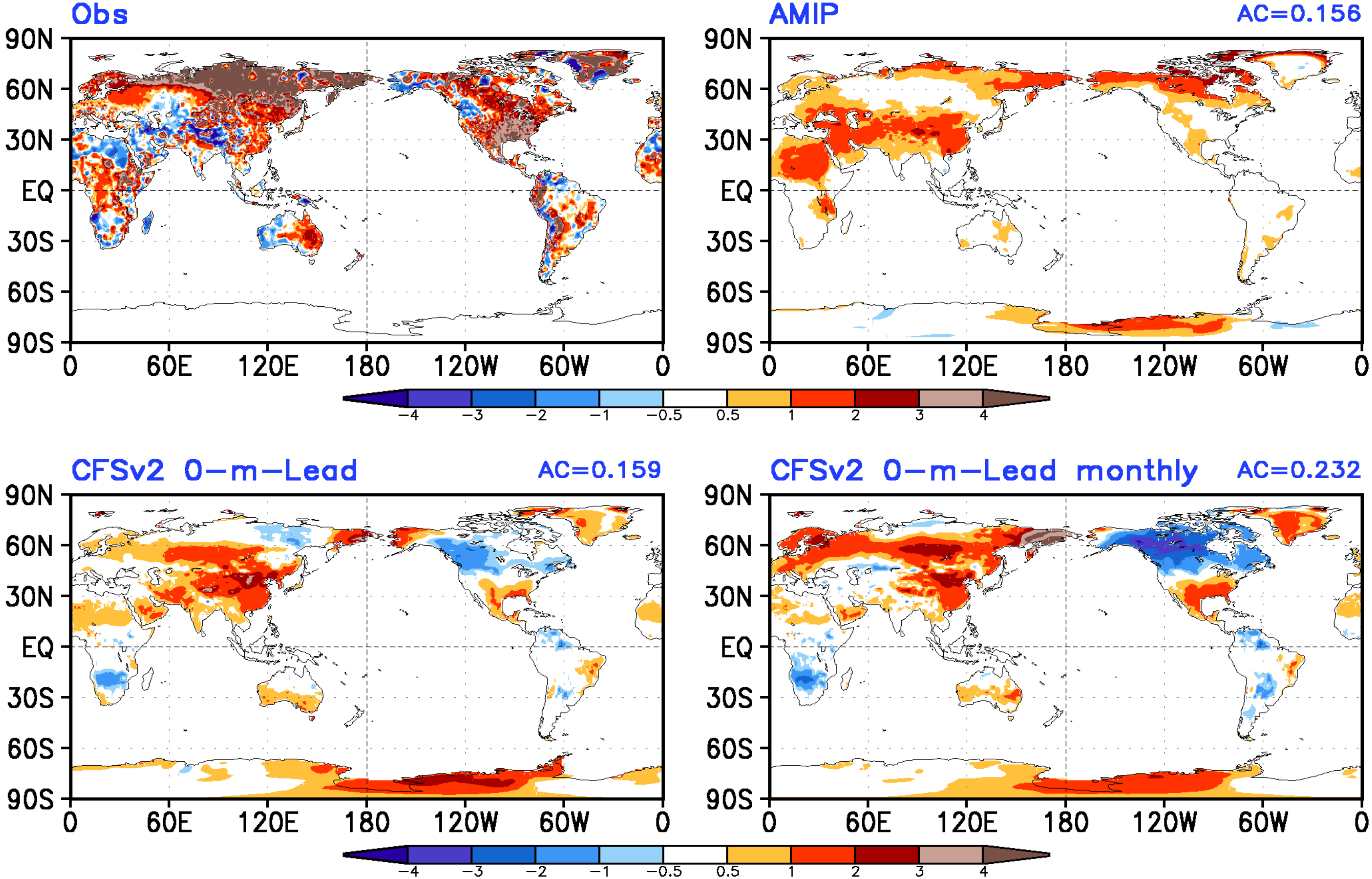
JFM2017 Observed & Model Simulated/Forecast Ensemble Average Anomalies Prec(mm/day)



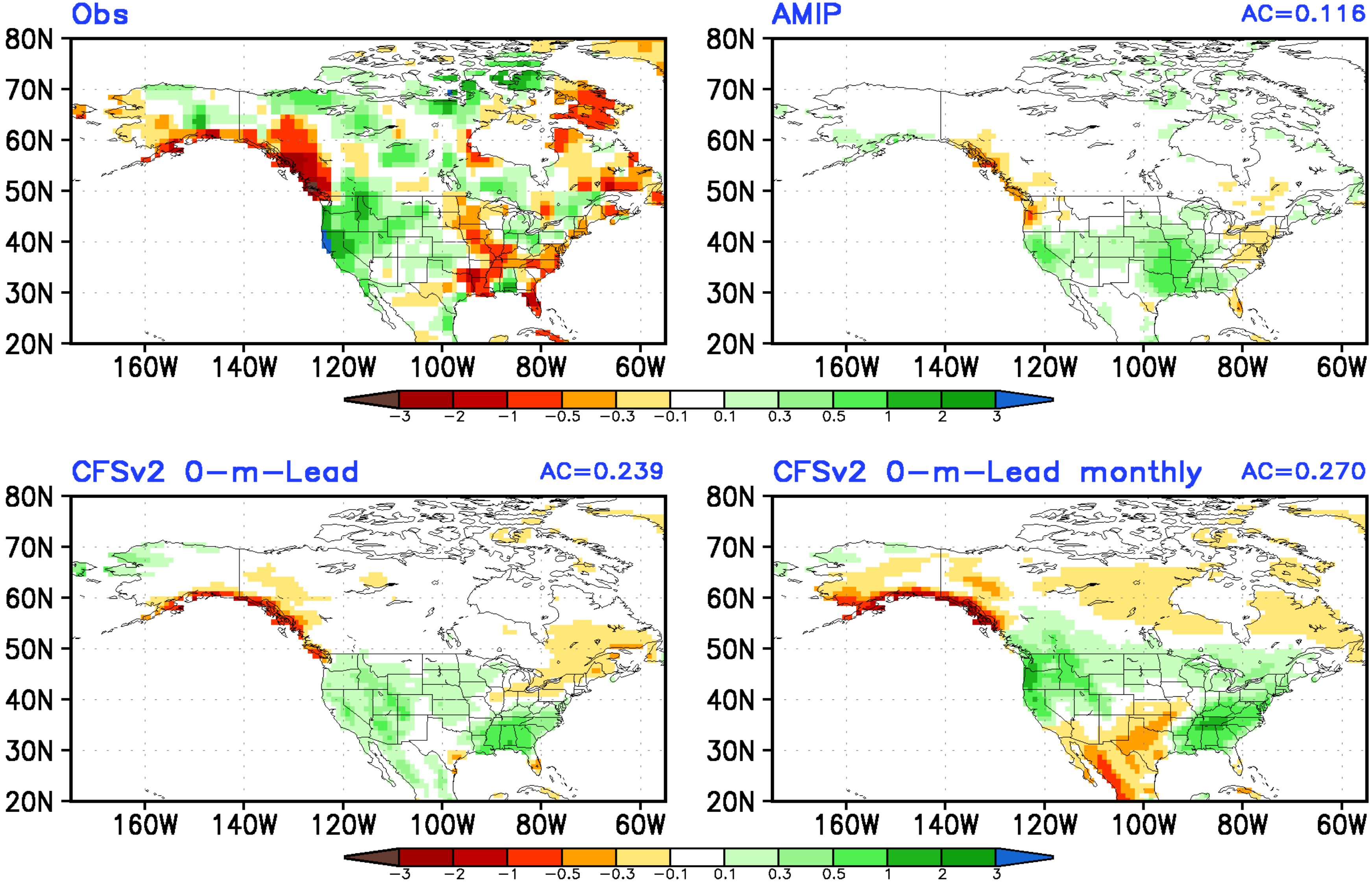
JFM2017 Observed & Model Simulated/Forecast Ensemble Average Anomalies z200(m)



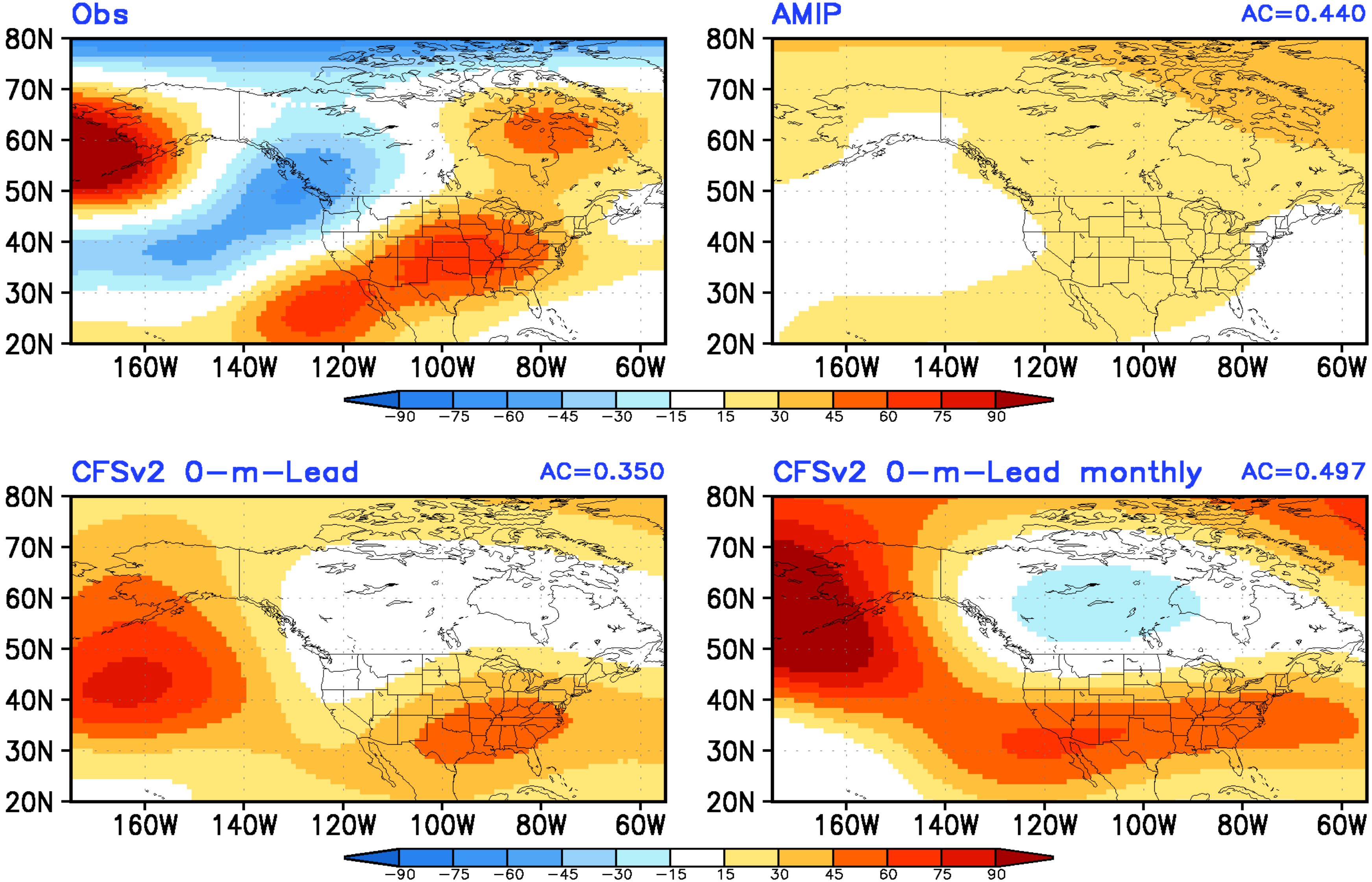
JFM2017 Observed & Model Simulated/Forecast Ensemble Average Anomalies T2m(K)



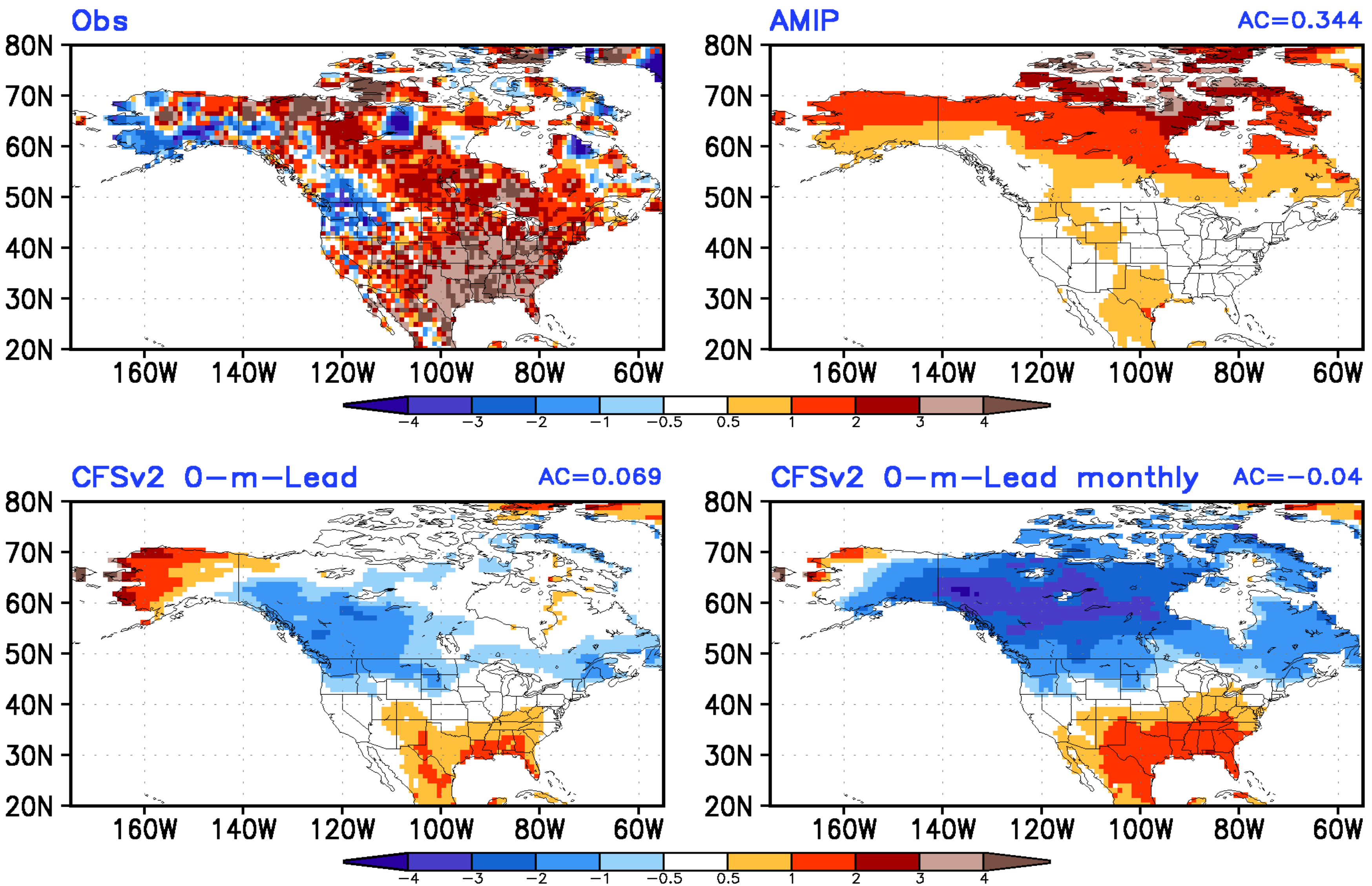
JFM2017 Observed & Model Simulated/Forecast Ensemble Average Anomalies Prec(mm/day)



JFM2017 Observed & Model Simulated/Forecast Ensemble Average Anomalies z200(m)



JFM2017 Observed & Model Simulated/Forecast Ensemble Average Anomalies T2m(K)

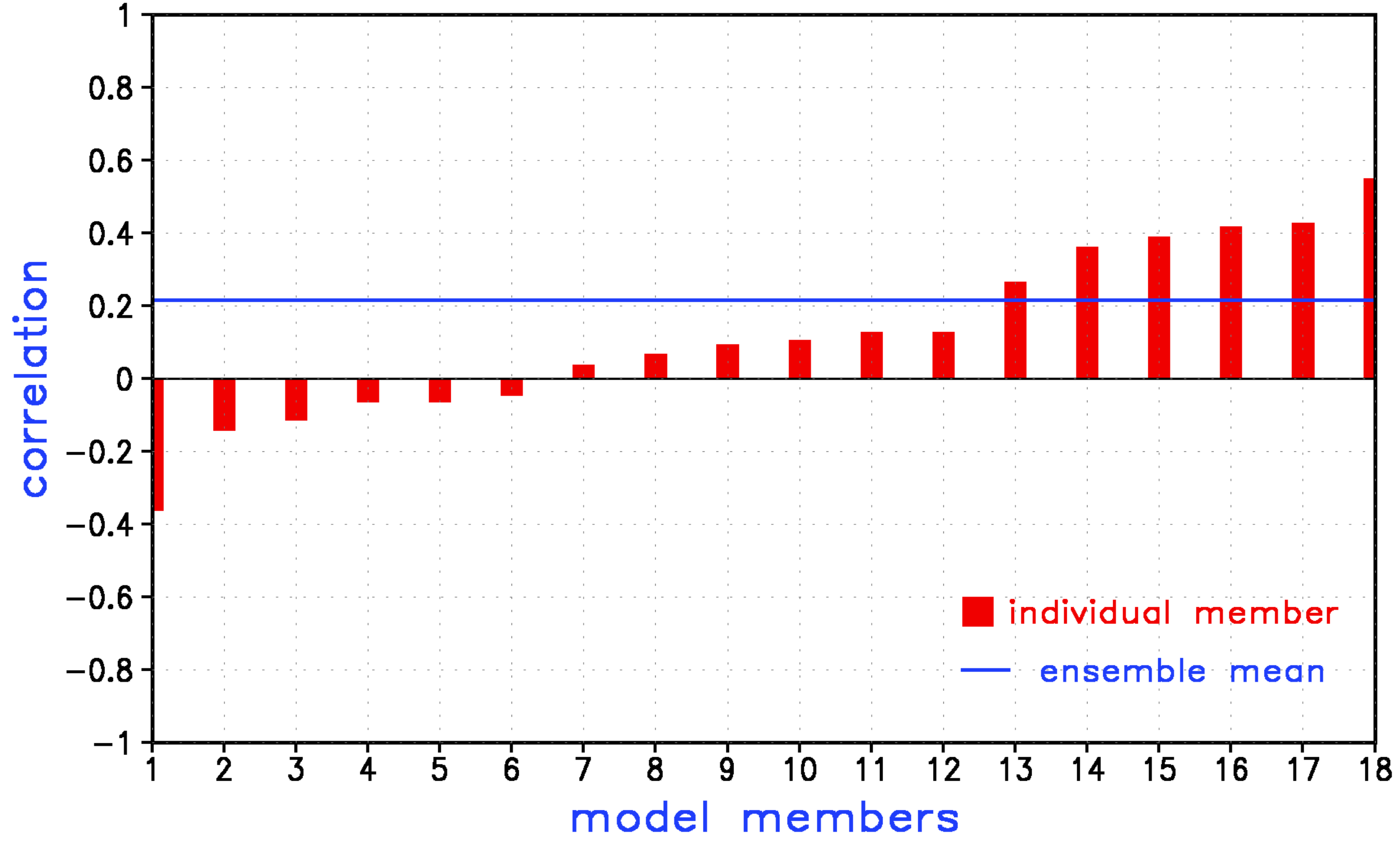


Model Simulated/Forecast Anomalies: Individual Runs

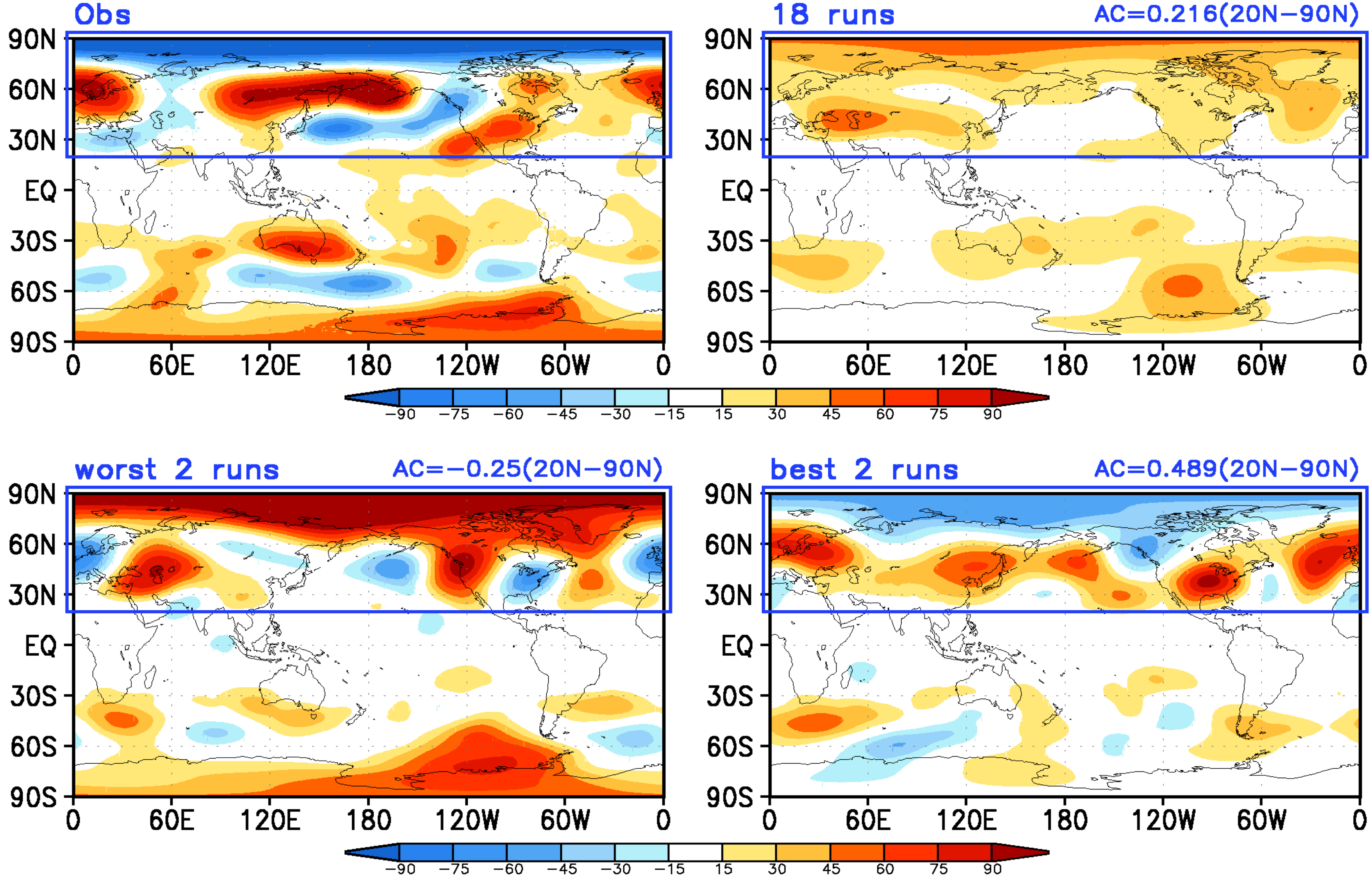
Model Simulated/Forecast Anomalies: Individual Runs

- 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 outcomes.

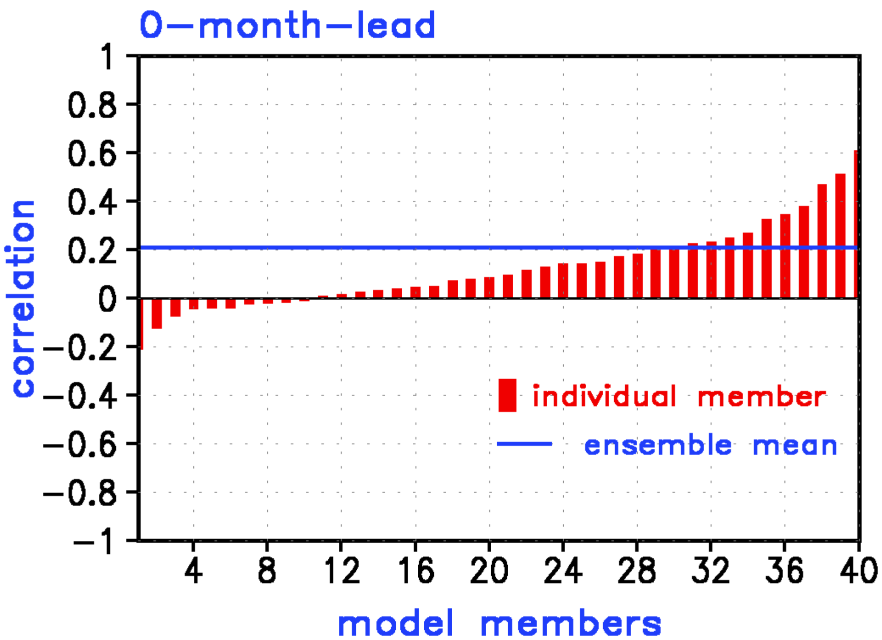
JFM2017 Anomaly Correlation for Individual AMIP Simulation with Observation -- z200(20N-90N)

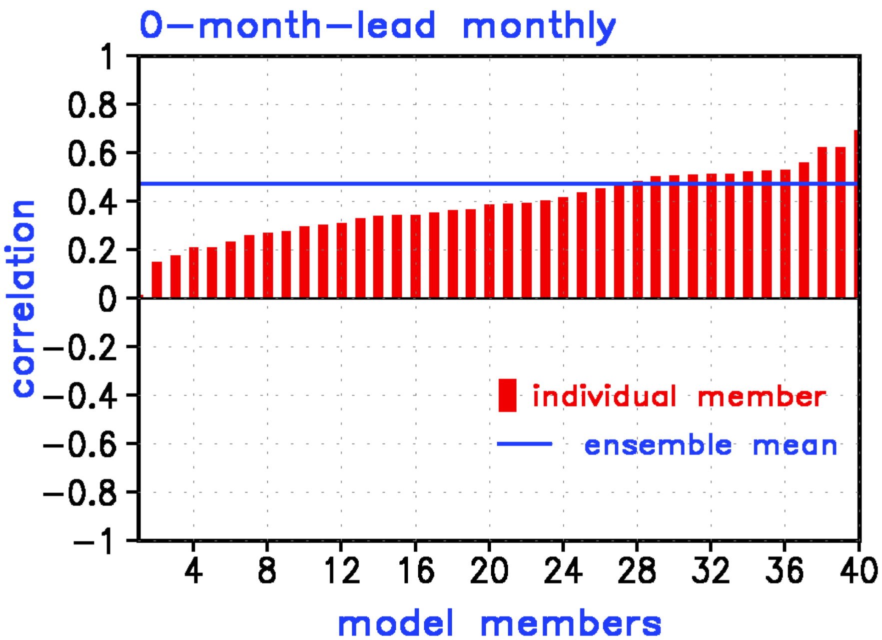


Observed & AMIP Ensemble Average Anomalies
JFM2017 z200(m) 18 runs/worst 2 runs/best 2 runs

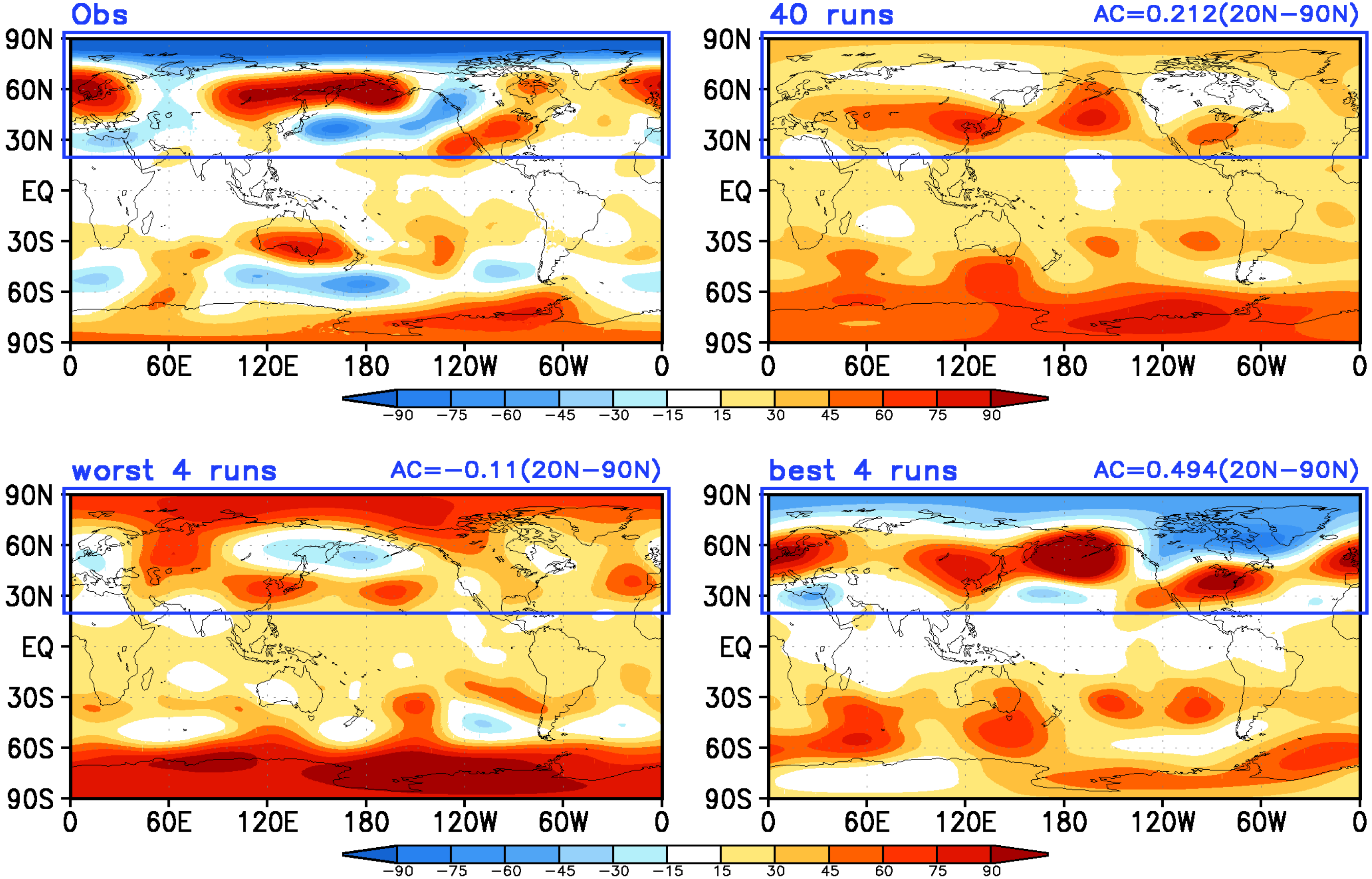


JFM2017 Anomaly Correlation for Individual CFSv2 Forecast with Observation -- z200 (20N-90N)

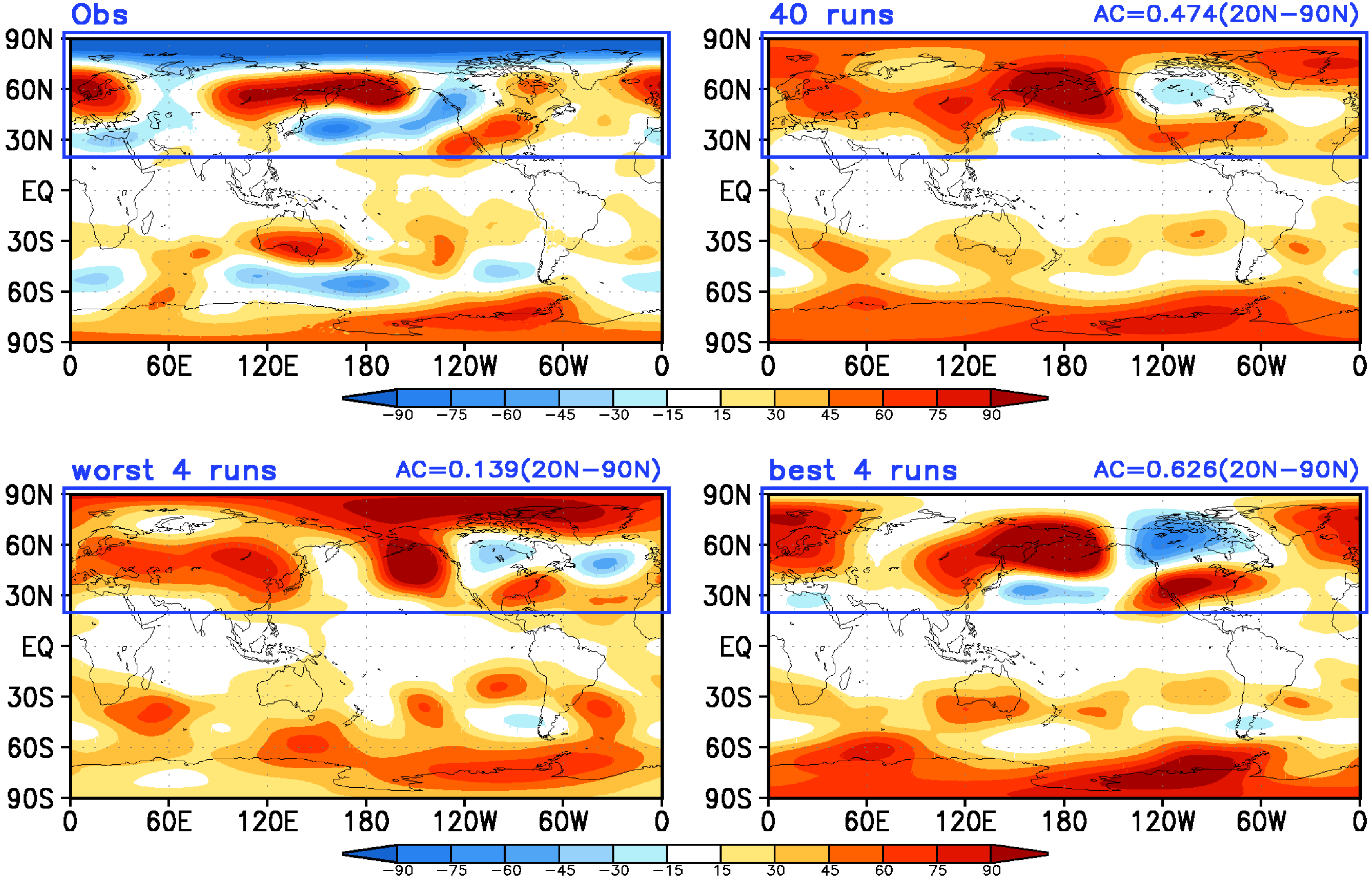




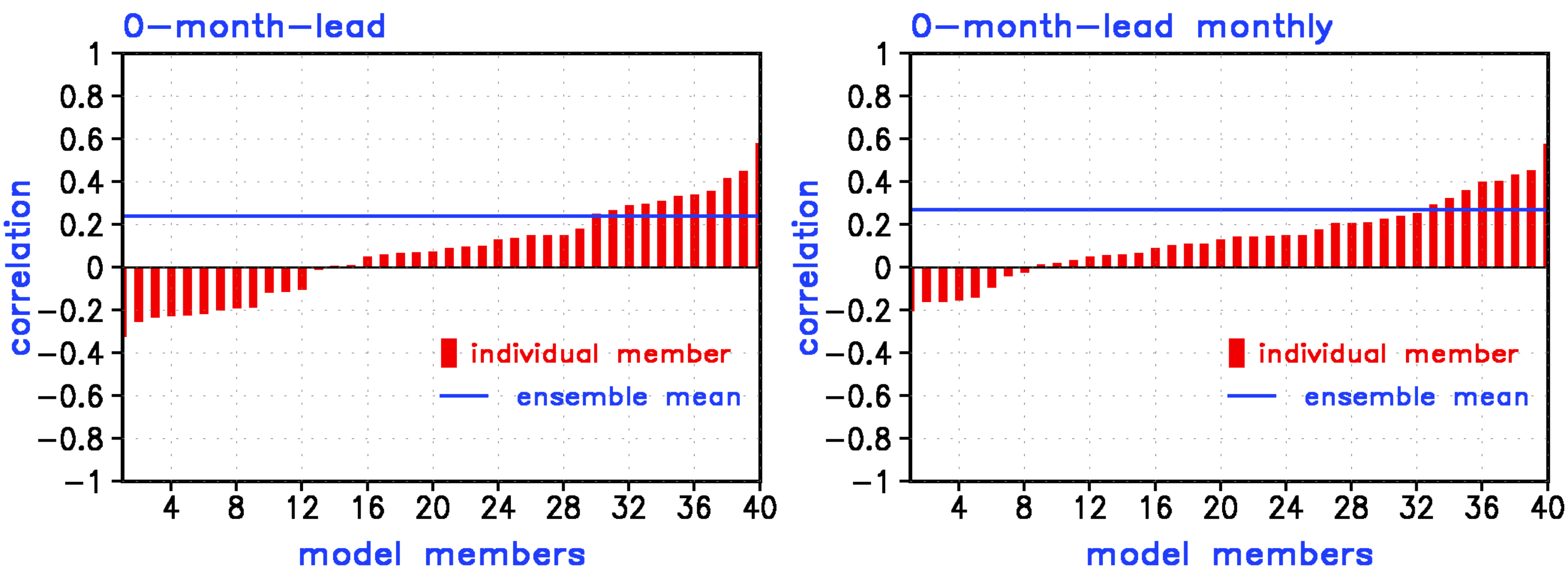
Observed & CFSv2 Forecast Ensemble Average Anomalies
JFM2017 z200(m) 40 runs/worst 4 runs/best 4 runs
0-month-lead



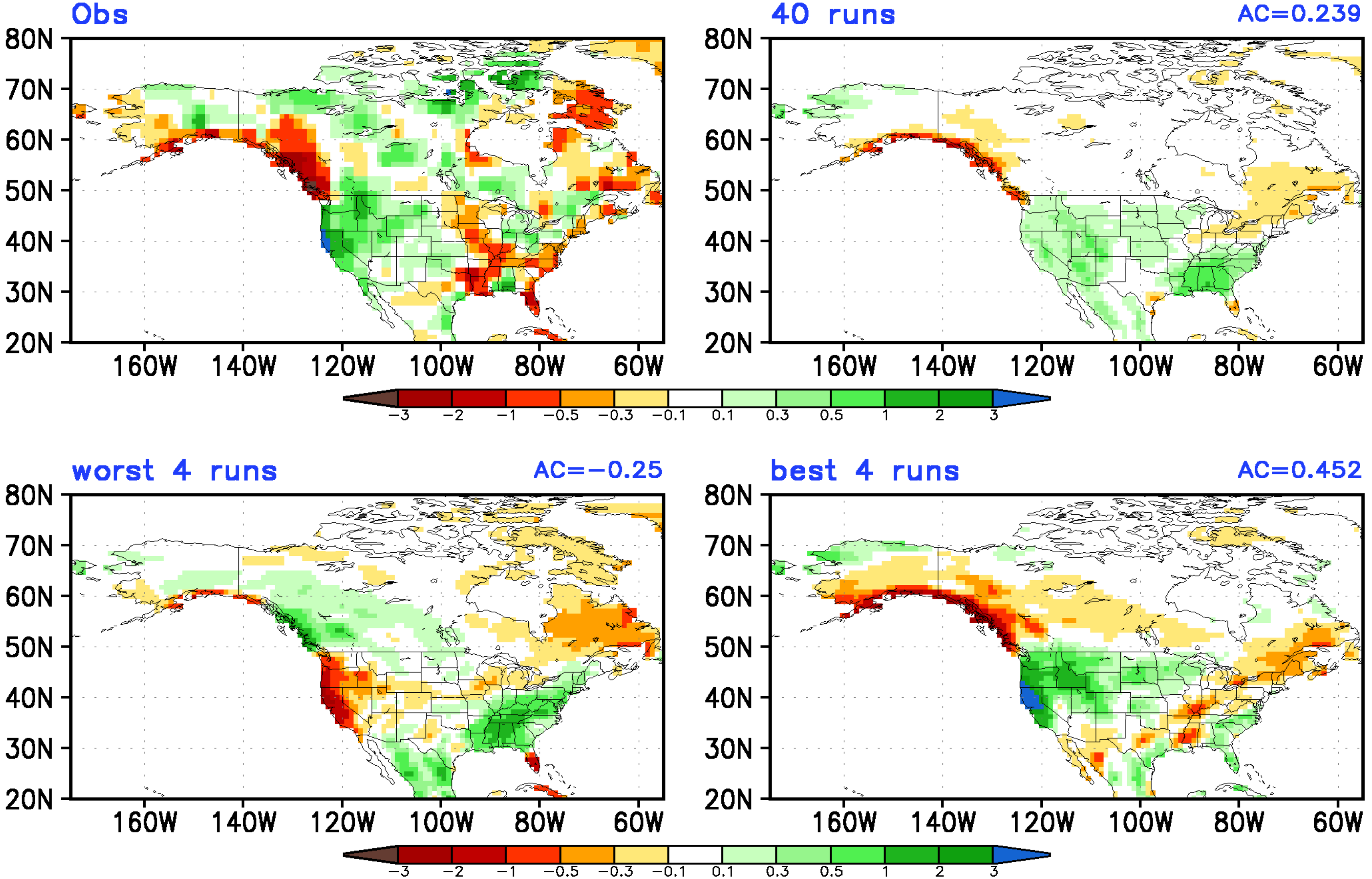
Observed & CFSv2 Forecast Ensemble Average Anomalies
JFM2017 z200(m) 40 runs/worst 4 runs/best 4 runs
0-month-lead monthly



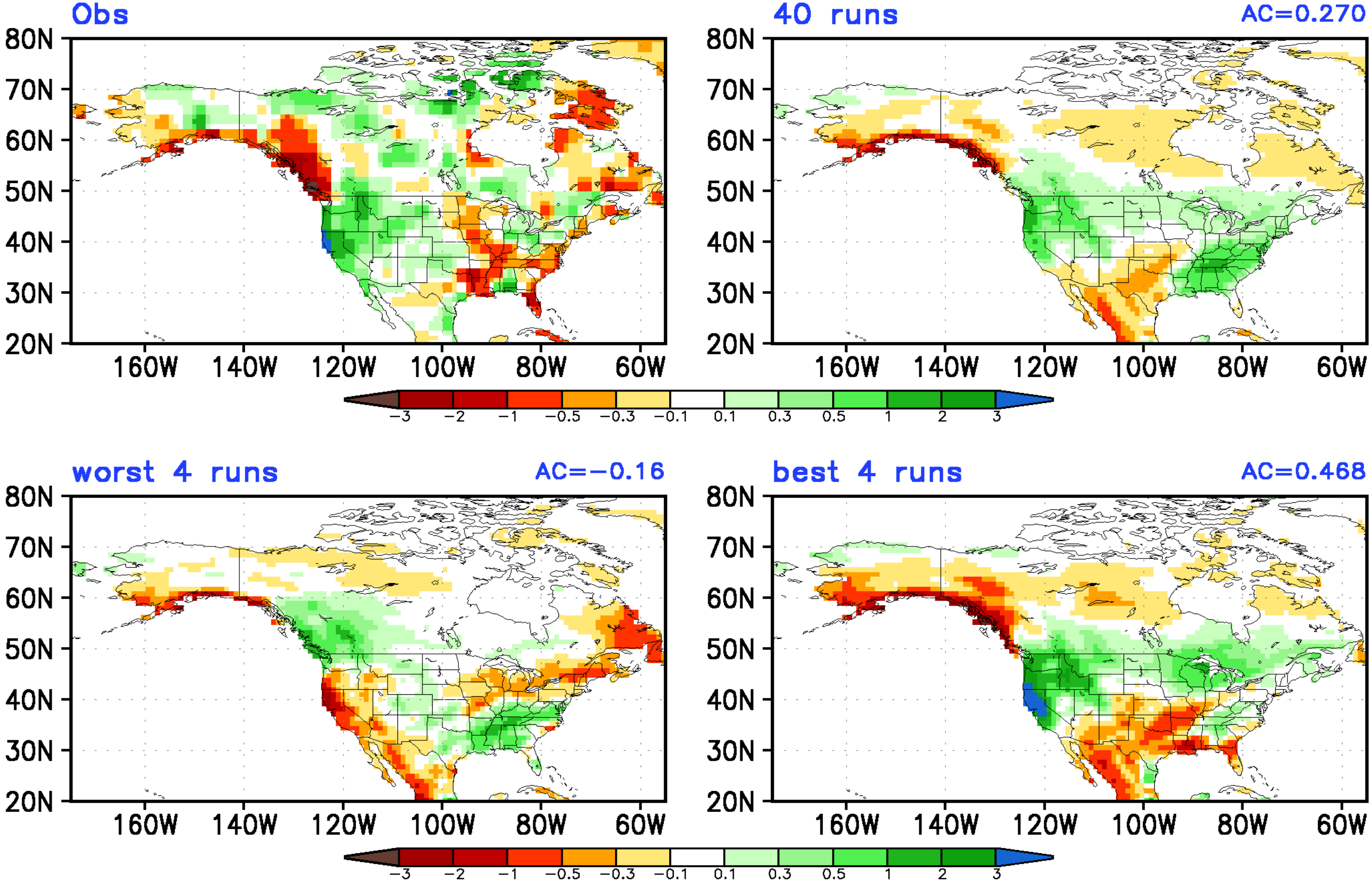
JFM2017 Anomaly Correlation for Individual CFSv2 Forecast with Observation -- Prec (NA)

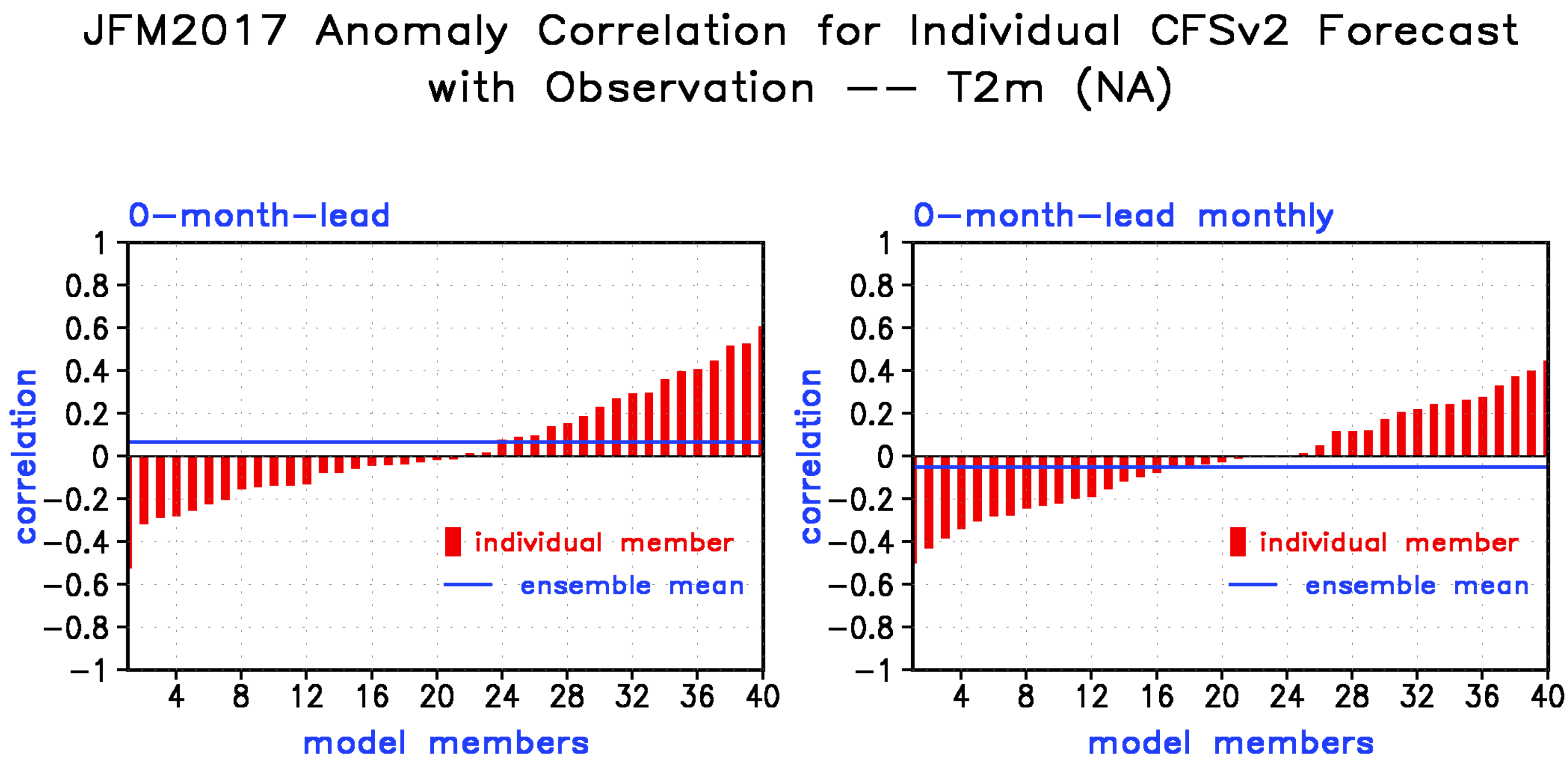


Observed & CFSv2 Forecast Ensemble Average Anomalies
JFM2017 Prec(mm/day) 40 runs/worst 4 runs/best 4 runs
0-month-lead

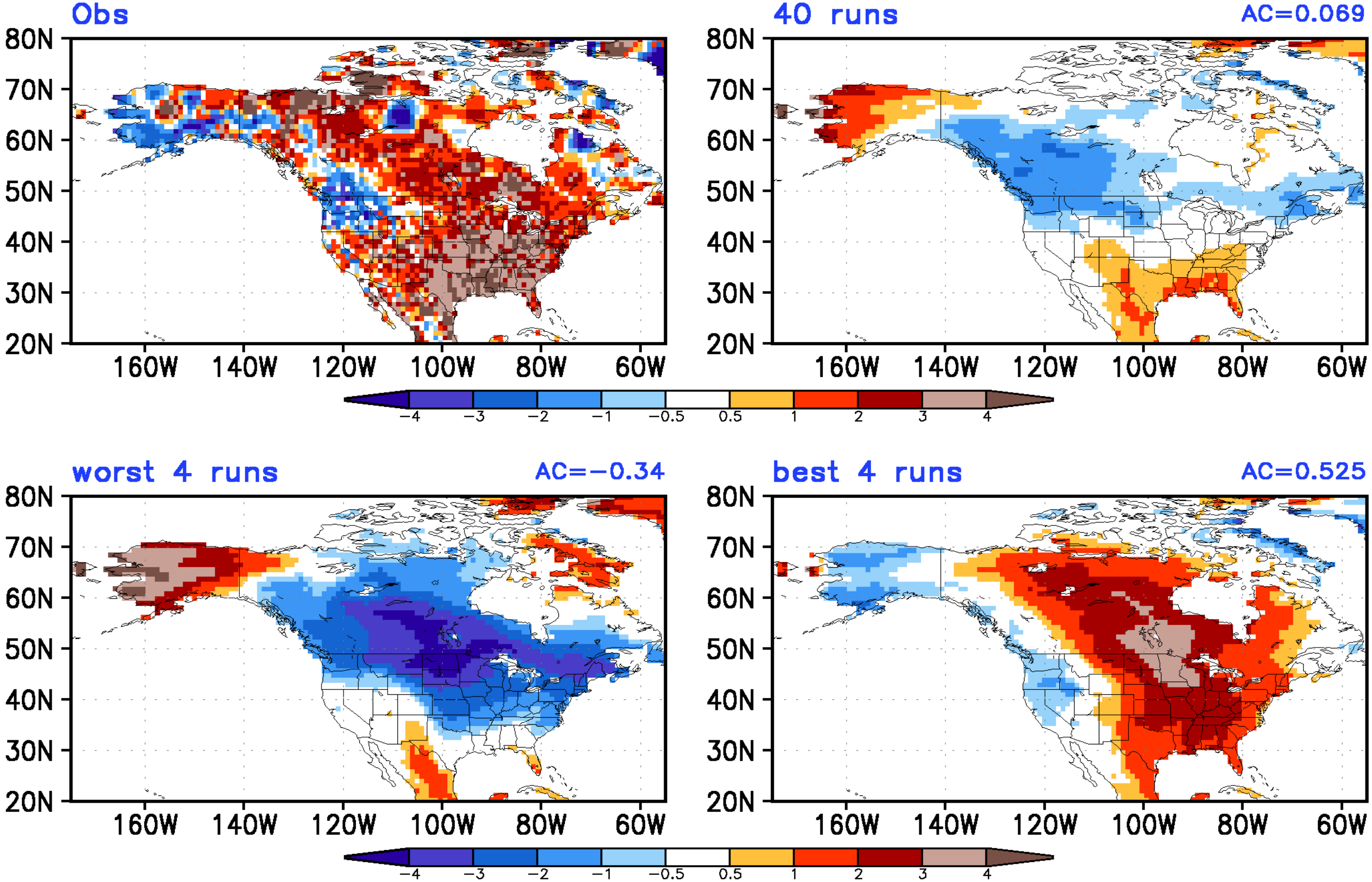


Observed & CFSv2 Forecast Ensemble Average Anomalies JFM2017 Prec(mm/day) 40 runs/worst 4 runs/best 4 runs 0-month-lead monthly

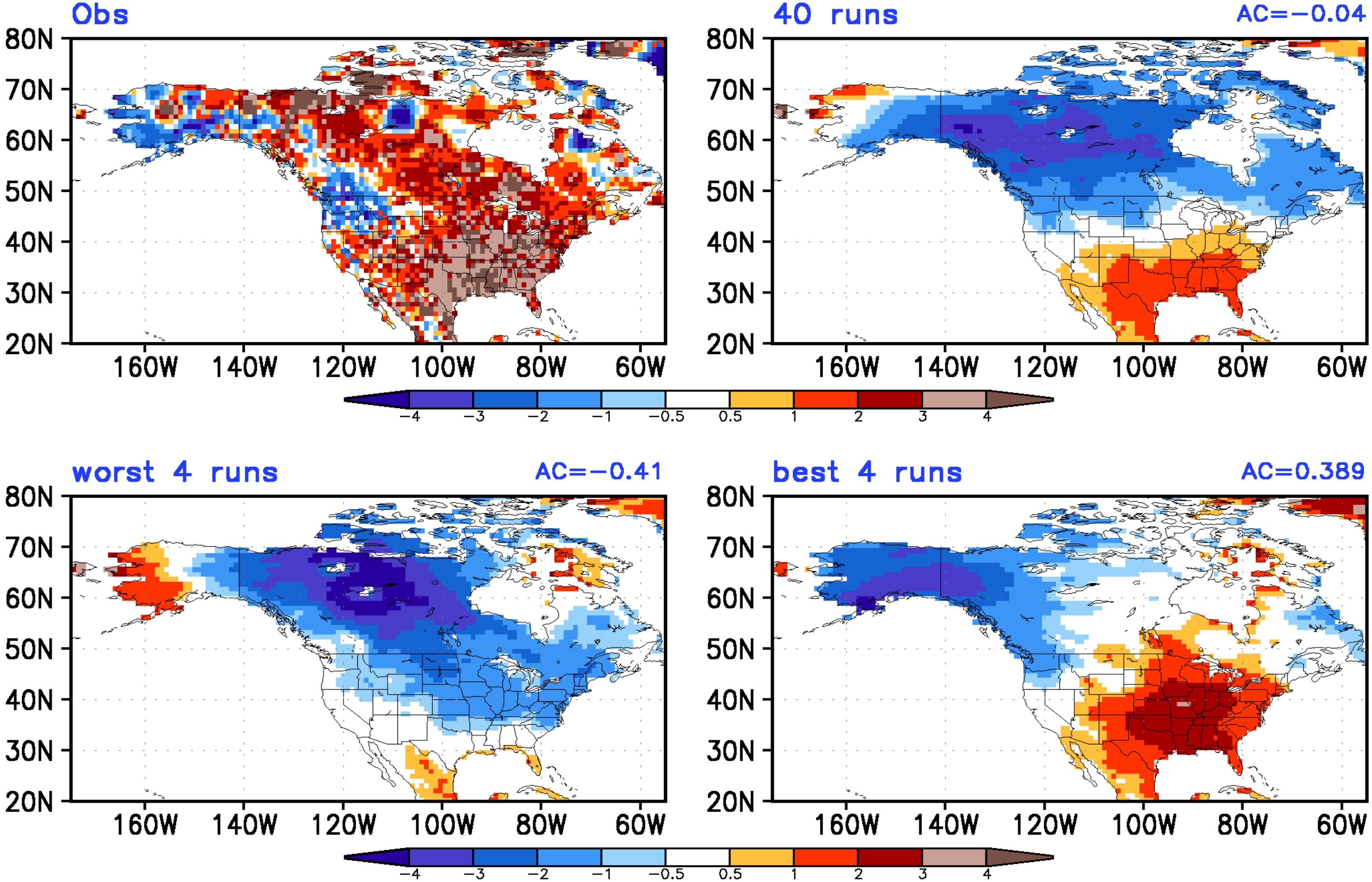



JFM2017 Anomaly Correlation for Individual CFSv2 Forecast with Observation -- T2m (NA)
0-month-lead
0-month-lead monthly
correlation
model members
individual member
ensemble mean
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
4
8
12
16
20
24
28
32
36
40

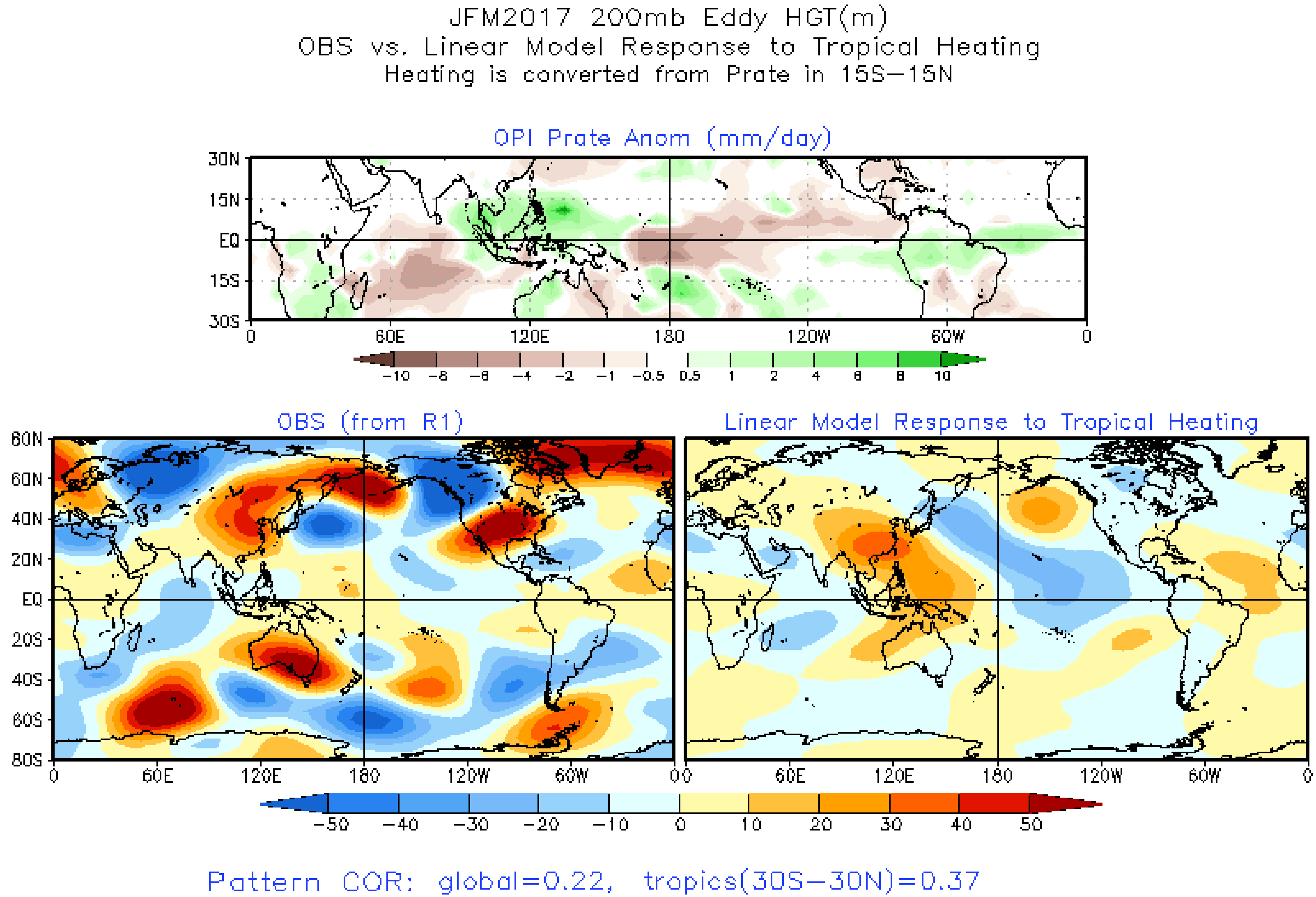
Observed & CFSv2 Forecast Ensemble Average Anomalies
JFM2017 T2m(K) 40 runs/worst 4 runs/best 4 runs
0-month-lead



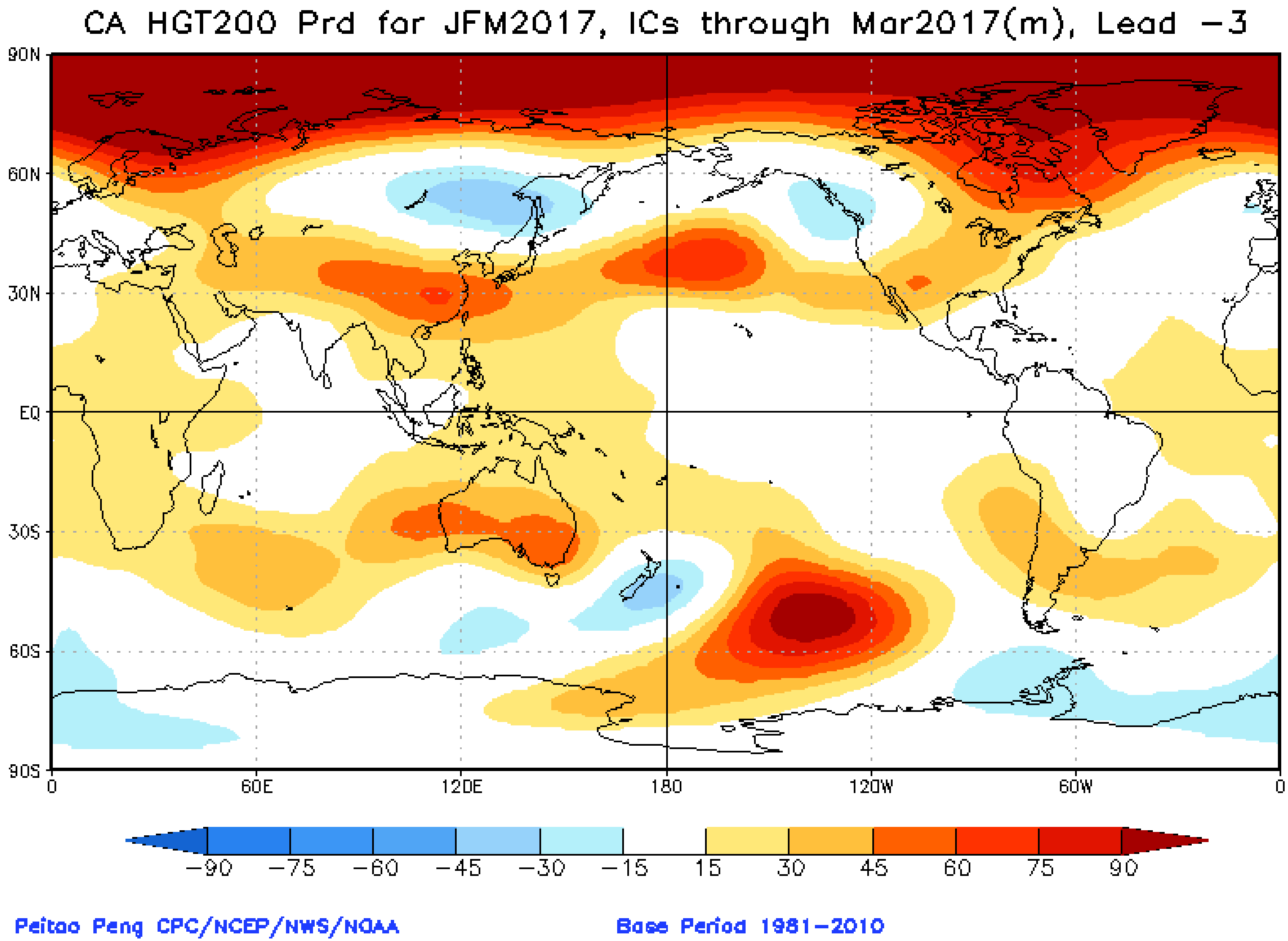
Observed & CFSv2 Forecast Ensemble Average Anomalies JFM2017 T2m(K) 40 runs/worst 4 runs/best 4 runs 0-month-lead monthly

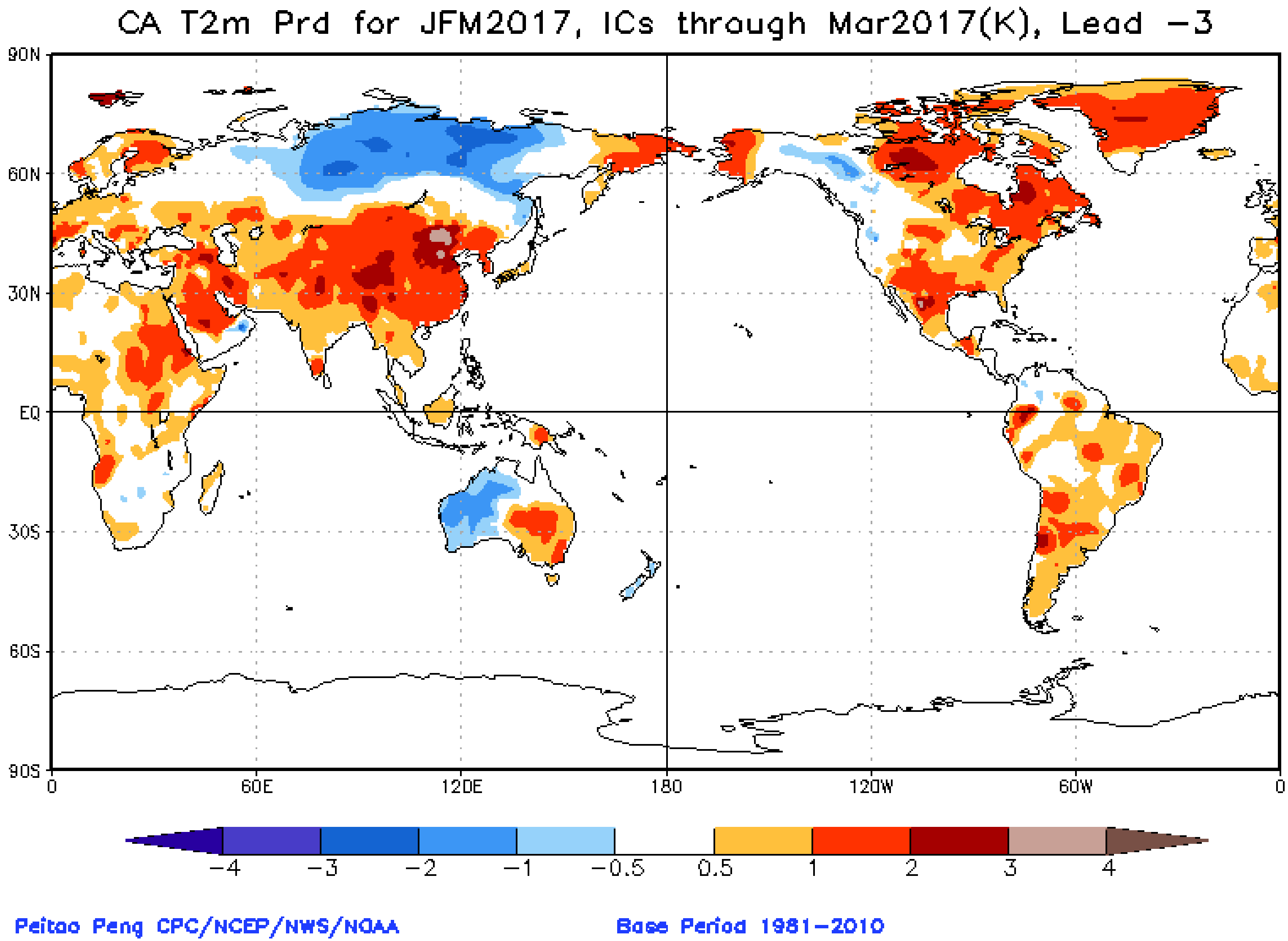


200mb Height from Linear Model

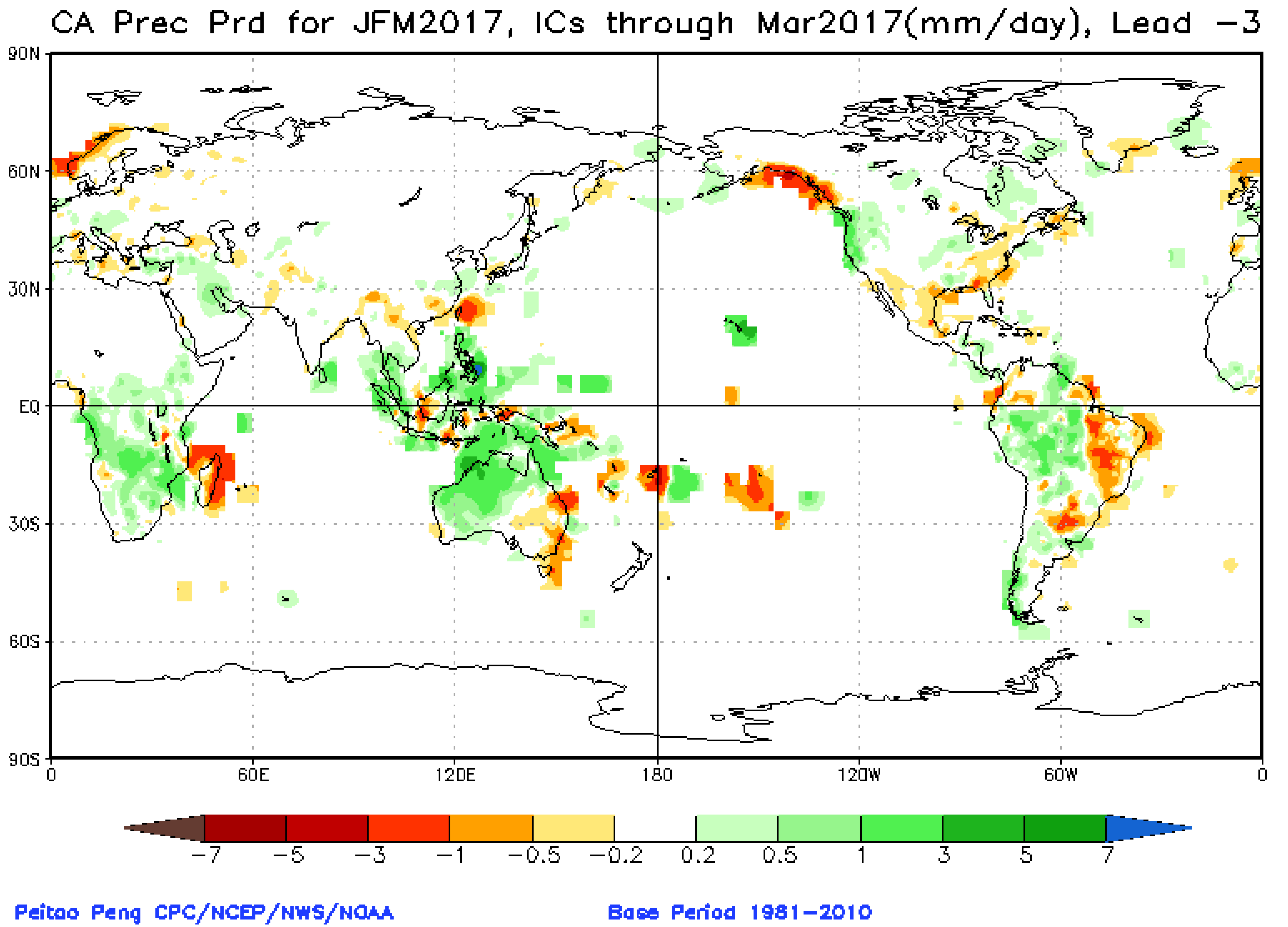

JFM2017 200mb Eddy HGT(m)
OBS vs. Linear Model Response to Tropical Heating
Heating is converted from Prate in 15S–15N
OPI Prate Anom (mm/day)
30N 15N EQ 15S 30S
0 60E 120E 180 120W 60W 0
−10 −8 −6 −4 −2 −1 −0.5 0.5 1 2 4 6 8 10
OBS (from R1)
Linear Model Response to Tropical Heating
80N 60N 40N 20N EQ 20S 40S 60S 80S
0 60E 120E 180 120W 60W 0
−50 −40 −30 −20 −10 0 10 20 30 40 50
Pattern COR: global=0.22, tropics(30S–30N)=0.37

Seasonal Forecasts from the Constructed Analog Model


CA HGT200 Prd for JFM2017, ICs through Mar2017(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 JFM2017, ICs through Mar2017(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 JFM2017, ICs through Mar2017(mm/day), Lead -3
90N
60N
30N
EQ
30S
60S
90S
0
60E
120E
180
120W
60W
0
-7
-5
-3
-1
-0.5
-0.2
0.2
0.5
1
3
5
7
Peitao Peng CPC/NCEP/NWS/NOAA
Base Period 1981-2010

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 not forecasted well in CFSv2, but the skill improved largely in the constructed monthly-seasonal mean forecasts because of the influences from the shorter lead initial conditions.
- For the ensemble means, both the AMIP runs and initialized forecasts captured only the negative anomalous precipitation over the central to eastern tropical Pacific, but not the positive anomalies over the western Pacific-Maritime Continent; the models didn’t forecast well the PNA height anomalies, and the NA Prec and T2m neither.
- For the individual members, the PNA z200, NA Prec and T2m correlation skills have large variations between members, almost half of 40 members show negative skills.
- The Constructed Analog model forecasted reasonably well the high/low centers in z200 over the NA, and seems showed better skill for NA Prec and T2m than that in the dynamical models.

References

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