Attribution of Seasonal Climate Anomalies

August-September-October 2016

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).

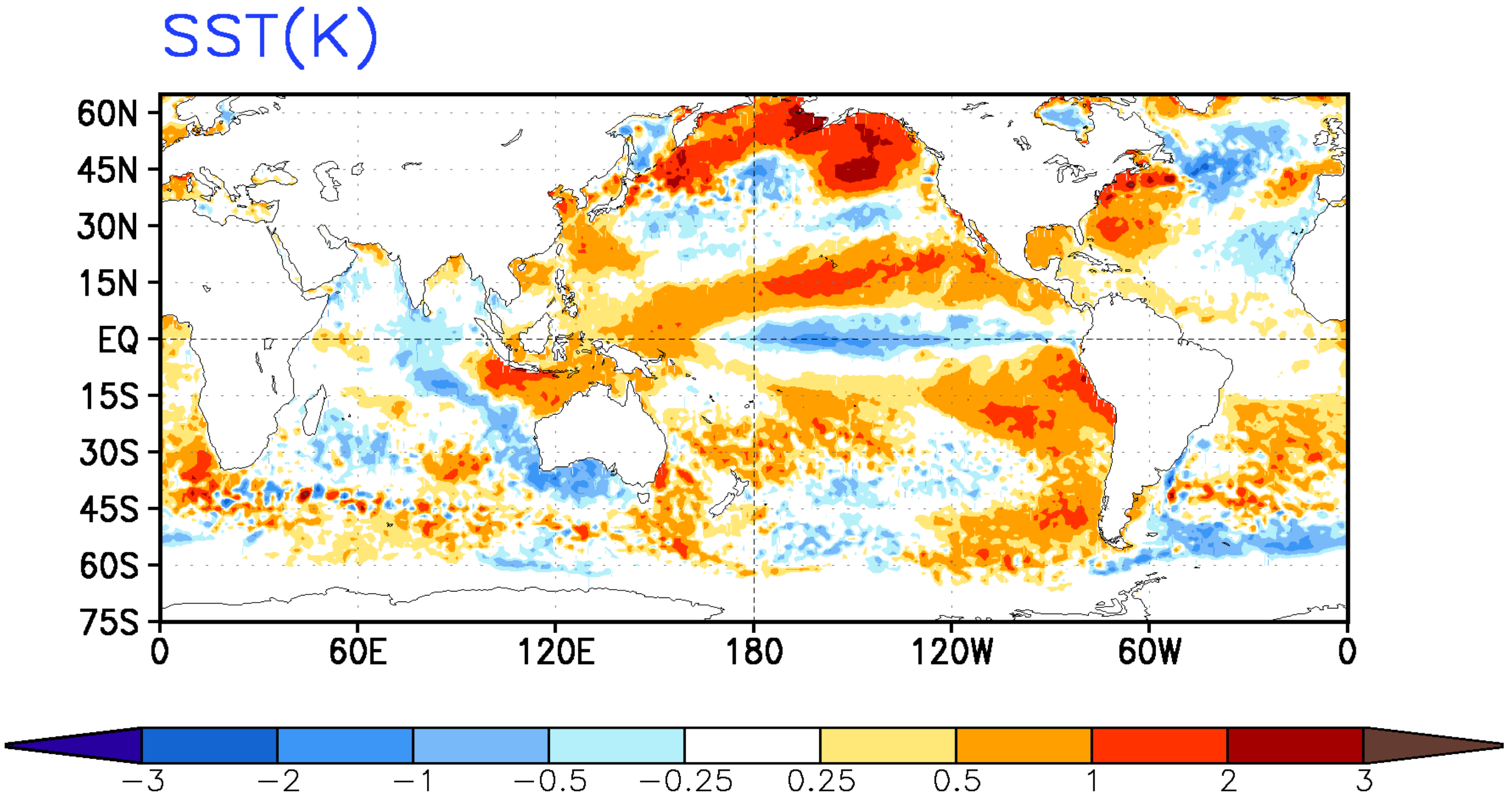
Data

- Observations
  - SST: NCDC daily OI analysis (Reynolds et al., 2007)
  - Prec: CAMS-OPI monthly analysis (Janowiak and Xie, 1999)
  - 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. Huug van den Dool)

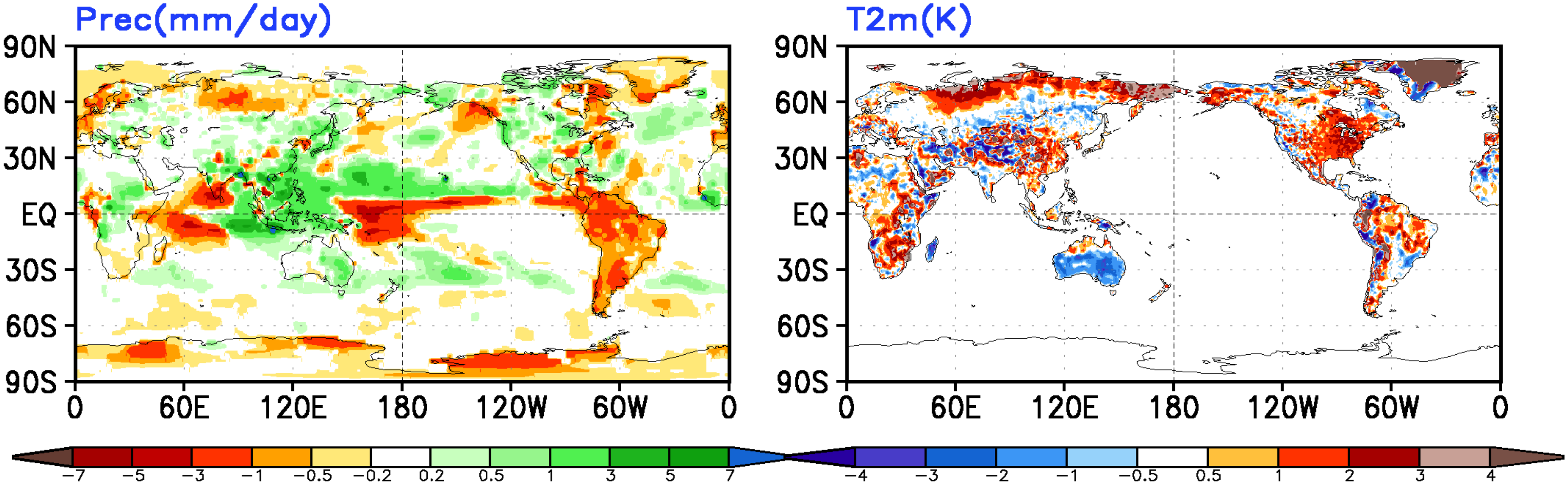
Observed Seasonal Anomalies

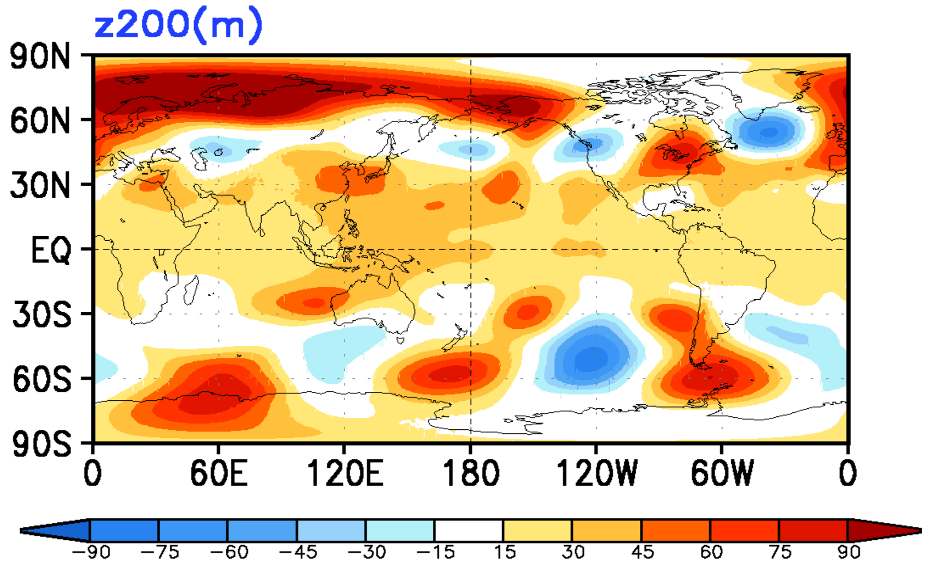
Global and North America

Observed Anomaly ASO2016

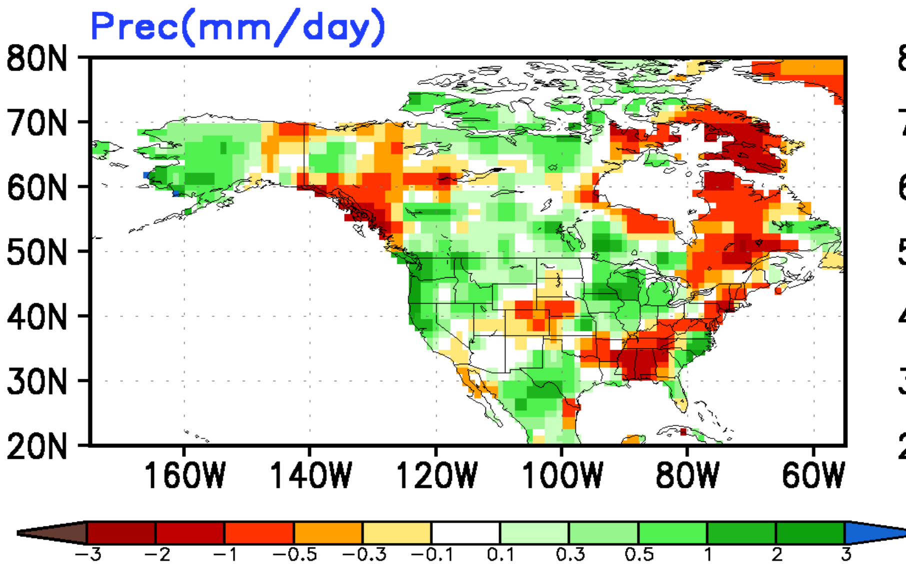


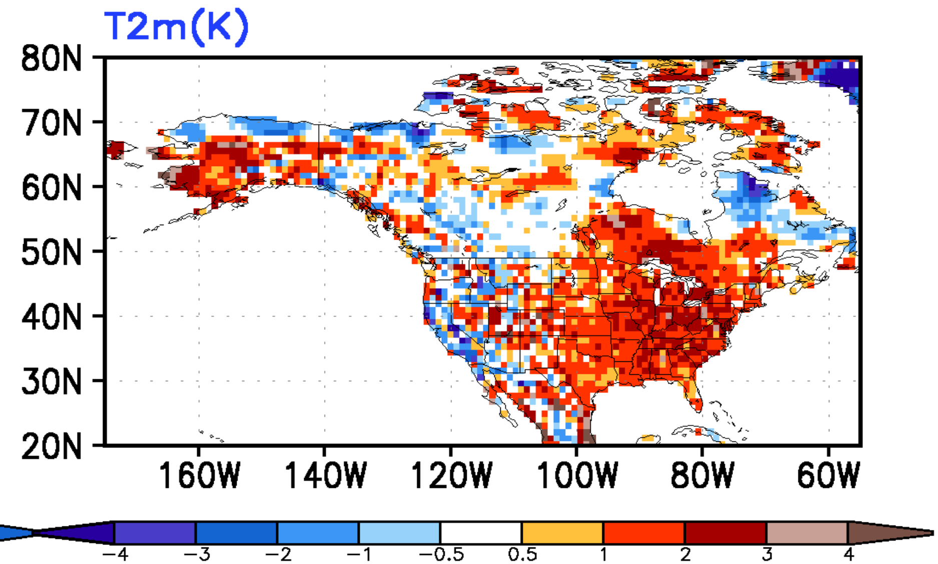
Observed Anomaly ASO2016

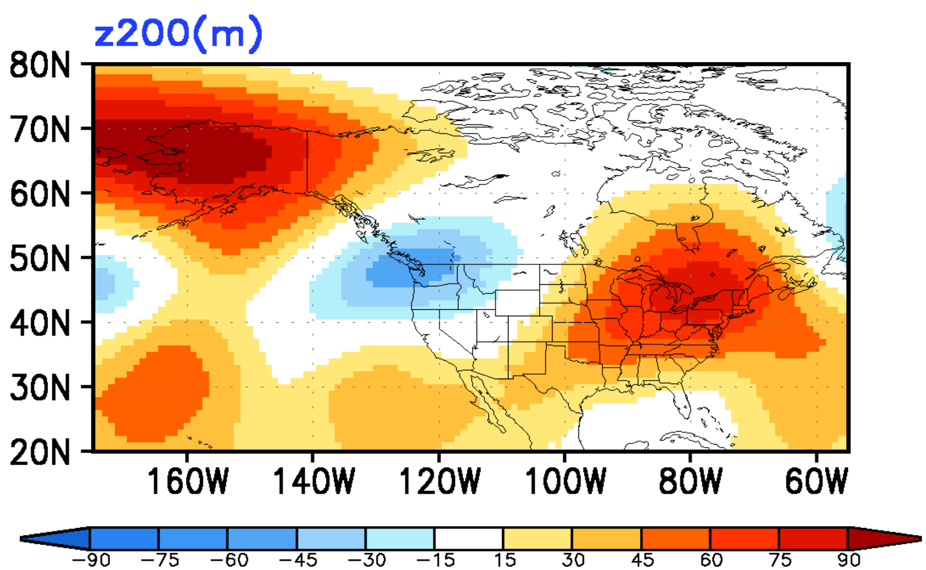




Observed Anomaly ASO2016





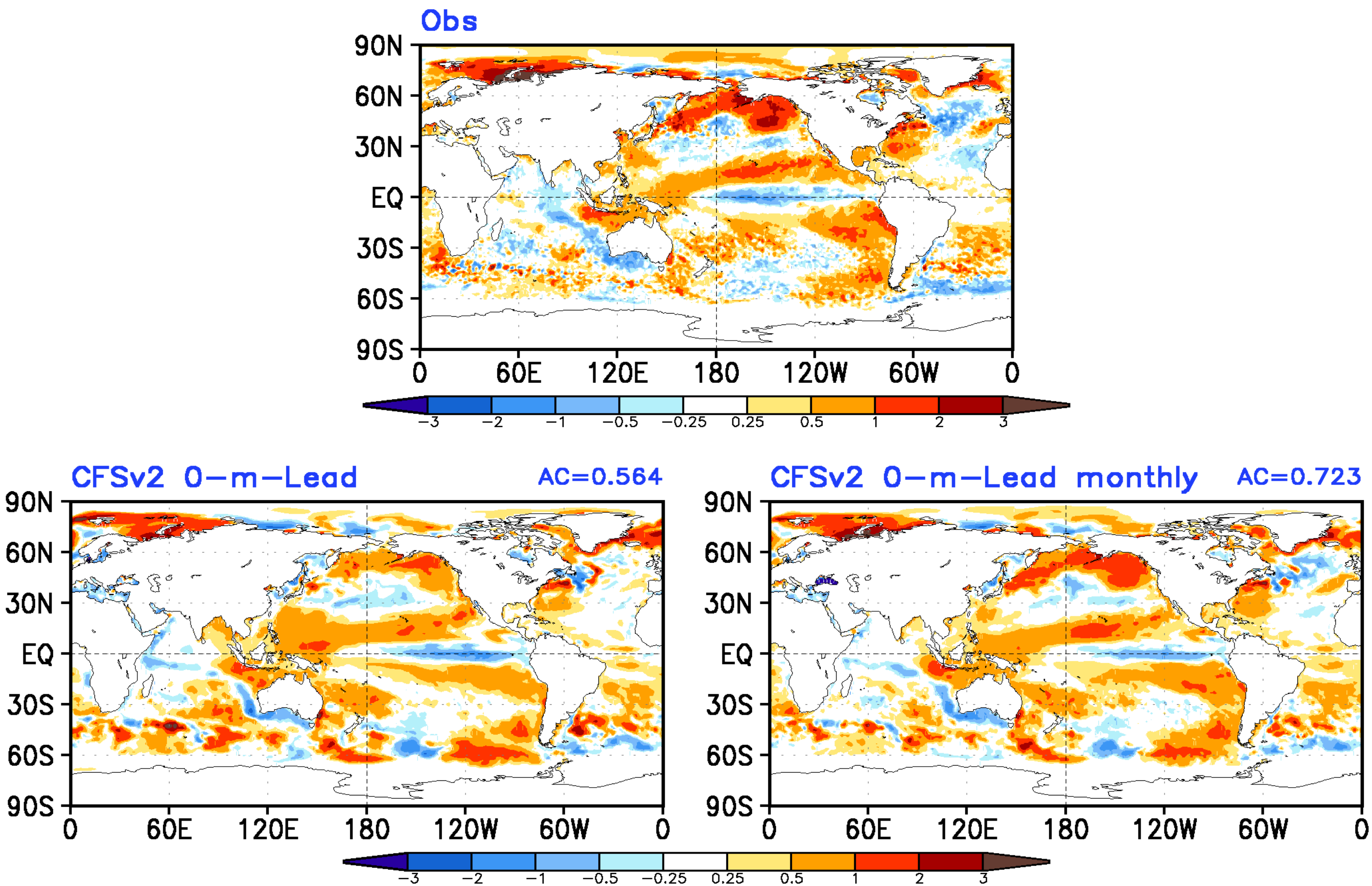


Model Simulated/Forecast Ensemble Average Anomalies

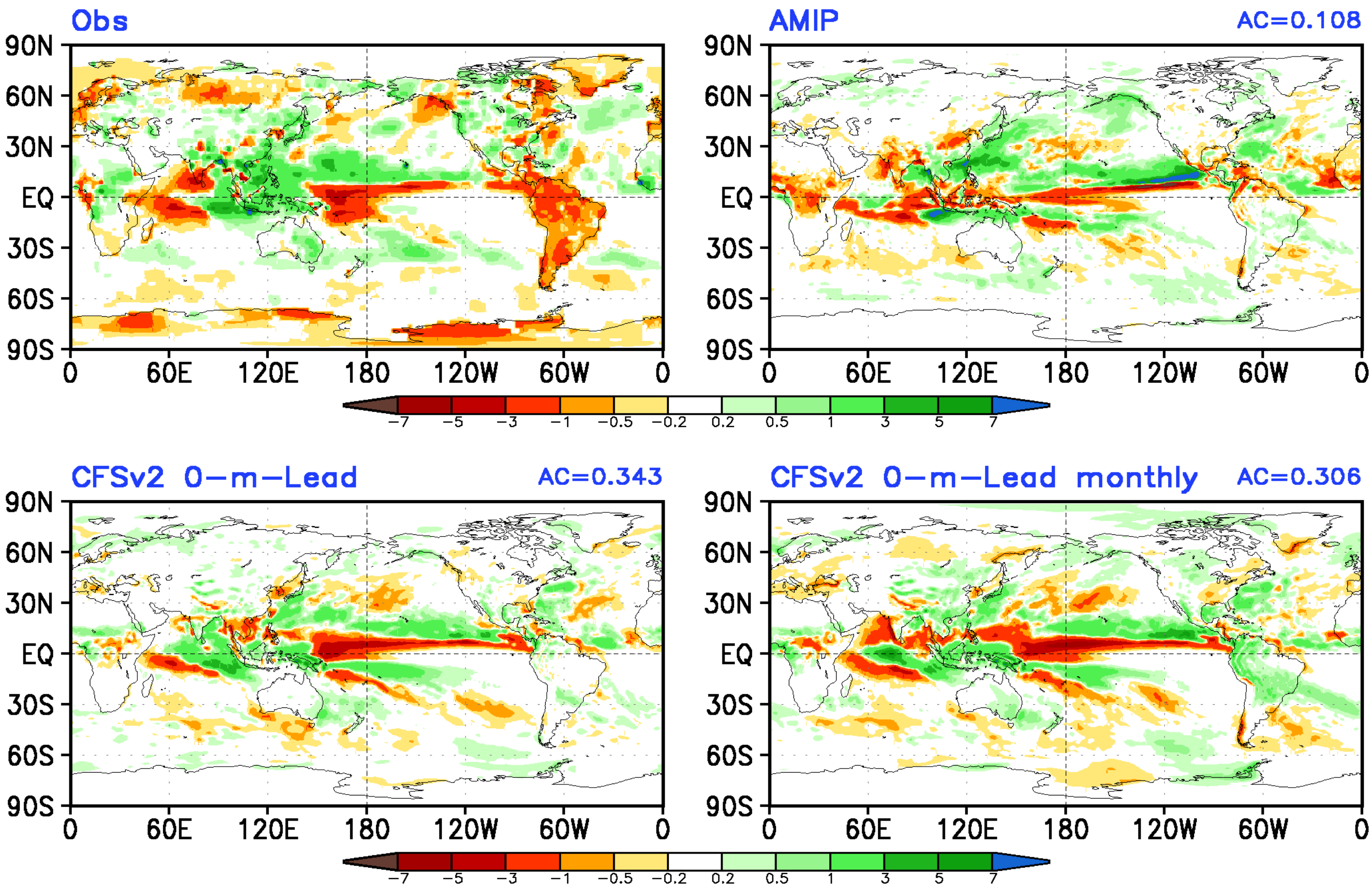
Model Simulated/Forecast Ensemble Average Anomalies

- 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).

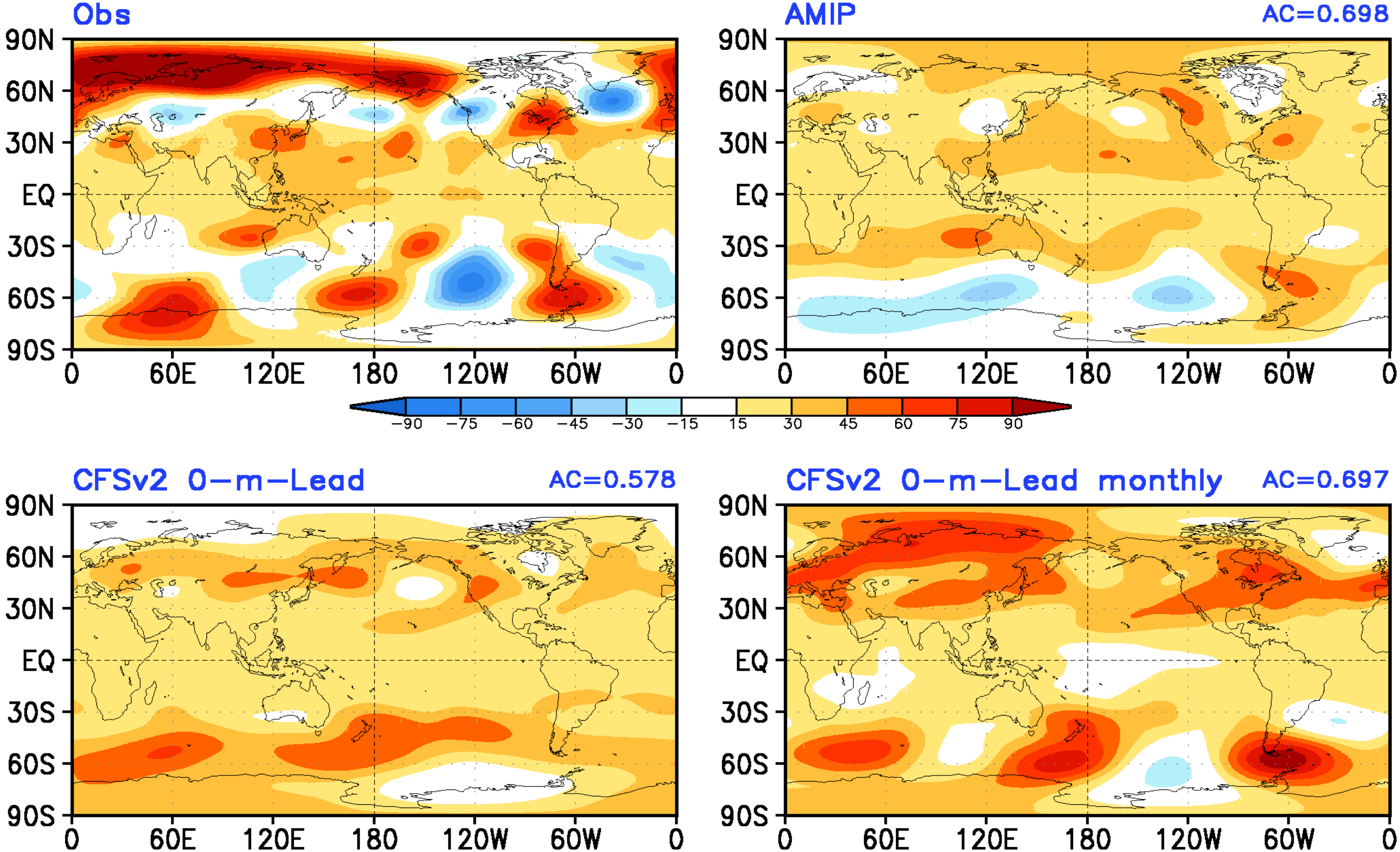
ASO2016 Observed & Model Simulated/Forecast Ensemble Average Anomalies SST(K)



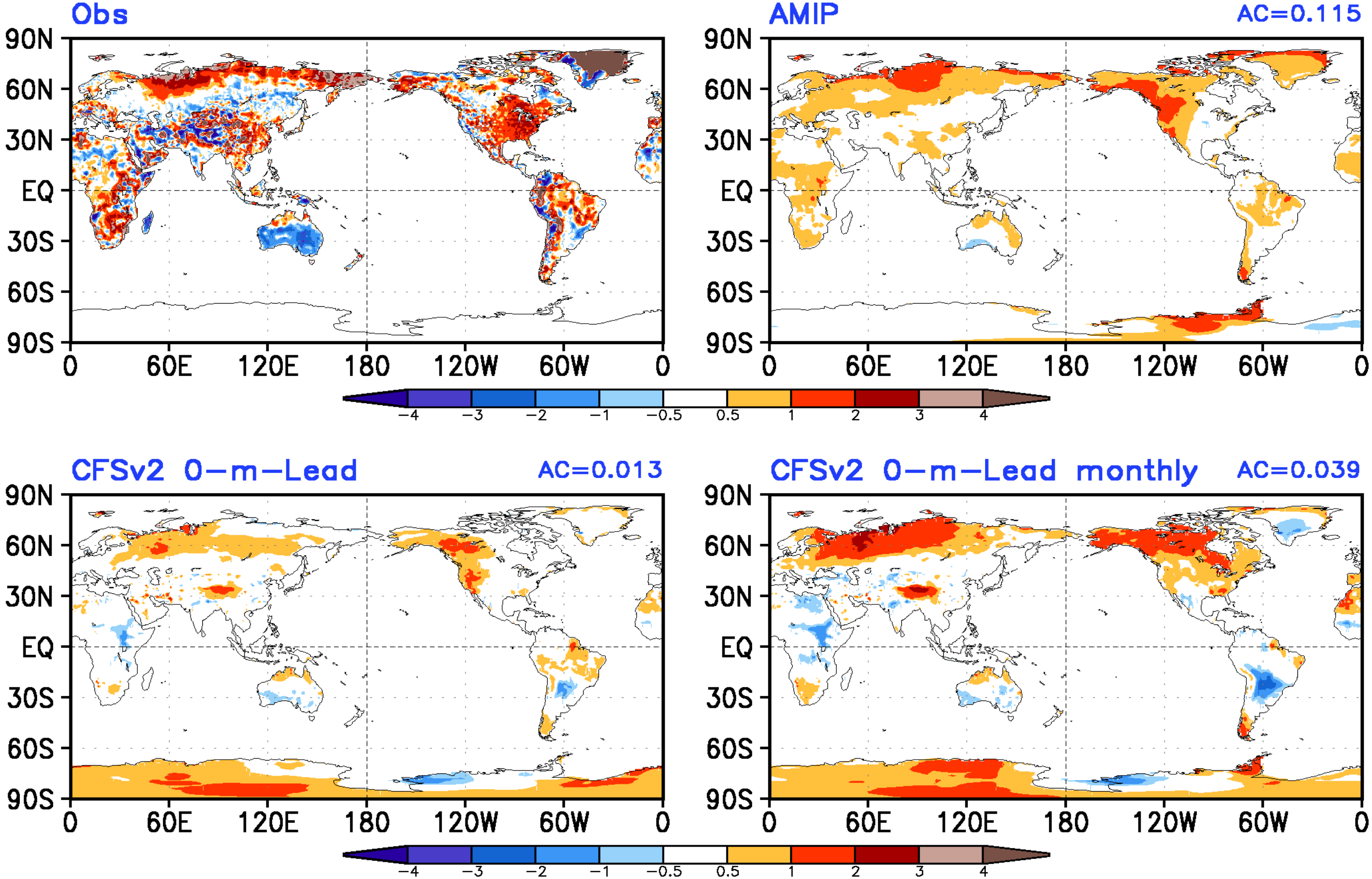
ASO2016 Observed & Model Simulated/Forecast Ensemble Average Anomalies Prec(mm/day)



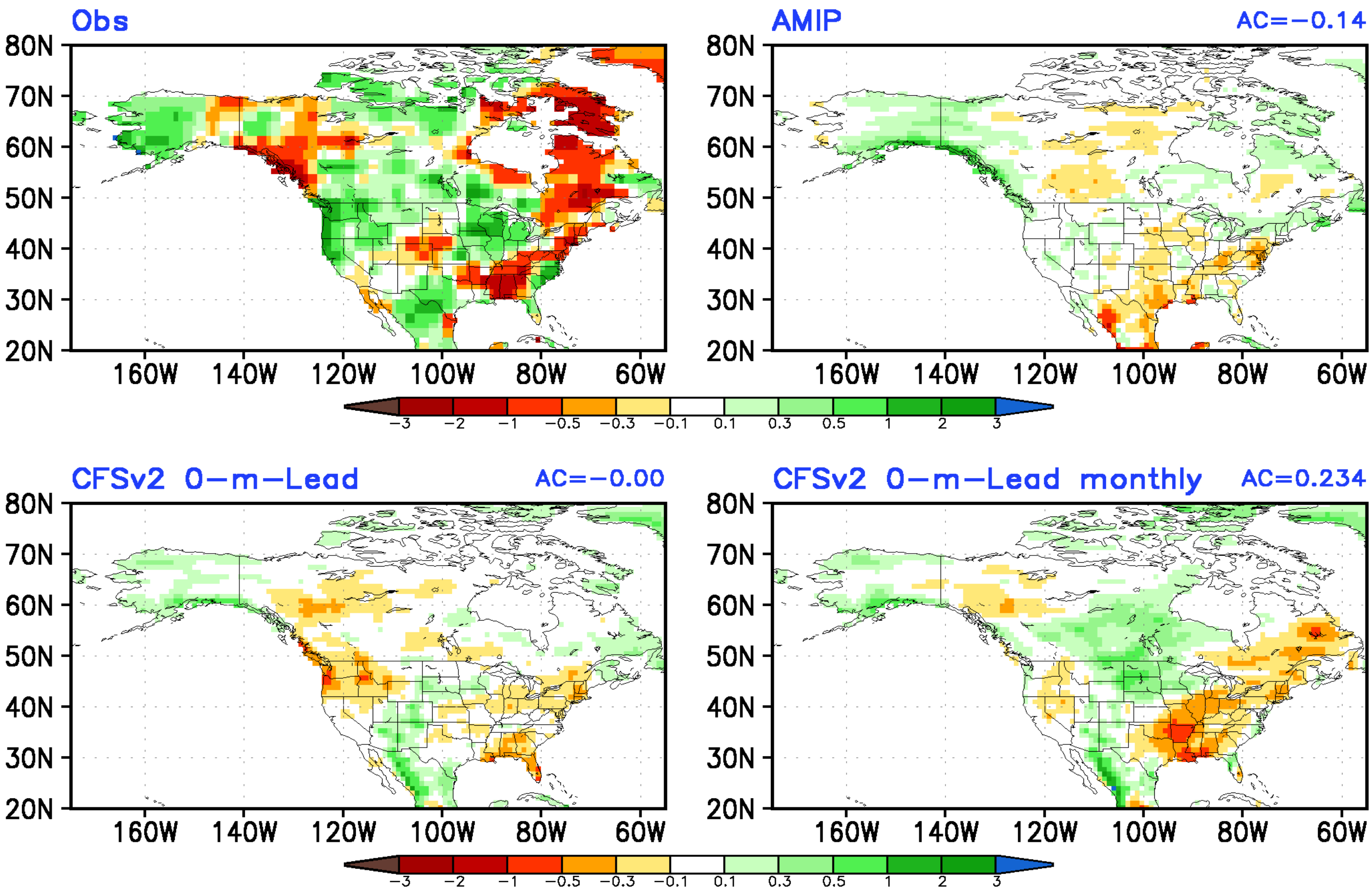
ASO2016 Observed & Model Simulated/Forecast Ensemble Average Anomalies z200(m)



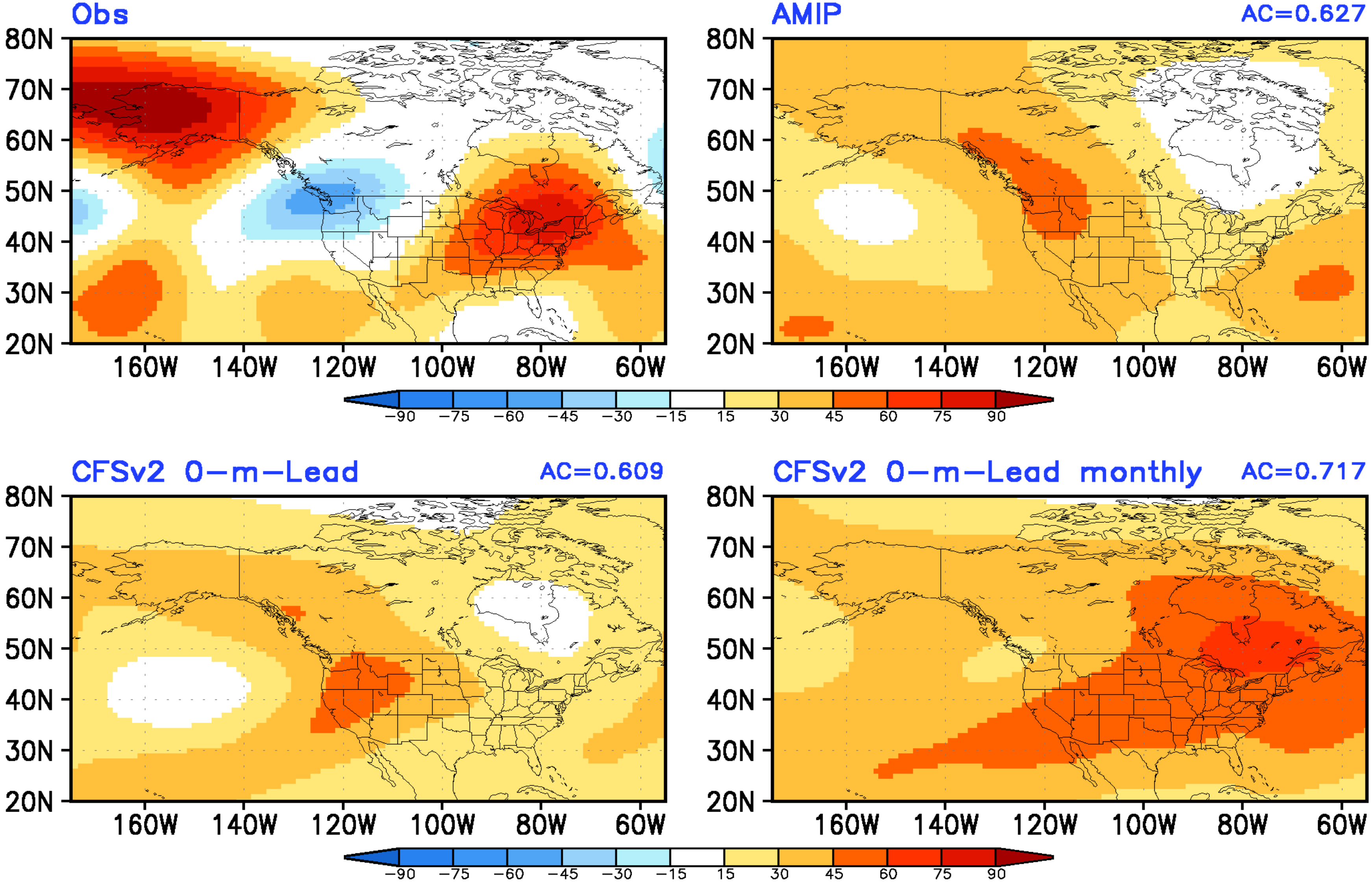
ASO2016 Observed & Model Simulated/Forecast Ensemble Average Anomalies T2m(K)



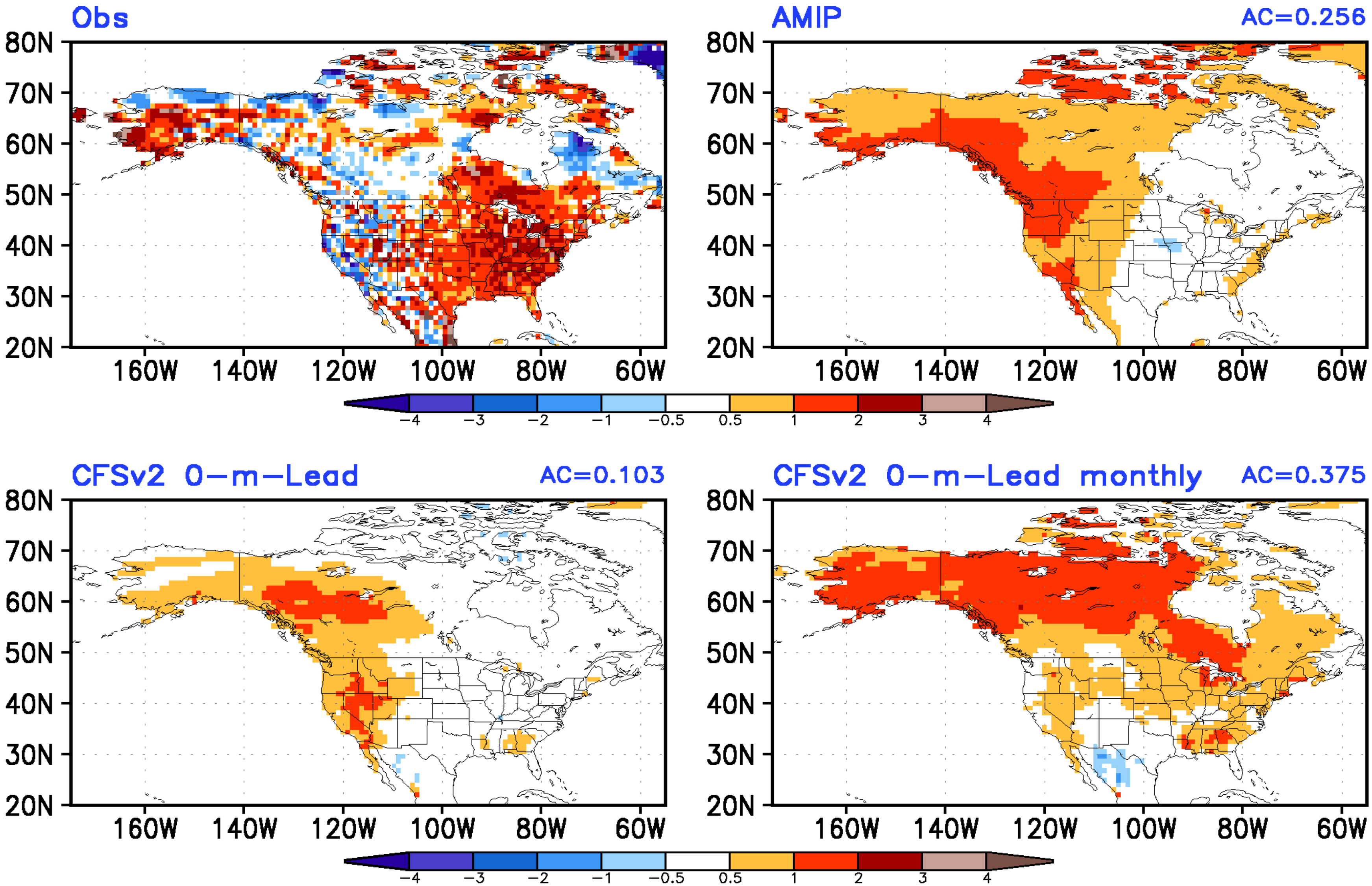
ASO2016 Observed & Model Simulated/Forecast Ensemble Average Anomalies Prec(mm/day)



ASO2016 Observed & Model Simulated/Forecast Ensemble Average Anomalies z200(m)



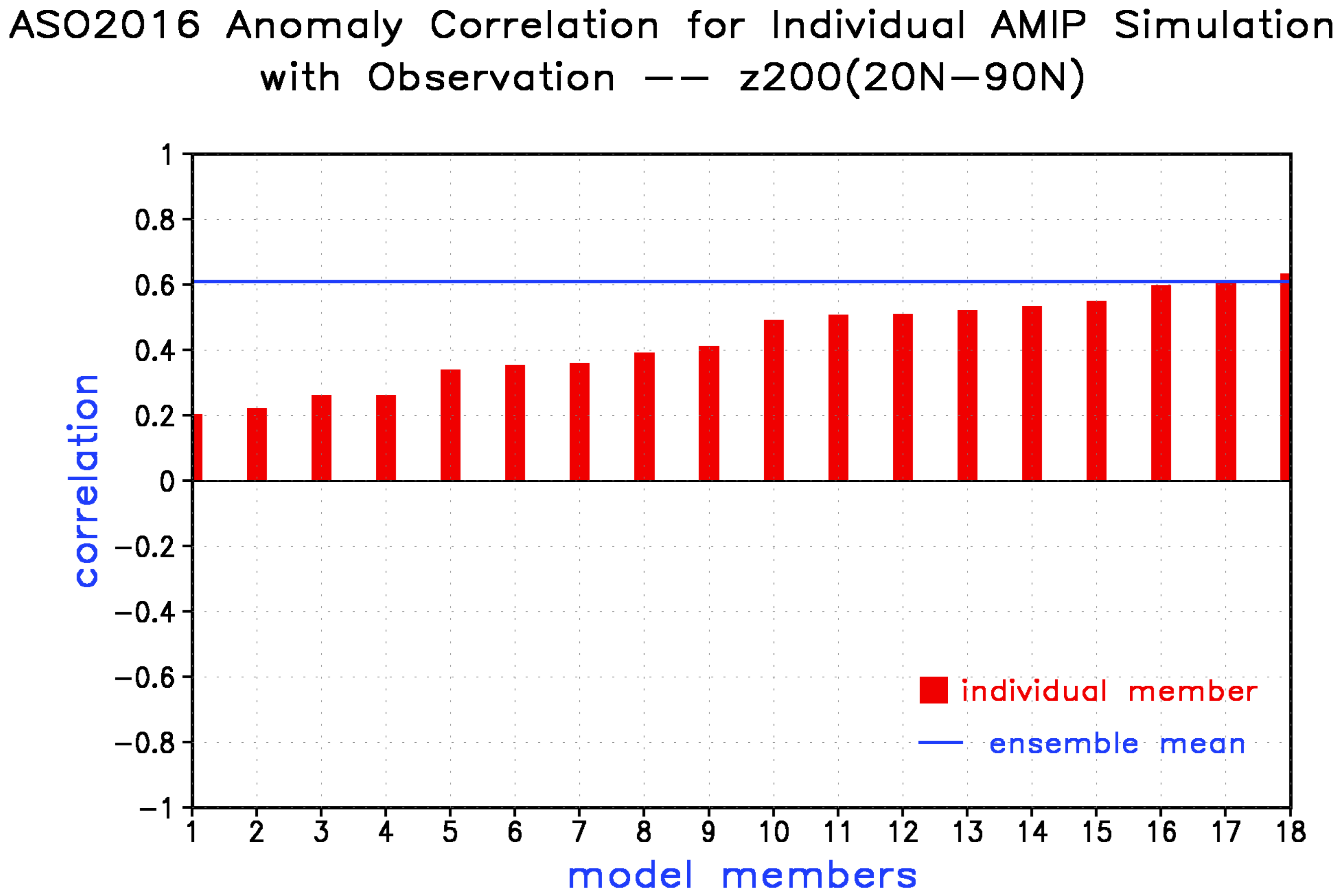
ASO2016 Observed & Model Simulated/Forecast Ensemble Average Anomalies T2m(K)



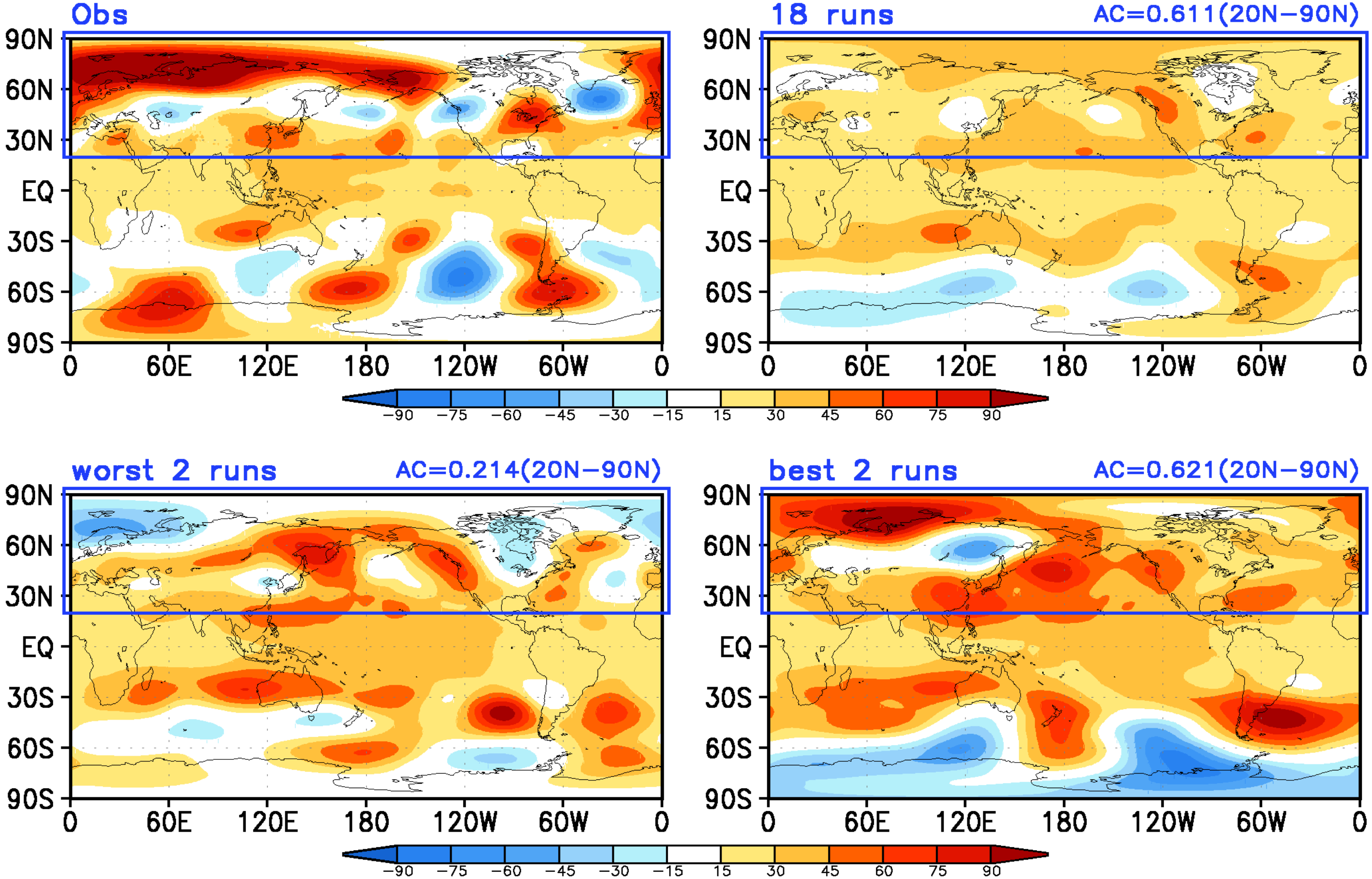
Model Simulated/Forecast Anomalies: Individual Runs

Model Simulated/Forecast Anomalies: Individual Runs

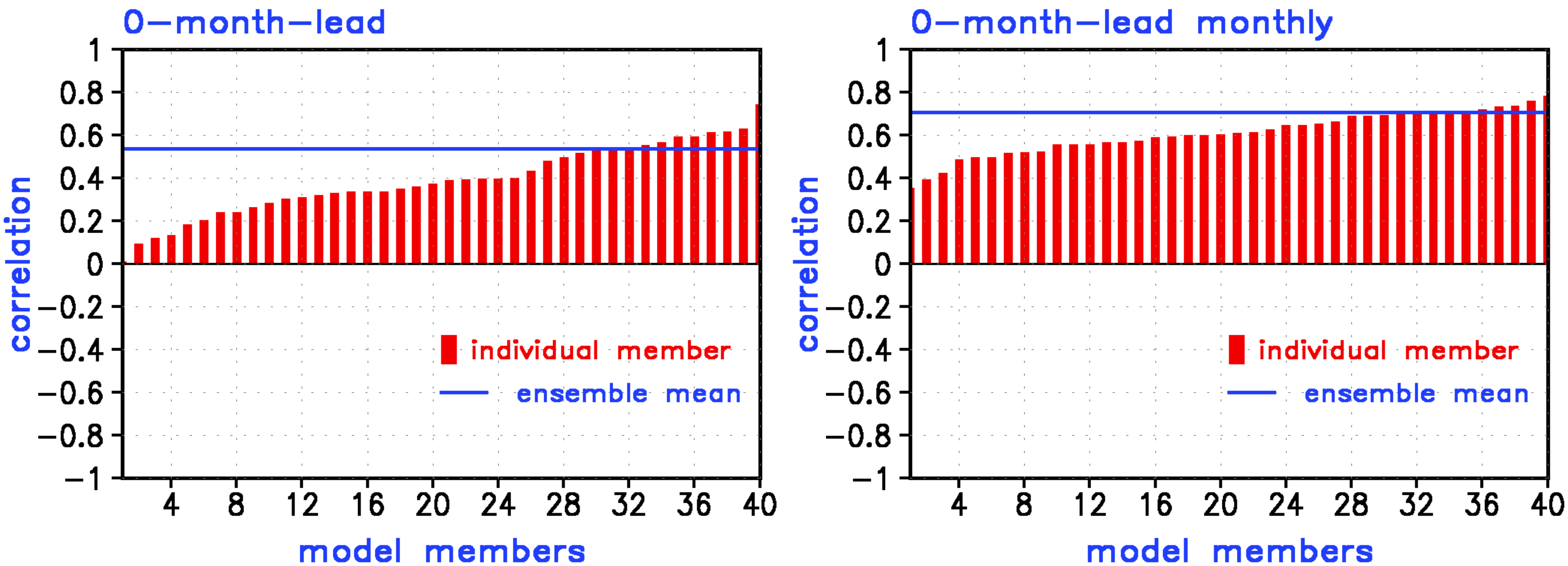
- In this analysis, anomalies from individual model runs are compared against the observed seasonal mean anomalies. The spatial resemblance between them is quantified based on anomaly correlation (AC).
- The distribution of AC across all model simulations is indicative of probability of observed anomalies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


ASO2016 Anomaly Correlation for Individual AMIP Simulation
with Observation -- z200(20N-90N)
correlation
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18
model members
individual member
ensemble mean

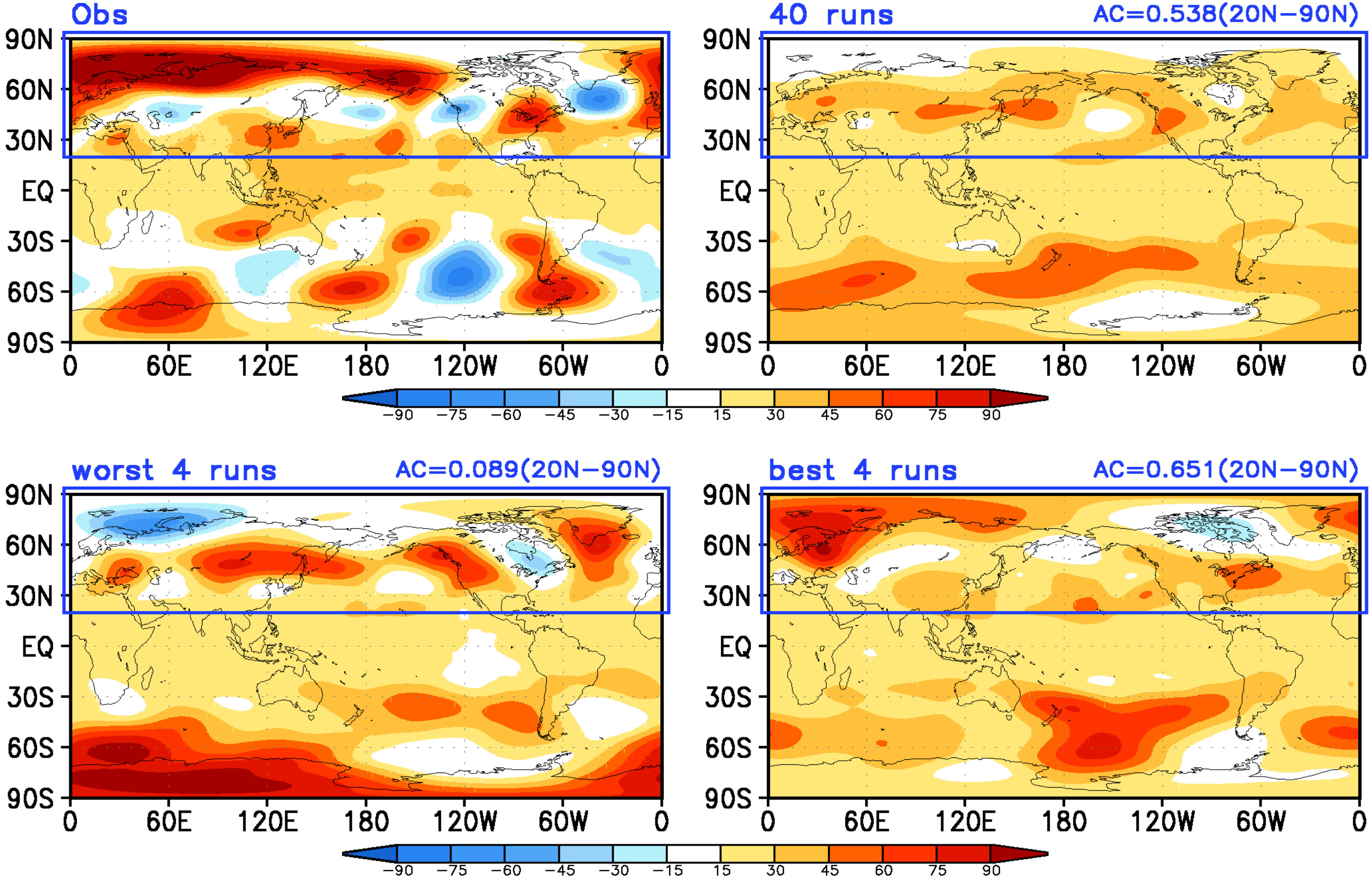
Observed & AMIP Ensemble Average Anomalies
ASO2016 z200(m) 18 runs/worst 2 runs/best 2 runs



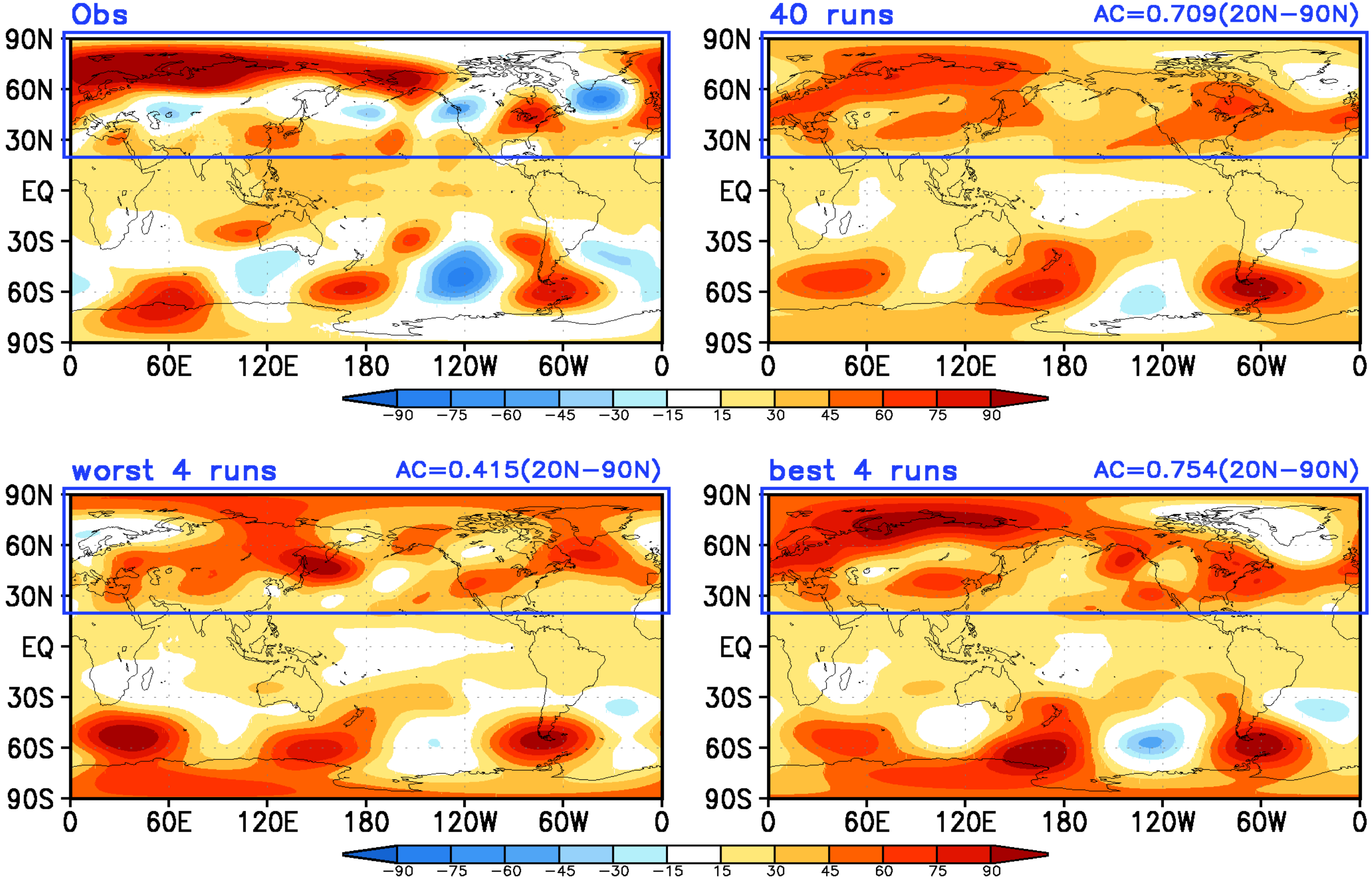
ASO2016 Anomaly Correlation for Individual CFSv2 Forecast with Observation -- z200 (20N-90N)



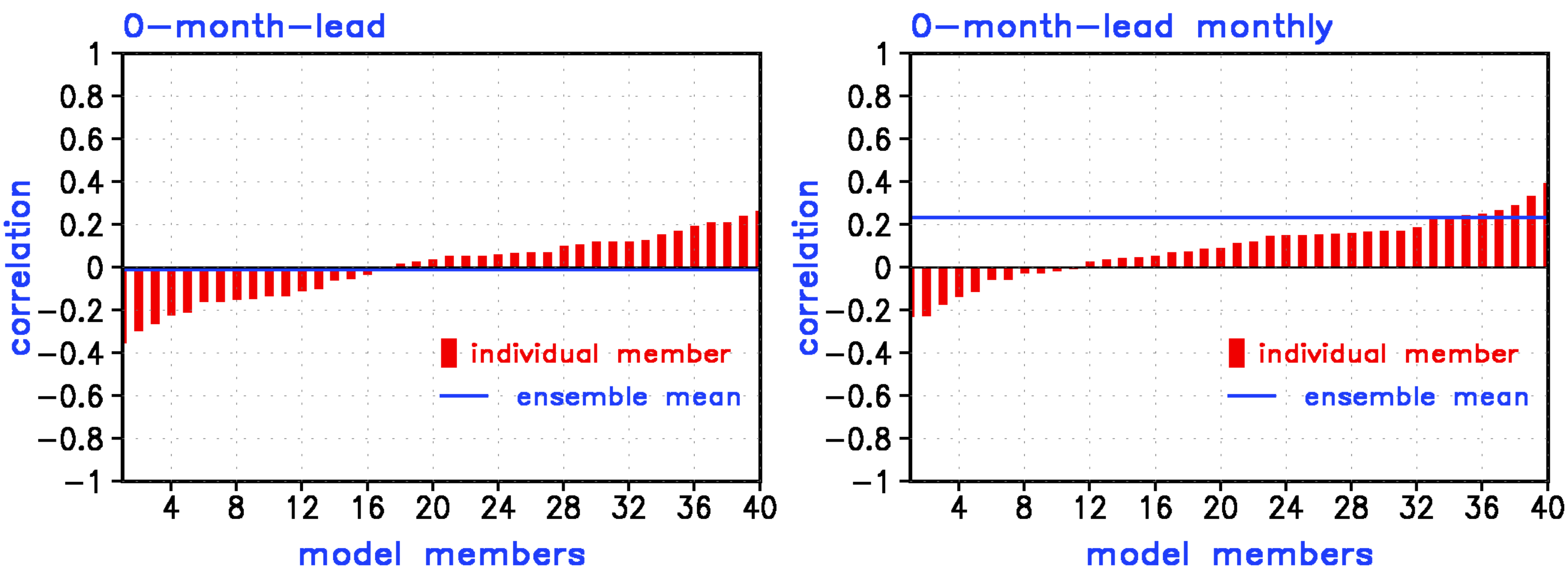
Observed & CFSv2 Forecast Ensemble Average Anomalies ASO2016 z200(m) 40 runs/worst 4 runs/best 4 runs 0-month-lead



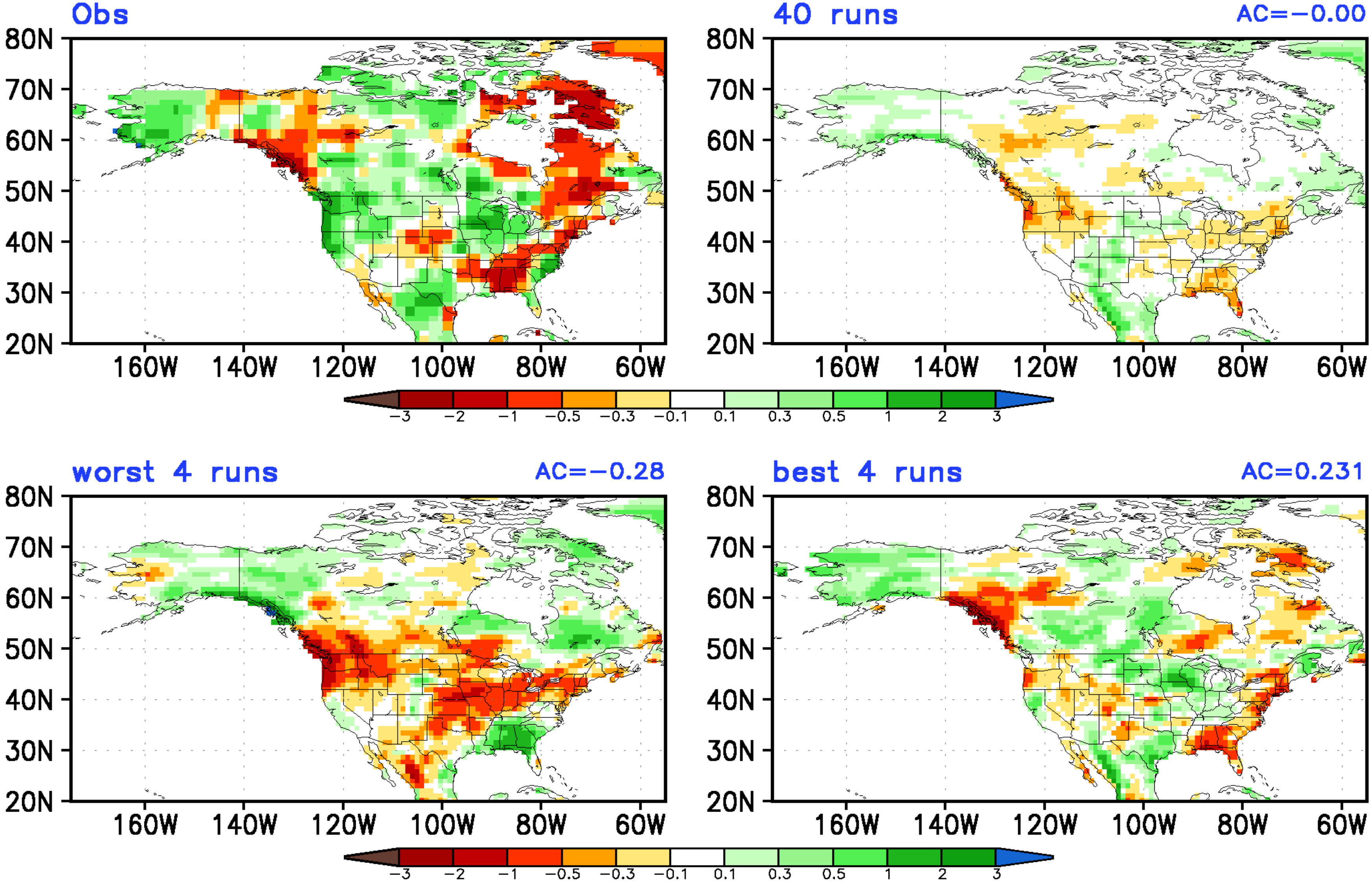
Observed & CFSv2 Forecast Ensemble Average Anomalies
ASO2016 z200(m) 40 runs/worst 4 runs/best 4 runs
0–month–lead monthly



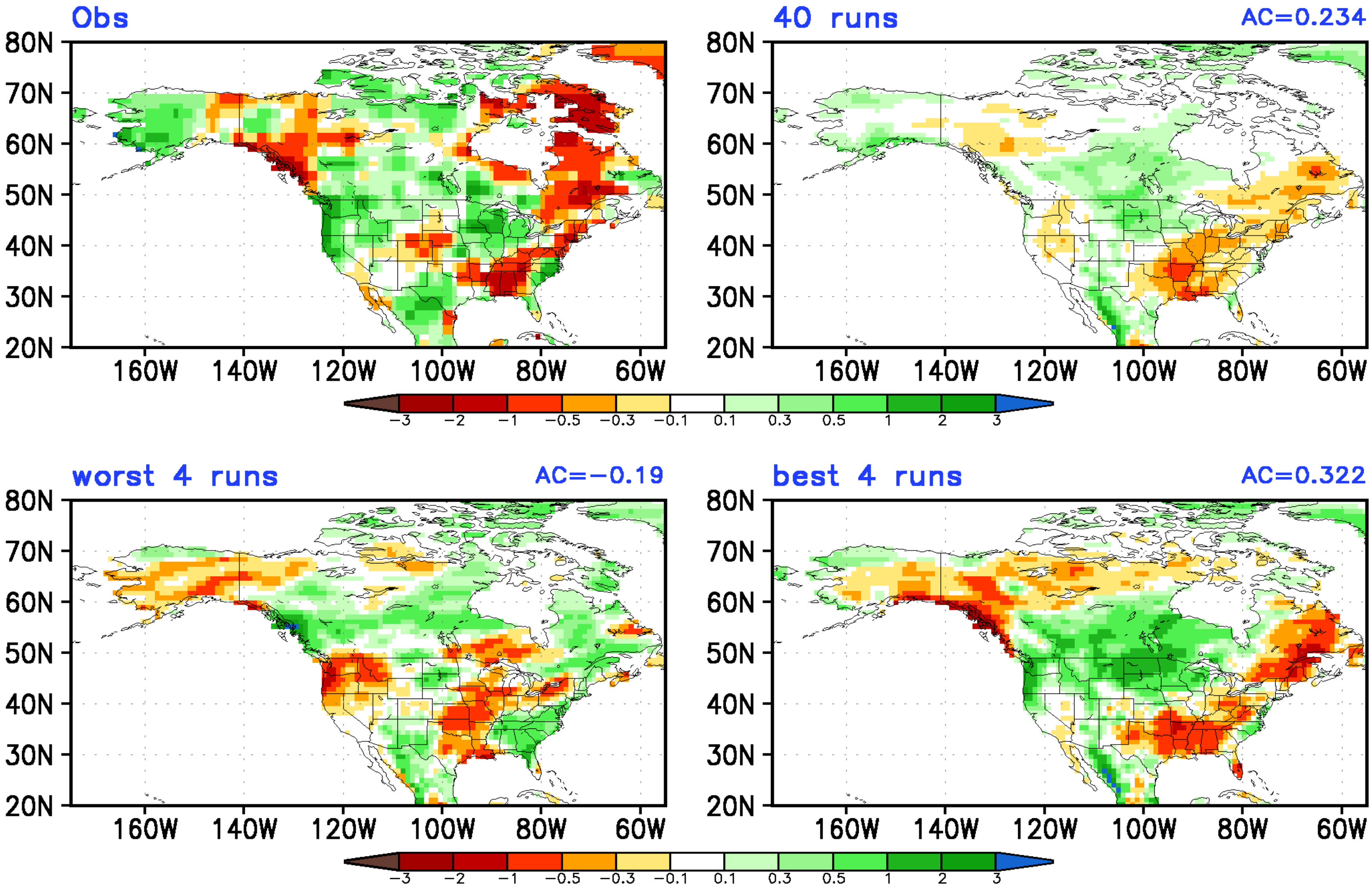
ASO2016 Anomaly Correlation for Individual CFSv2 Forecast with Observation -- Prec (NA)



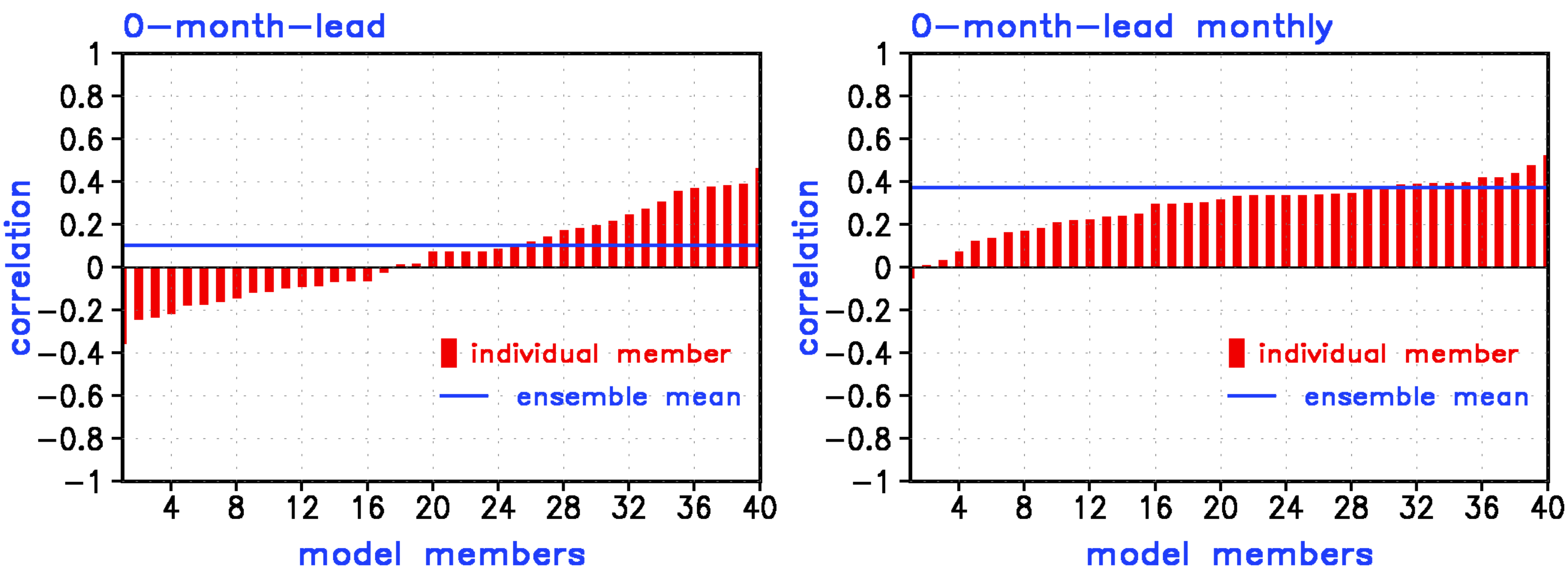
Observed & CFSv2 Forecast Ensemble Average Anomalies
ASO2016 Prec(mm/day) 40 runs/worst 4 runs/best 4 runs
0-month-lead



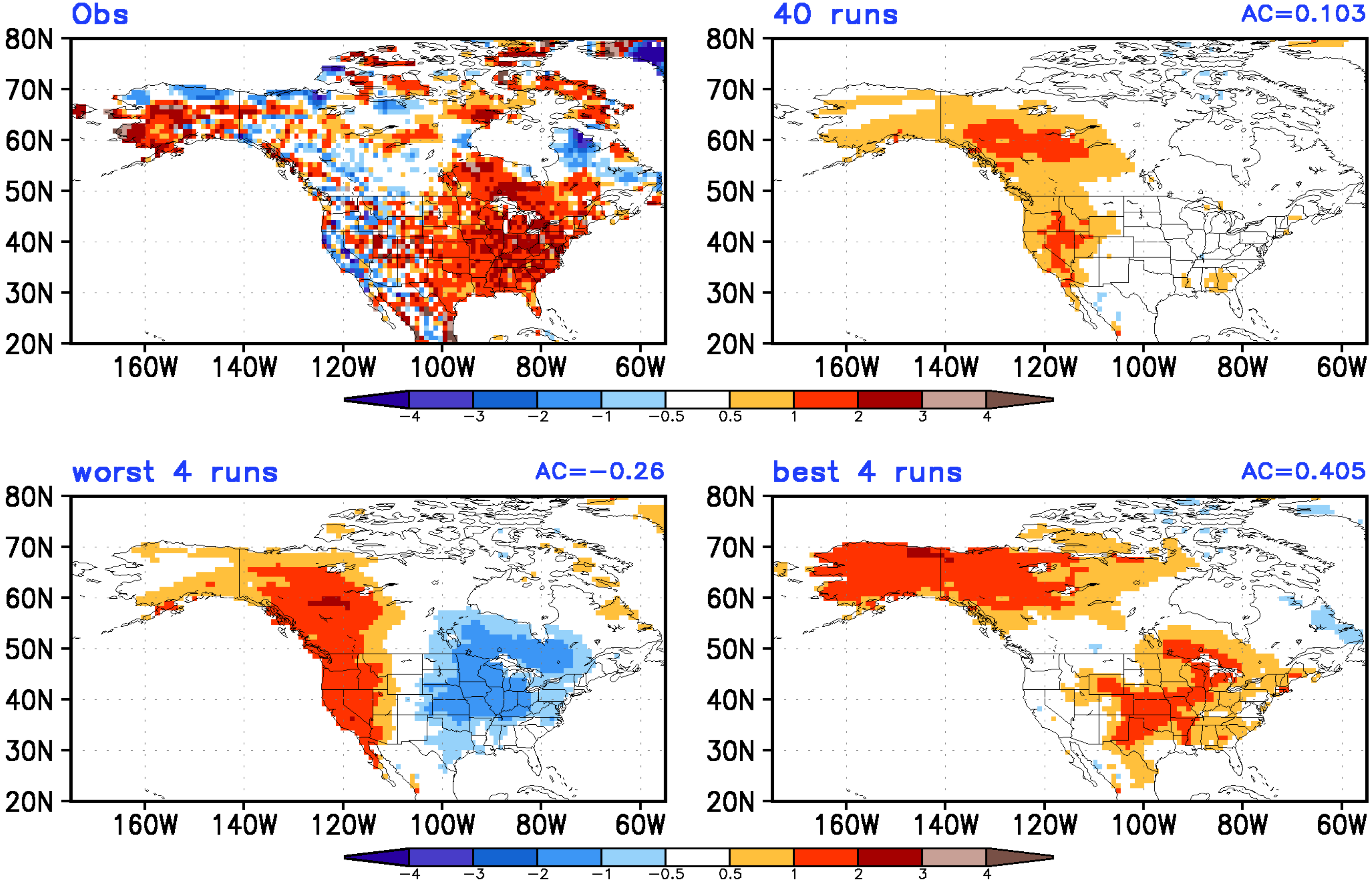
Observed & CFSv2 Forecast Ensemble Average Anomalies
ASO2016 Prec(mm/day) 40 runs/worst 4 runs/best 4 runs
0-month-lead monthly



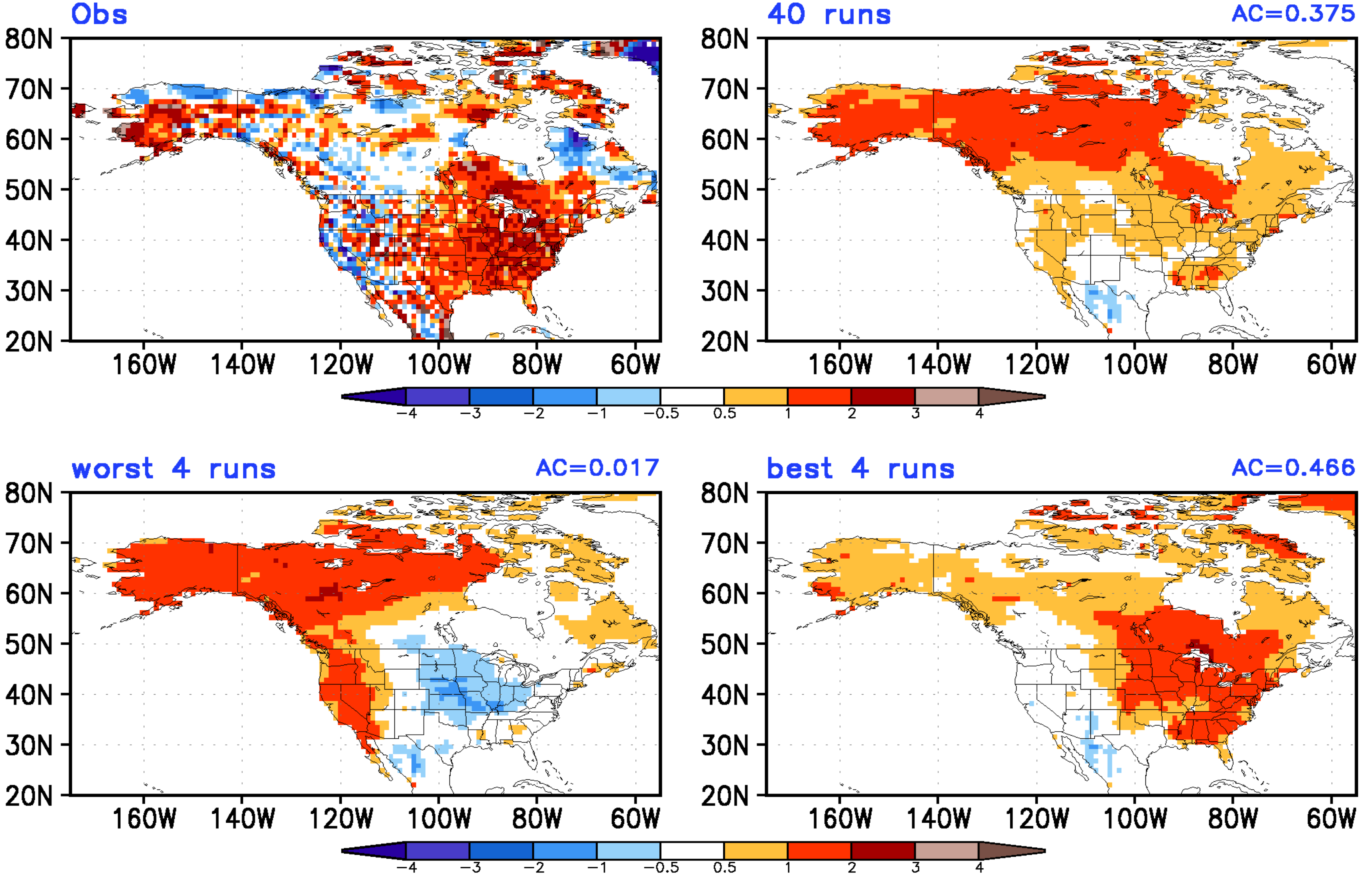
ASO2016 Anomaly Correlation for Individual CFSv2 Forecast with Observation -- T2m (NA)



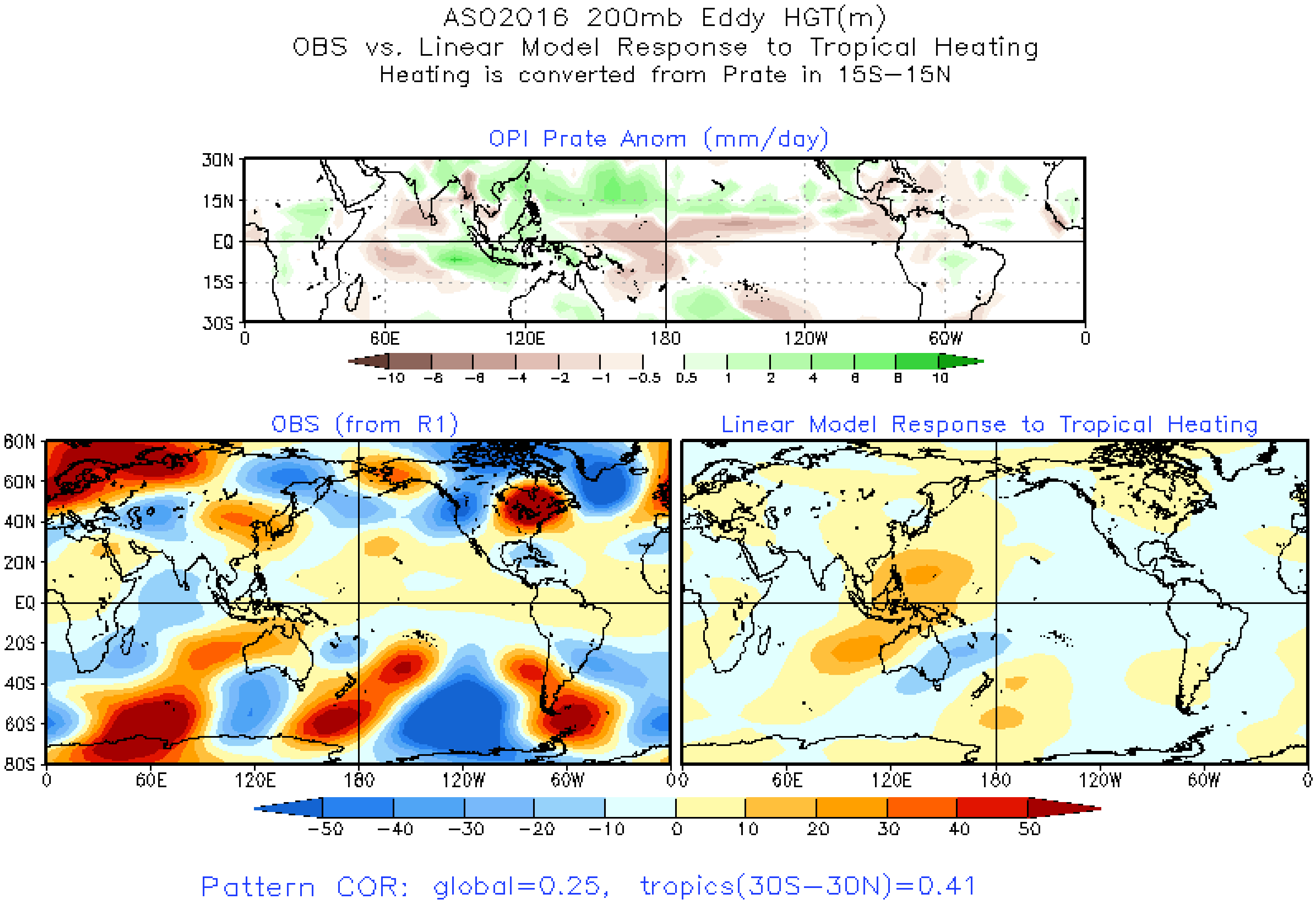
Observed & CFSv2 Forecast Ensemble Average Anomalies
ASO2016 T2m(K) 40 runs/worst 4 runs/best 4 runs
0-month-lead



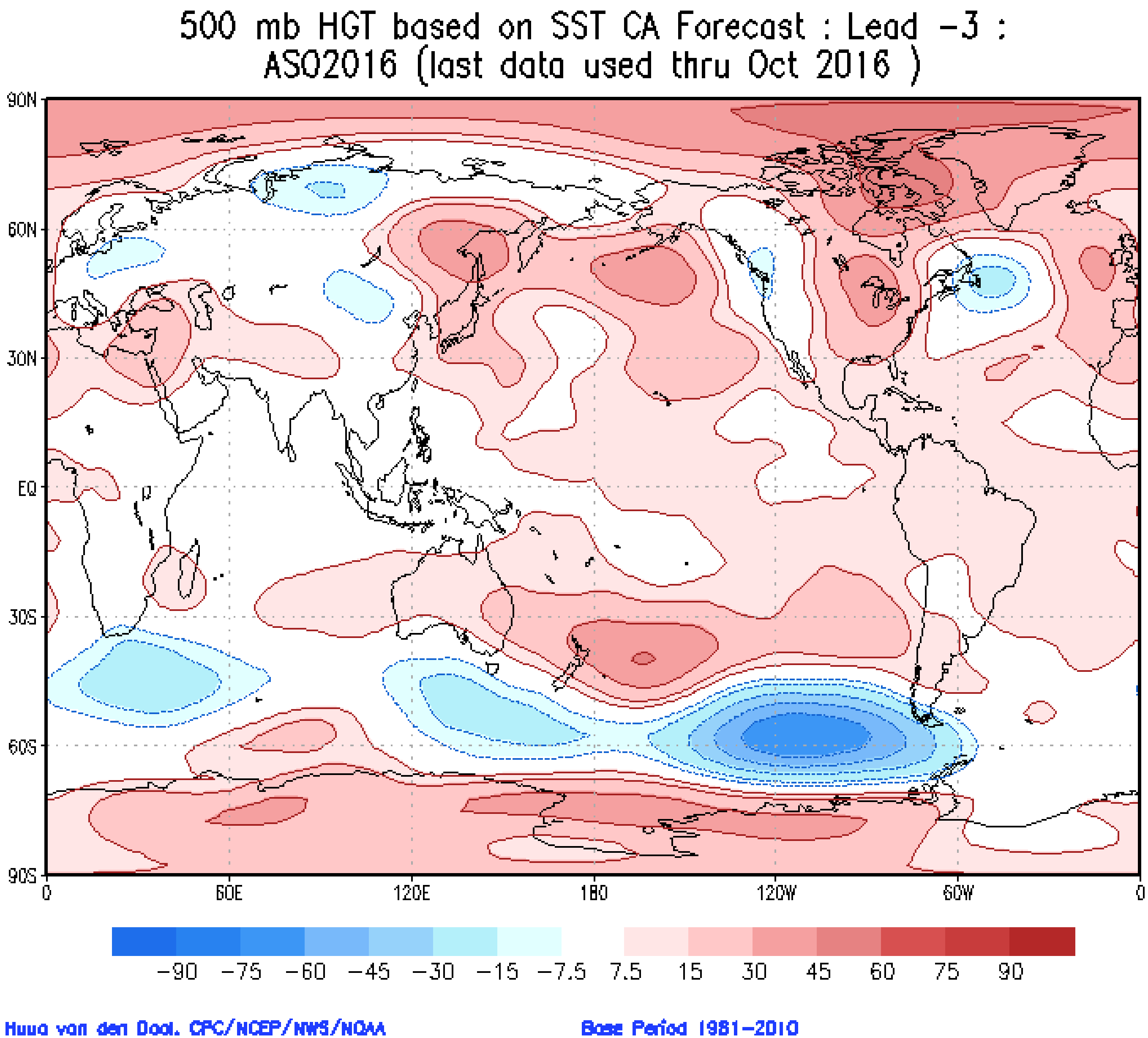
Observed & CFSv2 Forecast Ensemble Average Anomalies
ASO2016 T2m(K) 40 runs/worst 4 runs/best 4 runs
0-month-lead monthly

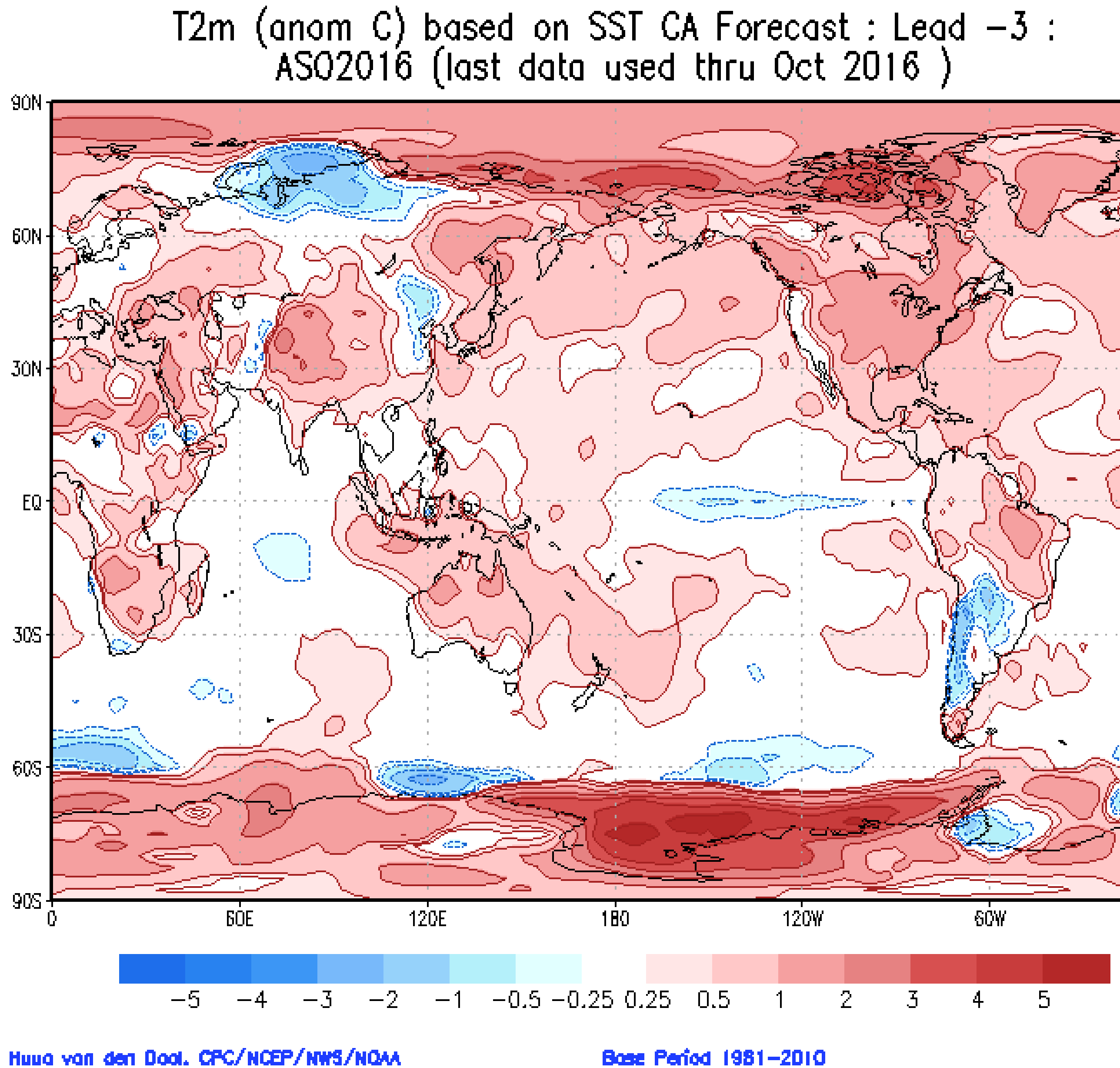


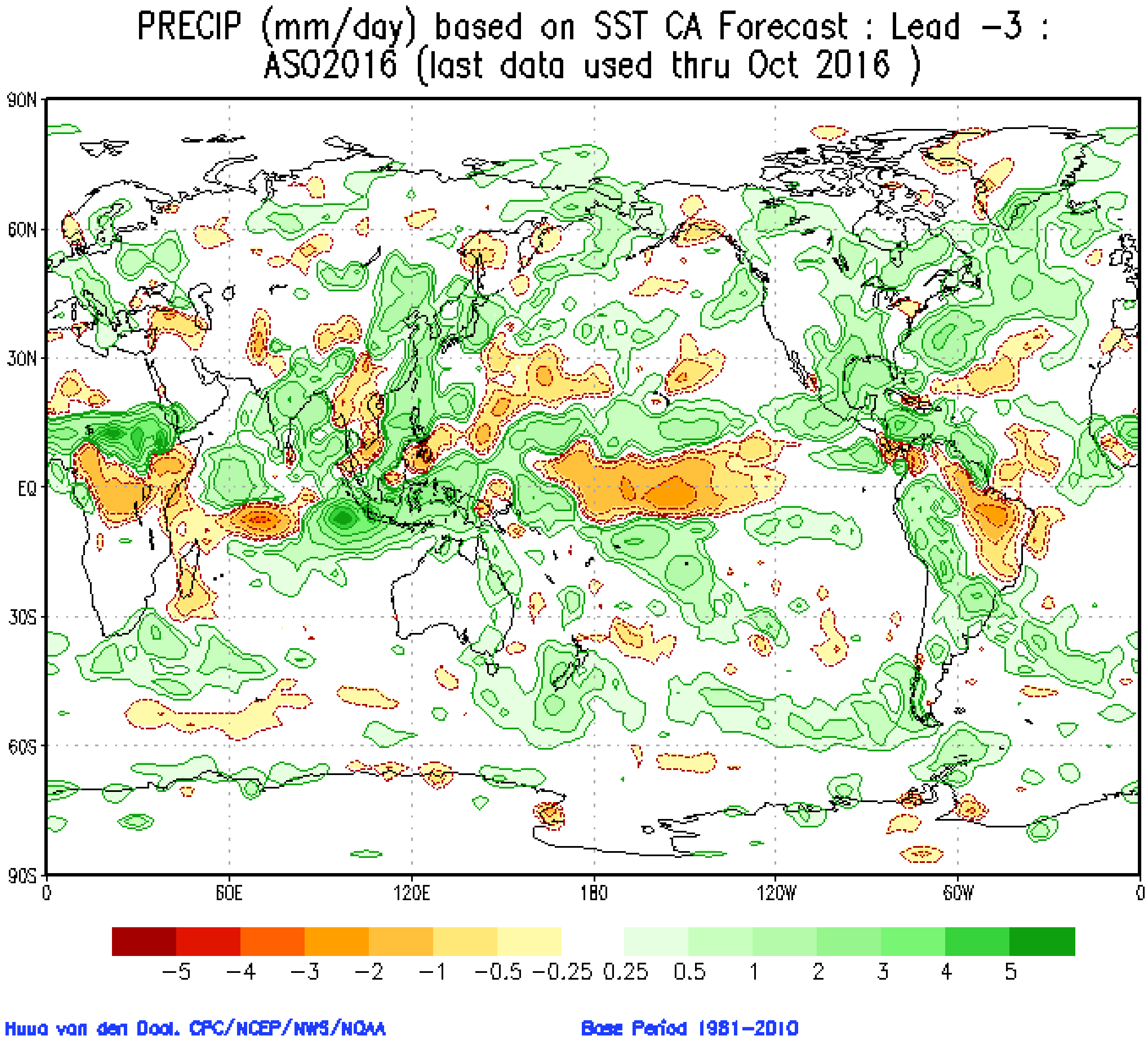
200mb Height from Linear Model


ASO2016 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=0.25, tropics(30S-30N)=0.41

Seasonal Forecasts from the Constructed Analog Model


500 mb HGT based on SST CA Forecast : Lead -3 :
ASO2016 (last data used thru Oct 2016)
90N
60N
30N
EQ
30S
60S
90S
0
60E
120E
180
120W
60W
0
-90 -75 -60 -45 -30 -15 -7.5 7.5 15 30 45 60 75 90
Huug van den Dool, CPC/NCEP/NWS/NOAA
Base Period 1981-2010


T2m (anom C) based on SST CA Forecast : Lead -3 :
ASO2016 (last data used thru Oct 2016)
90N
60N
30N
EQ
30S
60S
90S
0
60E
120E
180
120W
60W
0
-5
-4
-3
-2
-1
-0.5
-0.25
0.25
0.5
1
2
3
4
5
Huug van den Dool, CPC/NCEP/NWS/NOAA
Base Period 1981-2010


PRECIP (mm/day) based on SST CA Forecast : Lead -3 :
ASO2016 (last data used thru Oct 2016)
90N
60N
30N
EQ
30S
60S
90S
0
60E
120E
180
120W
60W
0
-5 -4 -3 -2 -1 -0.5 -0.25 0.25 0.5 1 2 3 4 5
Huug van den Dool, CPC/NCEP/NWS/NOAA
Base Period 1981-2010

Summary

- The observed tropical SST ASO2016 anomalies were weak; the z200 response to the tropical heating in the linear model was confined in tropical western Pacific;
- CFSv2 forecasted reasonably well for the major large scale features of SST anomalies;
- For the ensemble means, both the AMIP runs and initialized forecasts didn’t capture well the Prec and T2m anomalies over the tropics and extra-tropics; the initialized forecasts showed slightly higher skill for tropical Prec;
- For the individual members, the North America Prec and T2m correlation skills were also low and variations between members were large; 16 of 40 members Prec , and 18 of 40 members T2m showed negative correlations against the observations;
- The Constructed Analog model forecasted reasonably well for the large scale features of Prec anomalies over the tropical Pacific;

References

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