Attribution of Seasonal Climate Anomalies March-April-May 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).

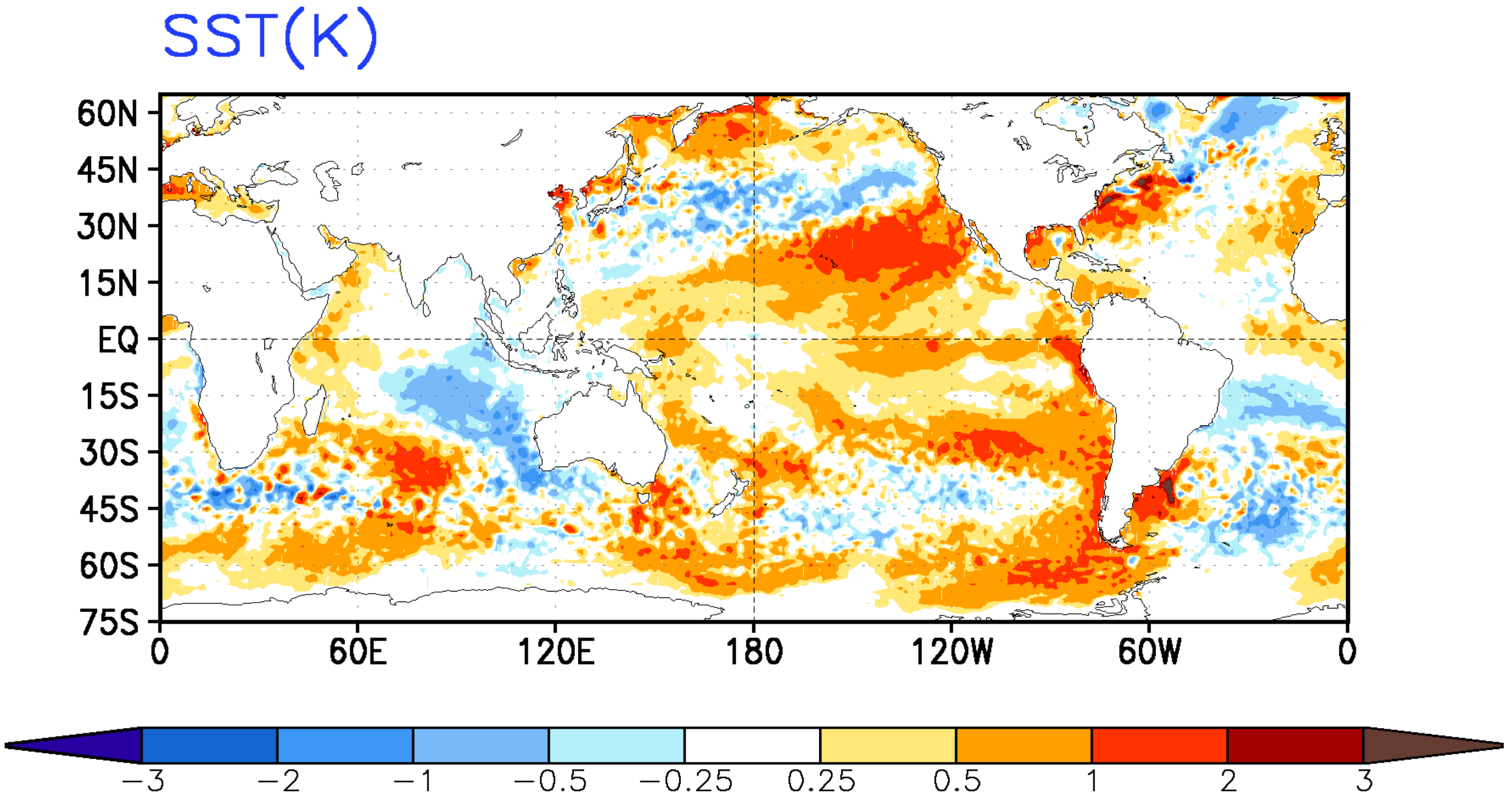
Data

- 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)

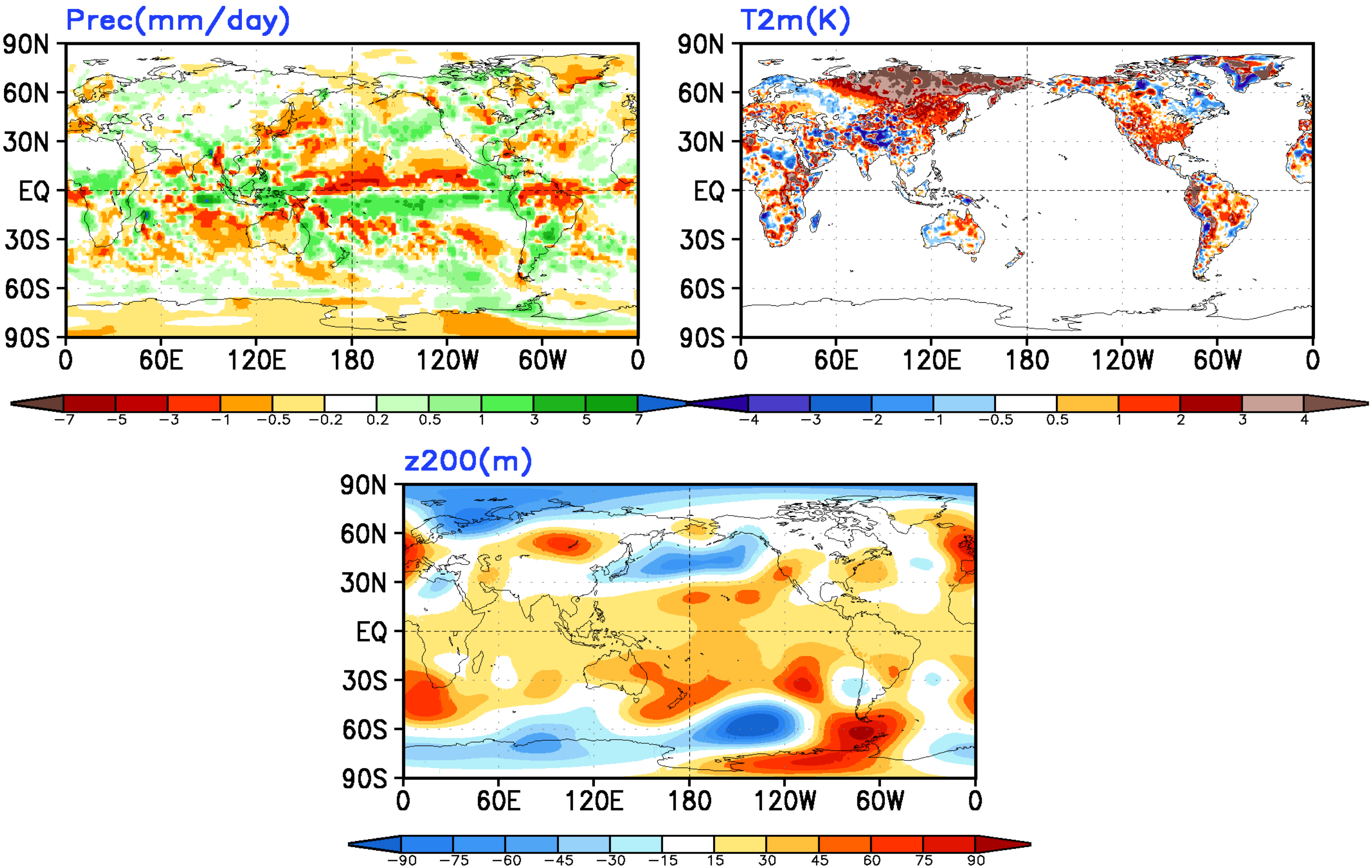
Observed Seasonal Anomalies

Global and North America

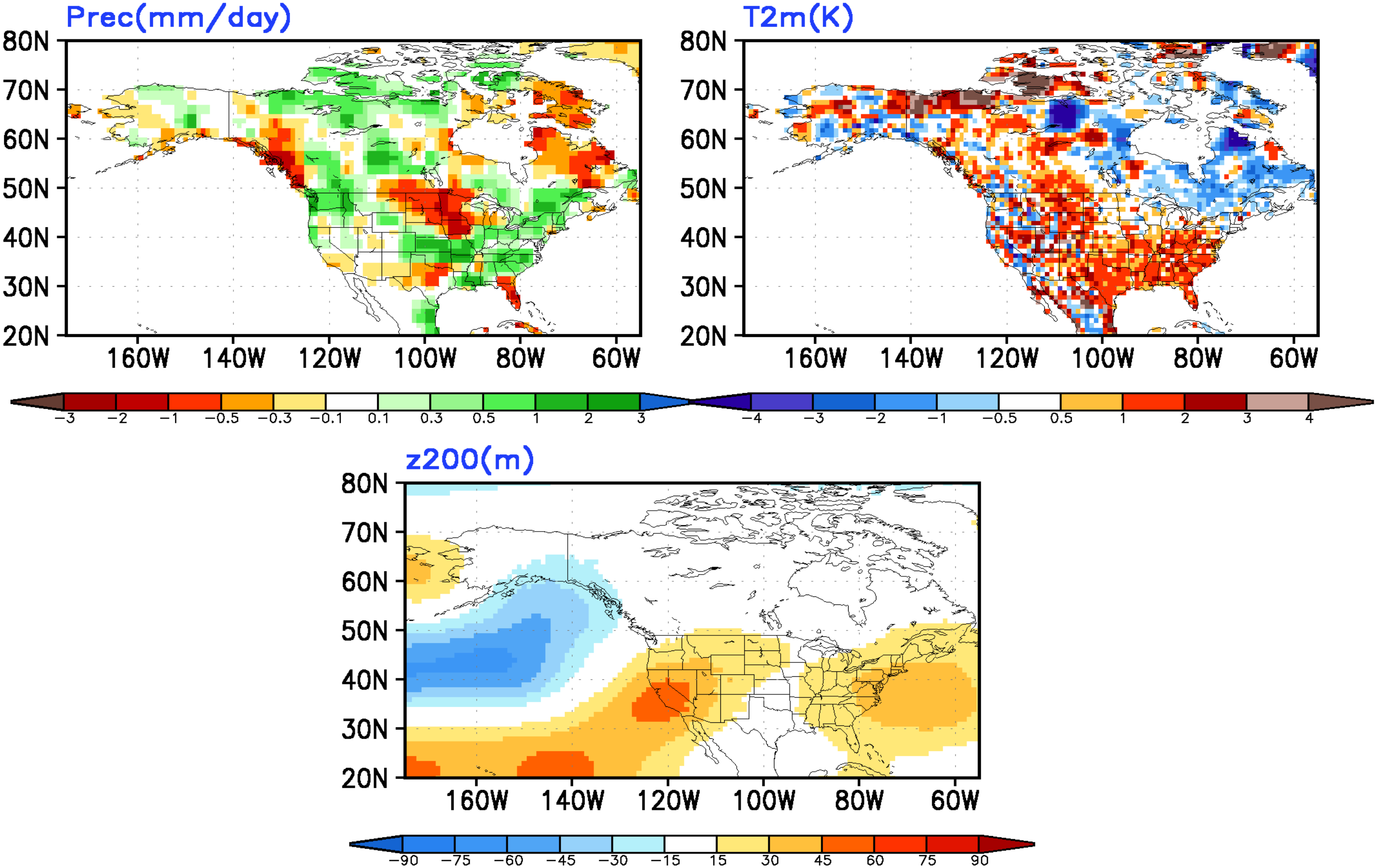
Observed Anomaly MAM2017



Observed Anomaly MAM2017



Observed Anomaly MAM2017

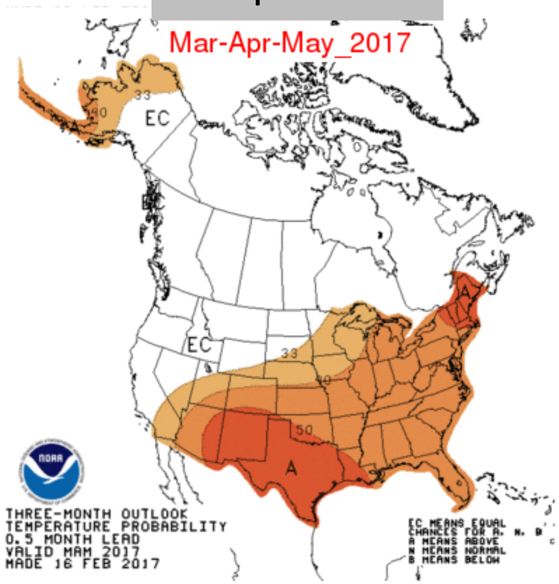


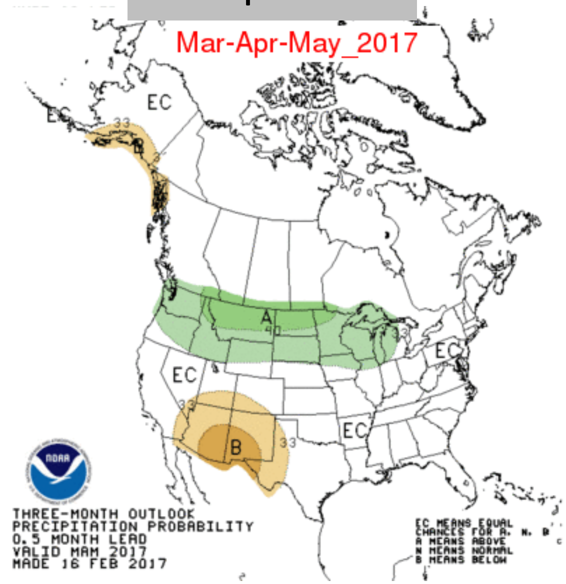
MAM2017 CPC Seasonal Outlooks and NMME Forecasts

Temperature

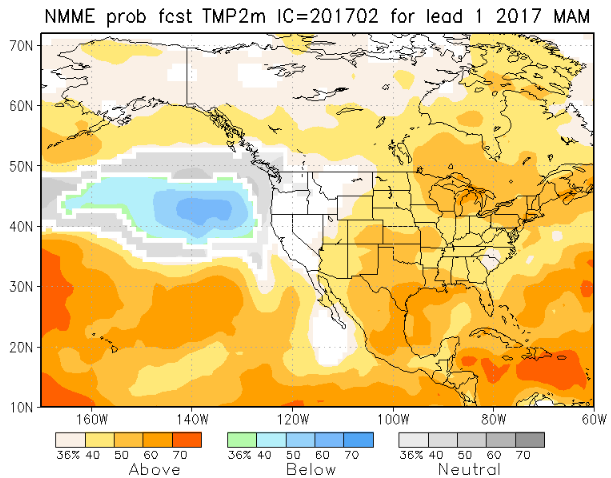
Precipitation

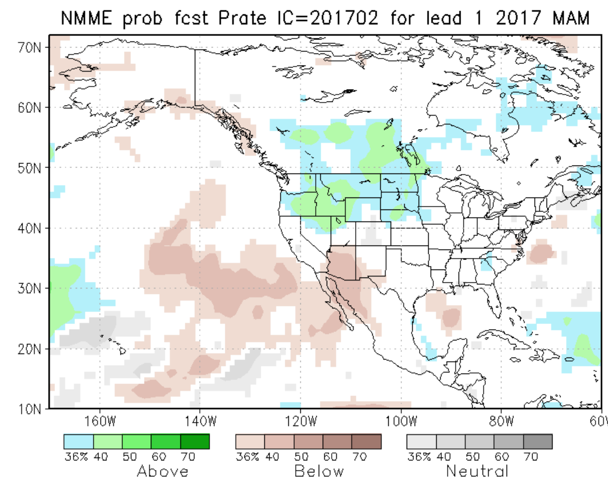
CPC





NMME



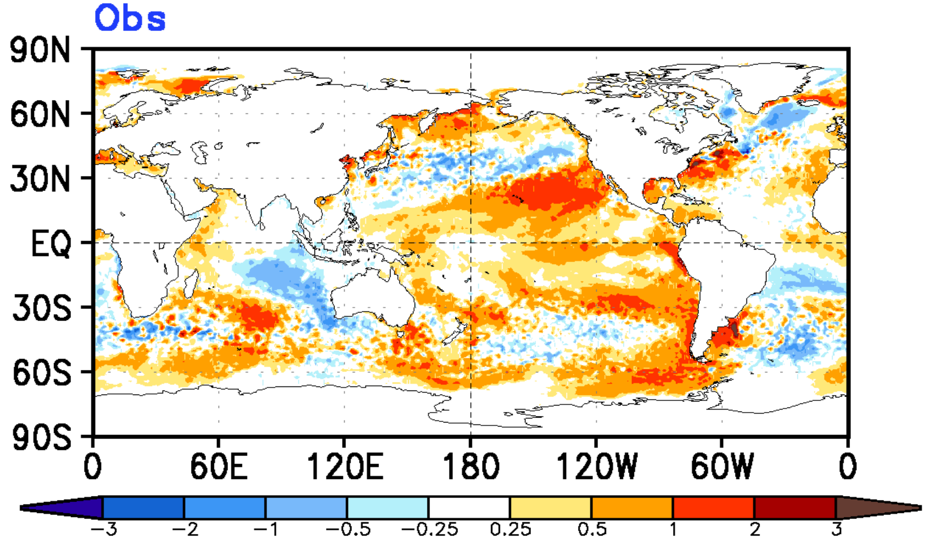


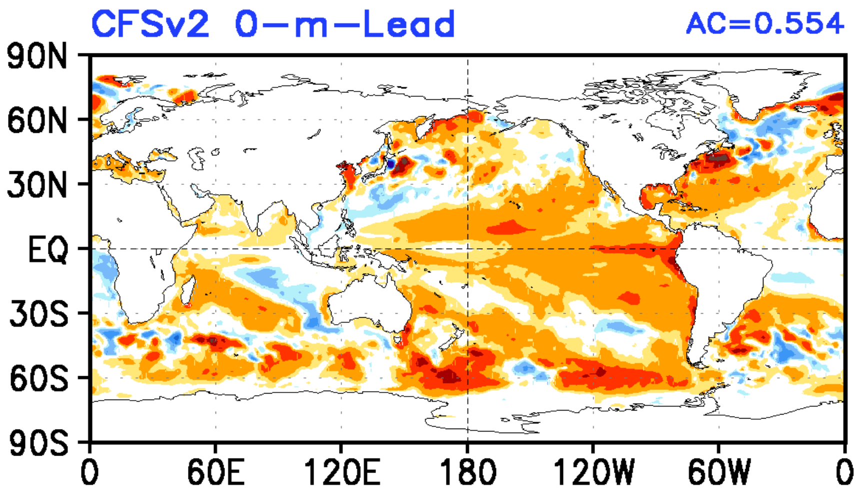
Model Simulated/Forecast Ensemble Average Anomalies

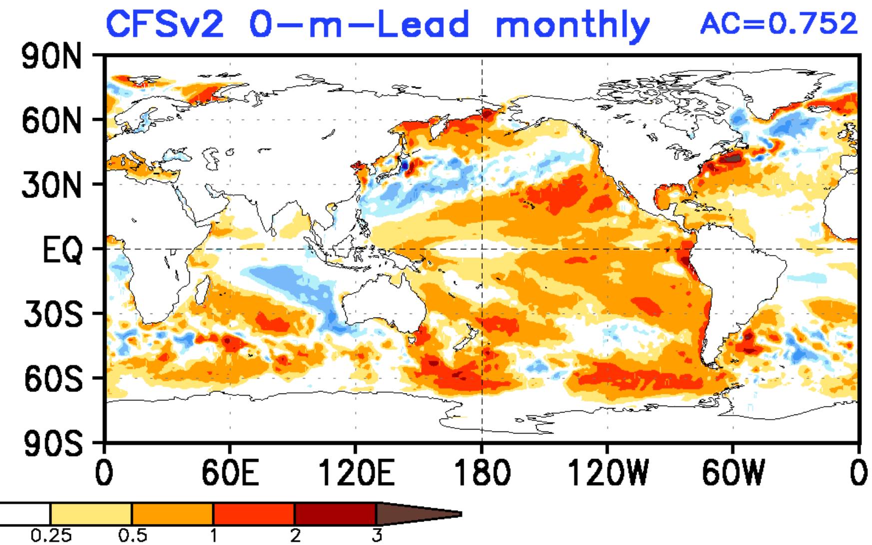
Model Simulated/Forecast Ensemble Average Anomalies

- 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).

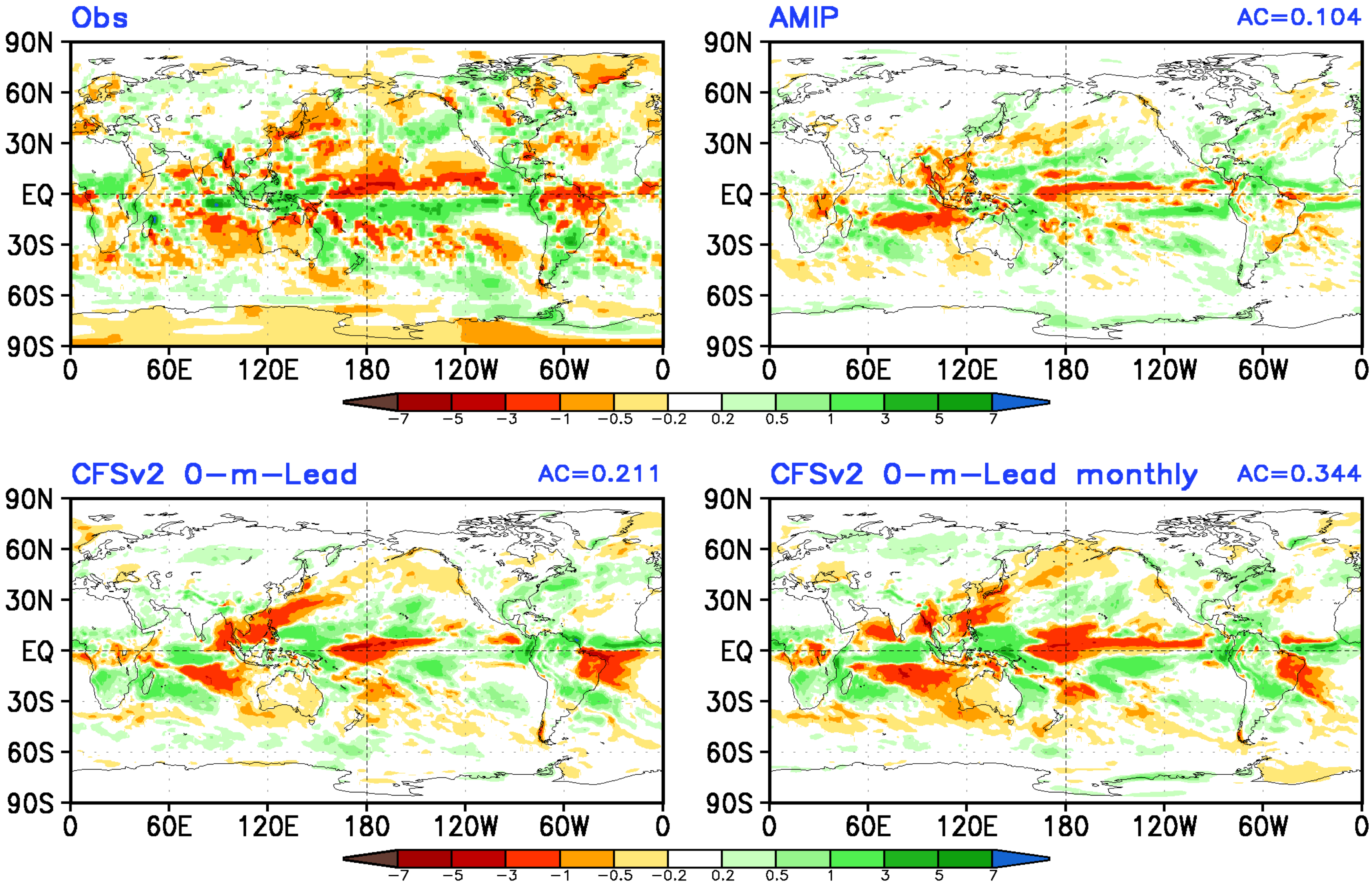
MAM2017 Observed & Model Simulated/Forecast Ensemble Average Anomalies SST(K)



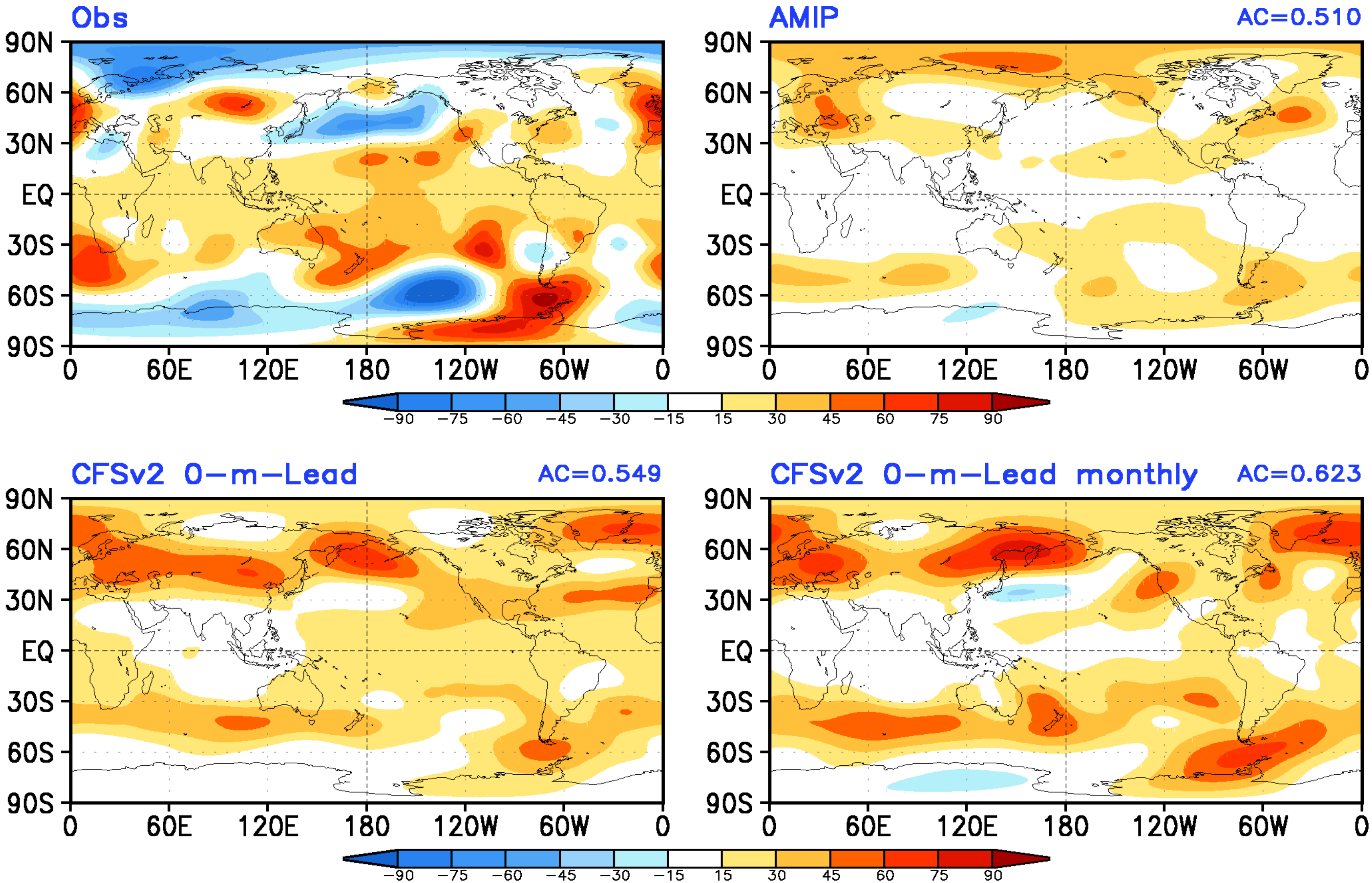




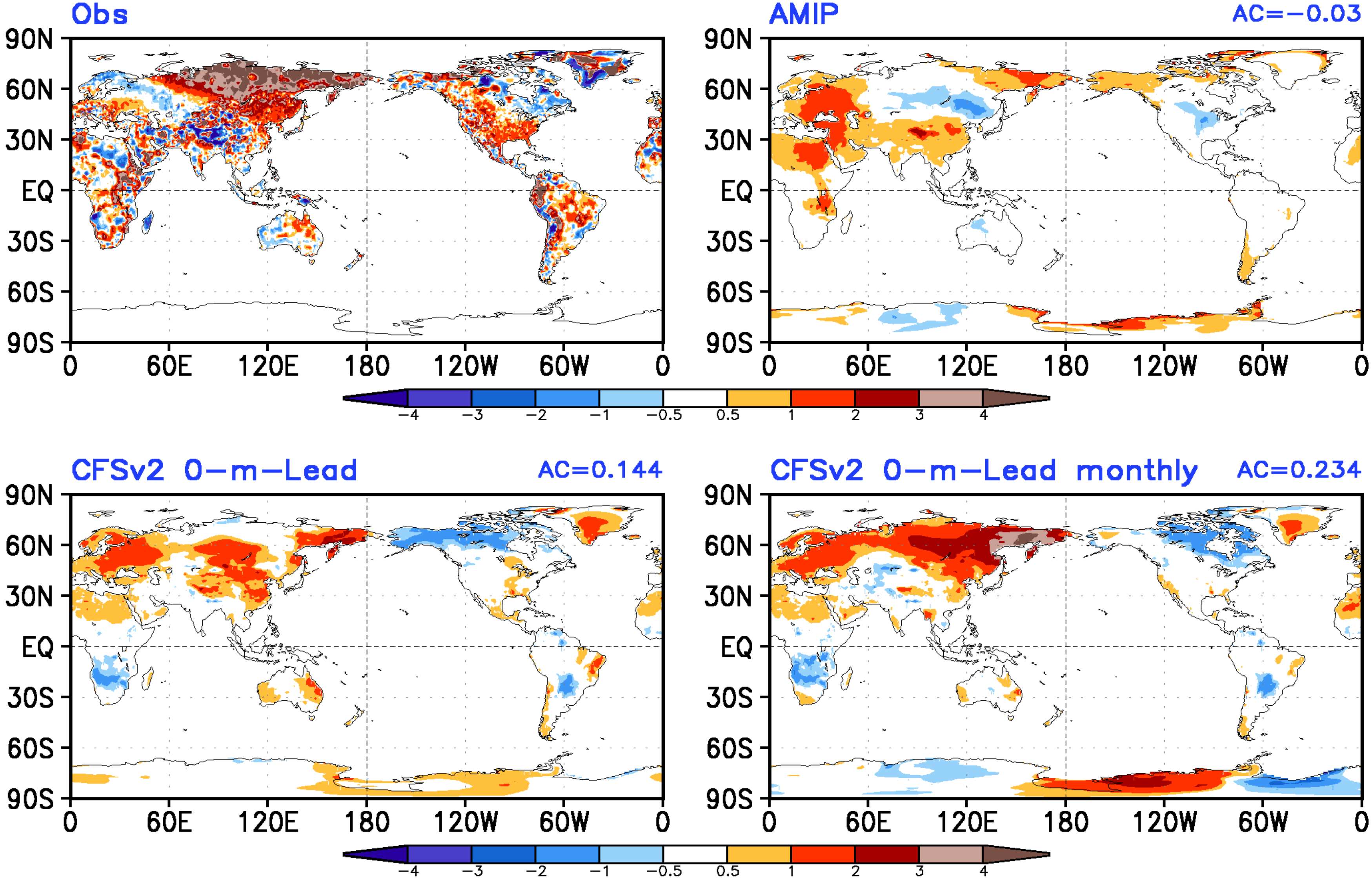
MAM2017 Observed & Model Simulated/Forecast Ensemble Average Anomalies Prec(mm/day)



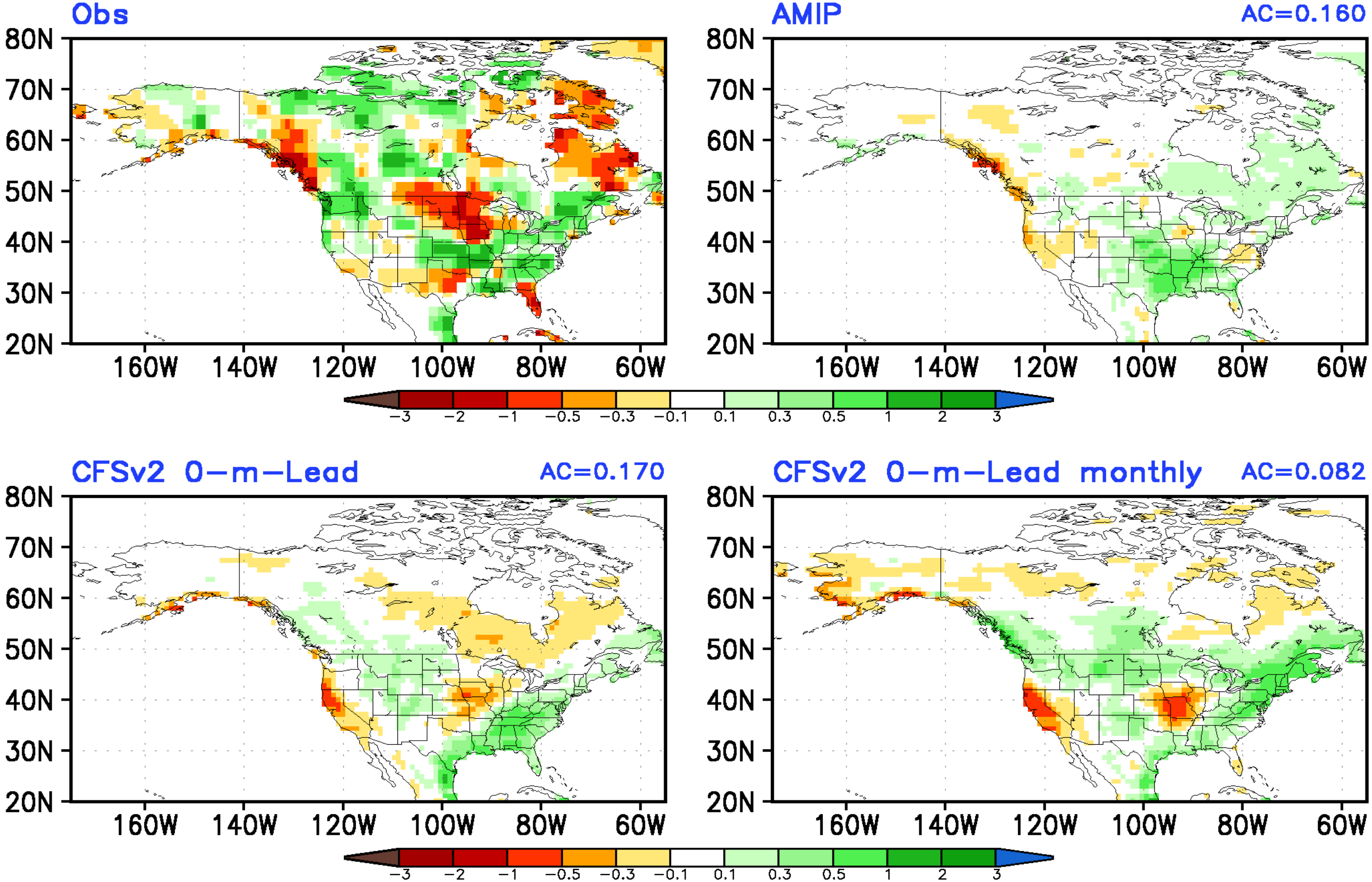
MAM2017 Observed & Model Simulated/Forecast Ensemble Average Anomalies z200(m)



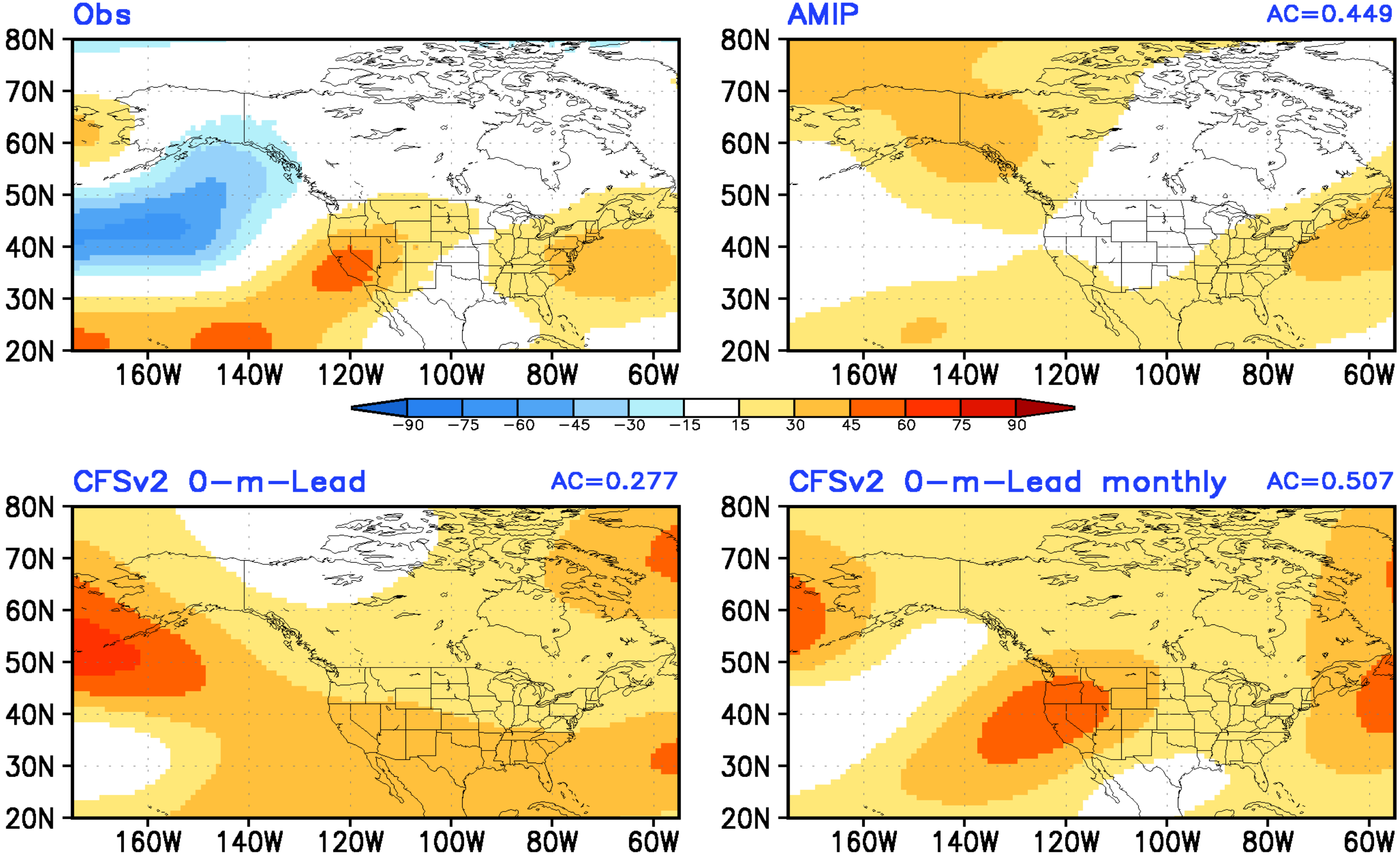
MAM2017 Observed & Model Simulated/Forecast Ensemble Average Anomalies T2m(K)



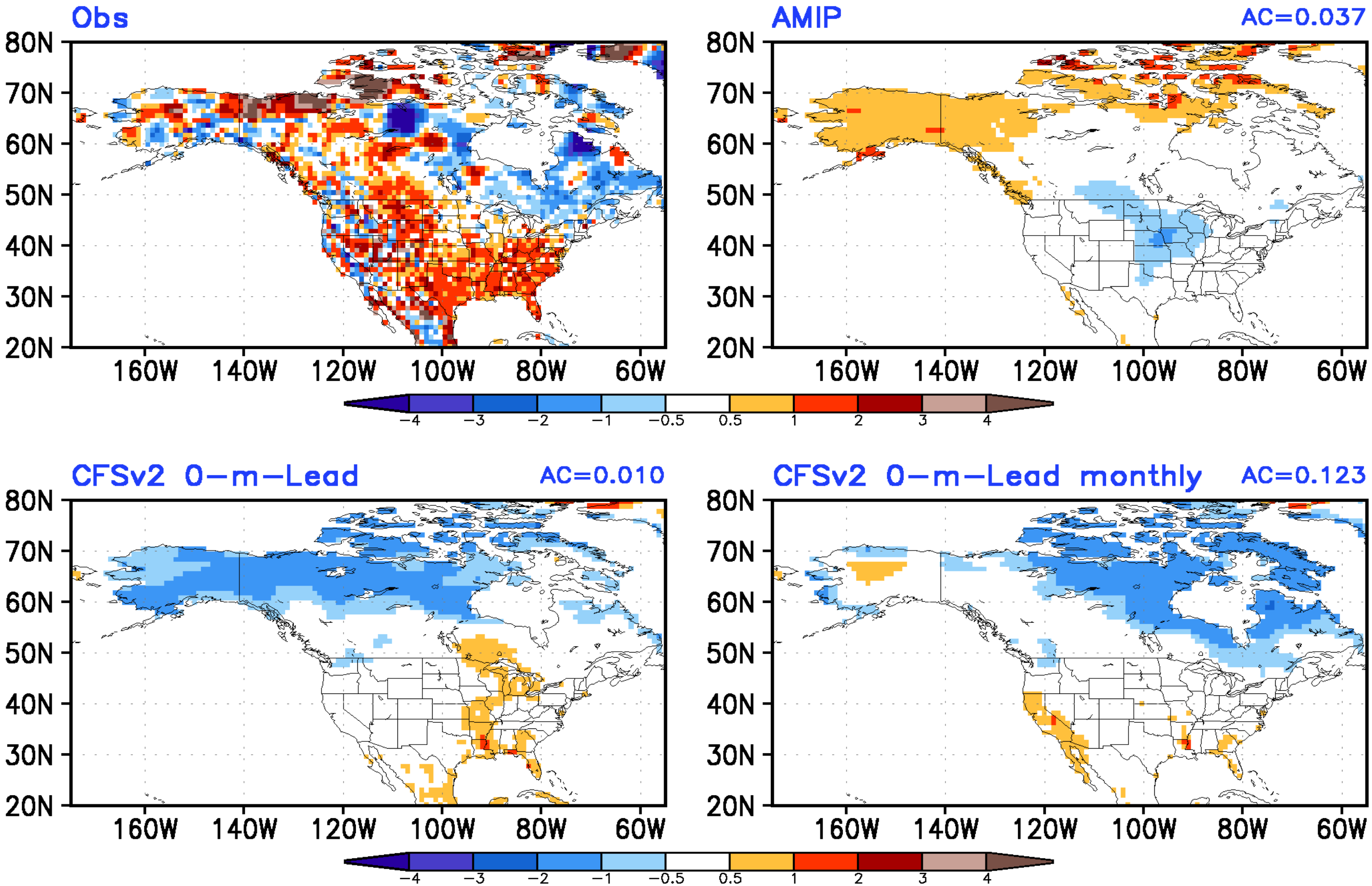
MAM2017 Observed & Model Simulated/Forecast Ensemble Average Anomalies Prec(mm/day)



MAM2017 Observed & Model Simulated/Forecast Ensemble Average Anomalies z200(m)



MAM2017 Observed & Model Simulated/Forecast Ensemble Average Anomalies T2m(K)

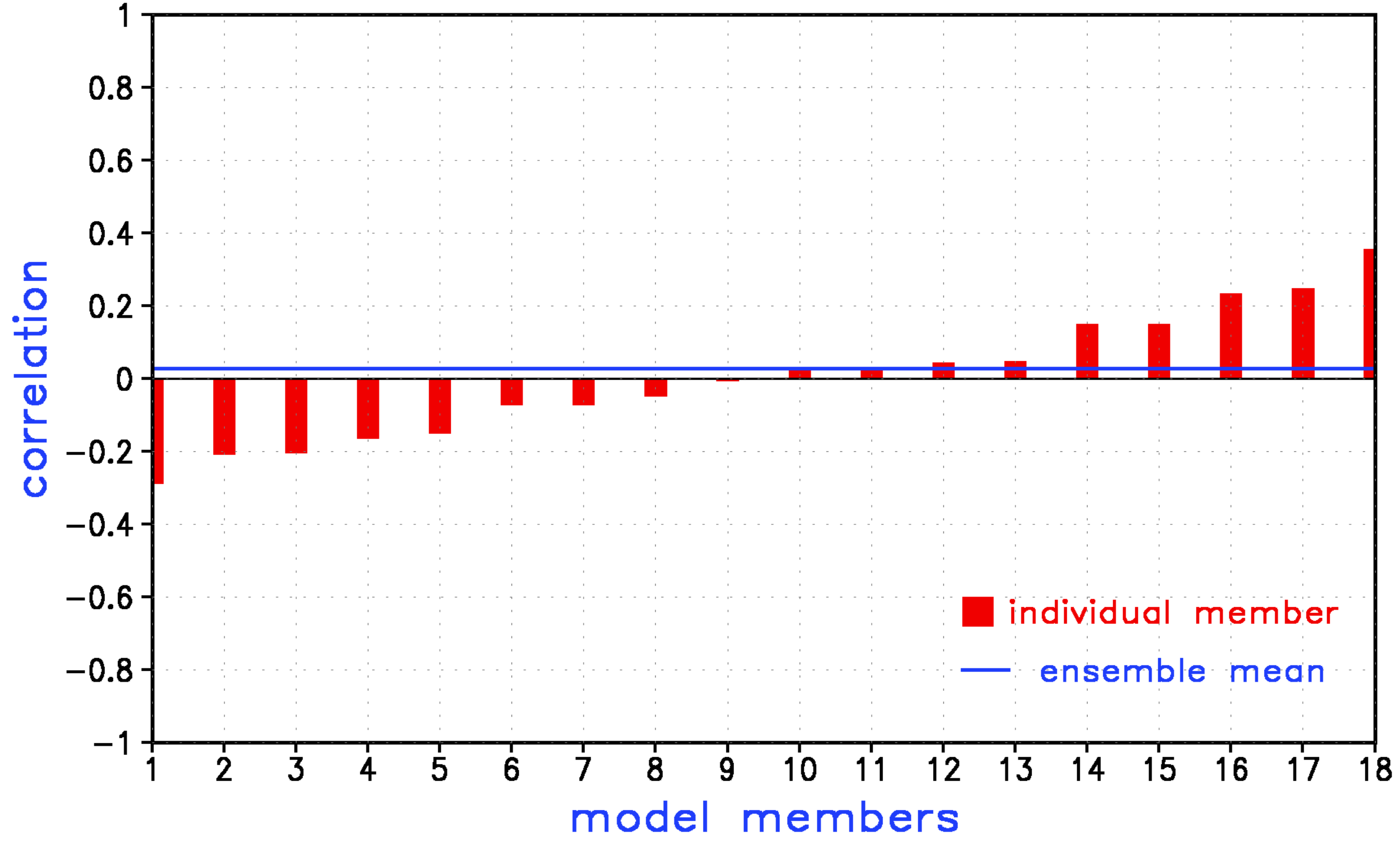


Model Simulated/Forecast Anomalies: Individual Runs

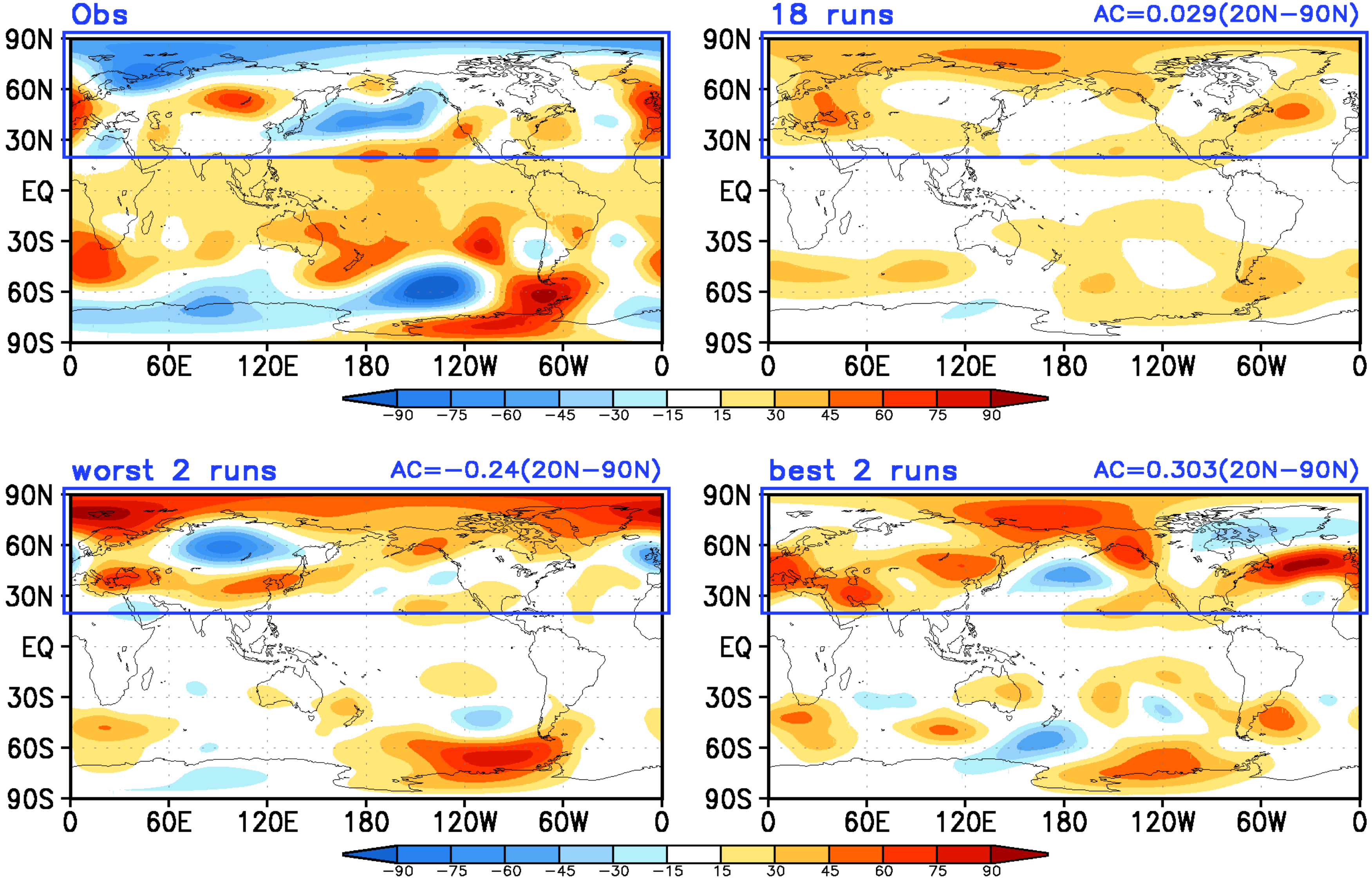
Model Simulated/Forecast Anomalies: Individual Runs

- 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.

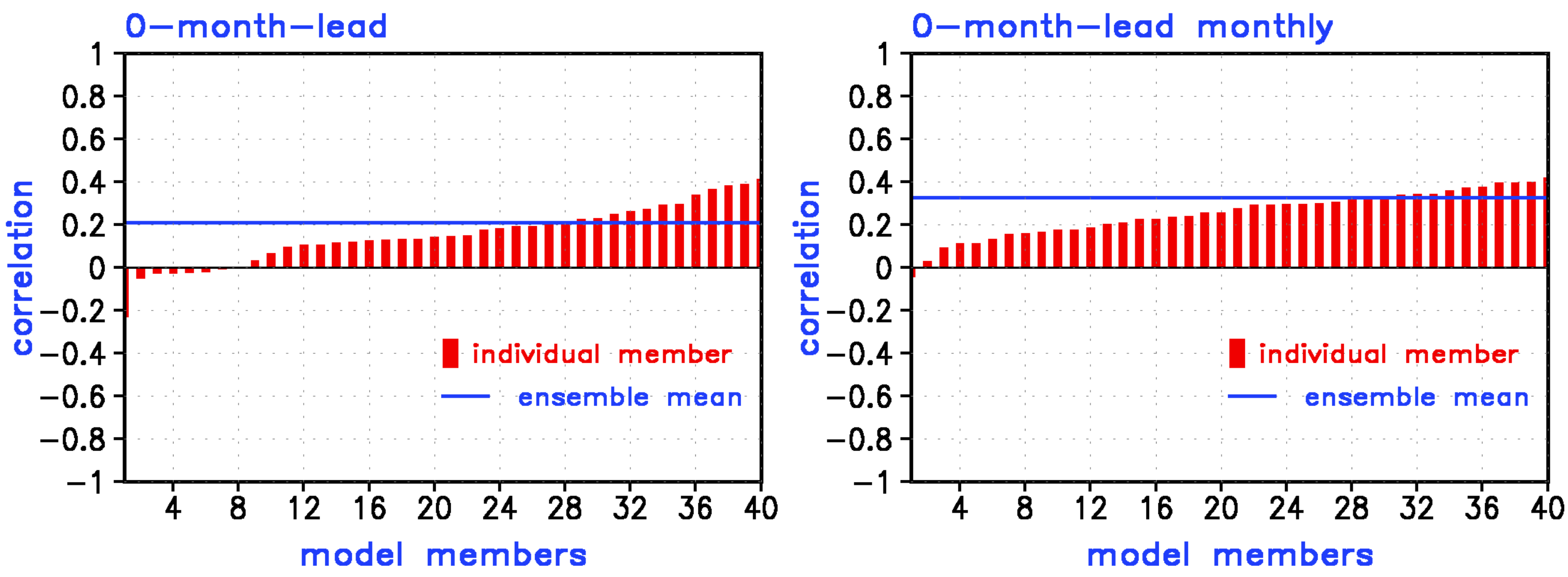
MAM2017 Anomaly Correlation for Individual AMIP Simulation with Observation -- z200(20N-90N)



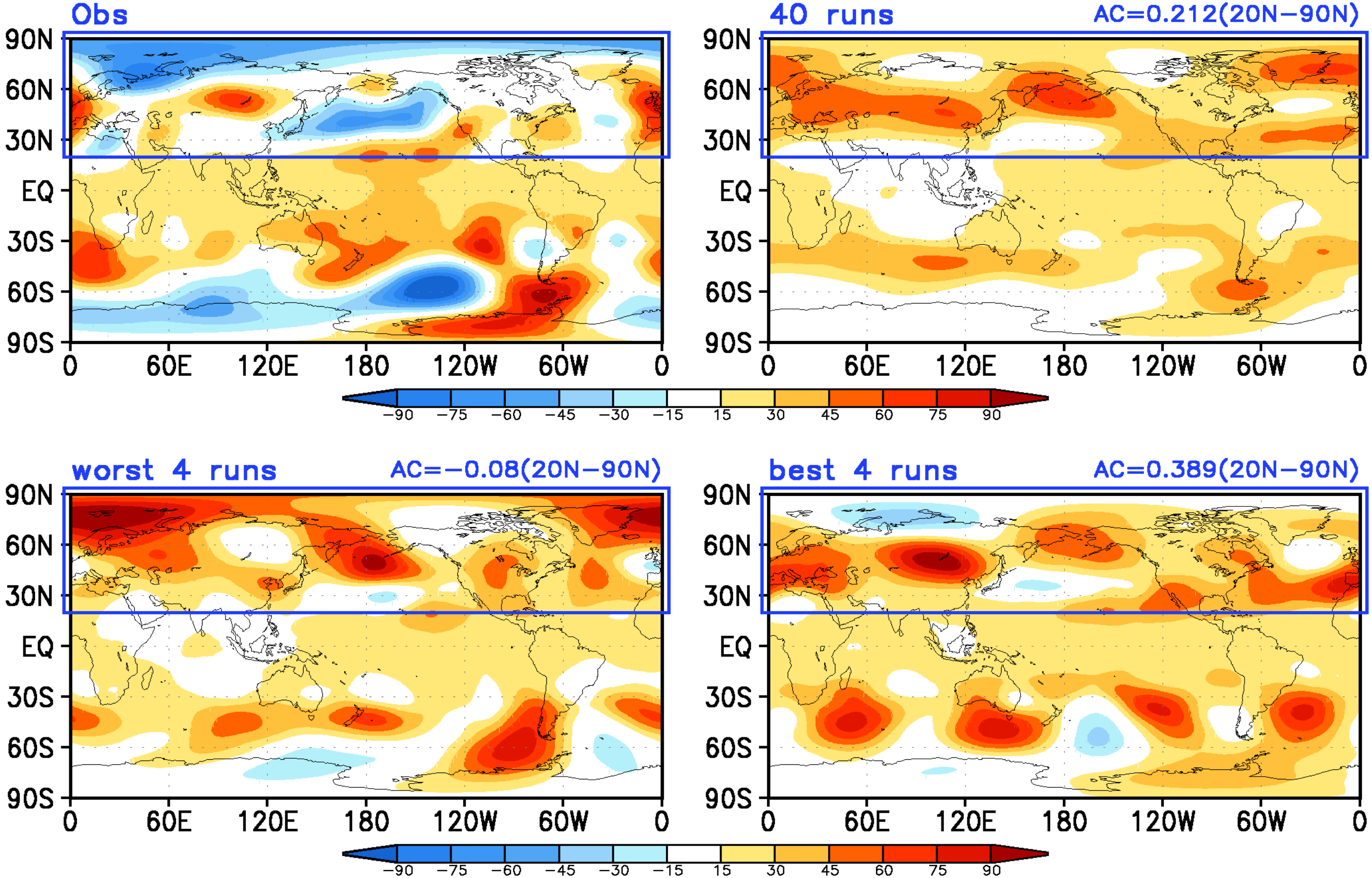
Observed & AMIP Ensemble Average Anomalies
MAM2017 z200(m) 18 runs/worst 2 runs/best 2 runs



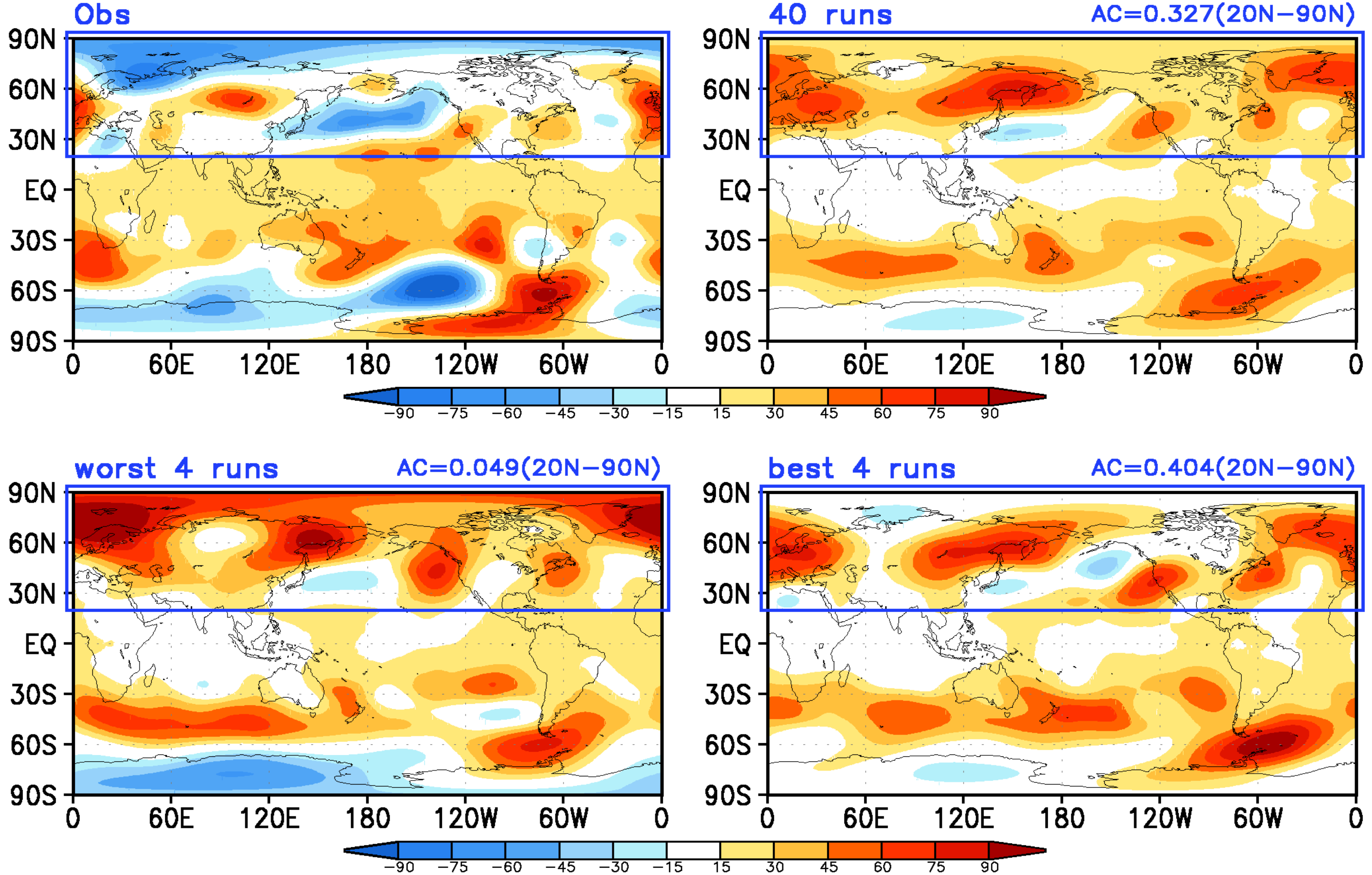
MAM2017 Anomaly Correlation for Individual CFSv2 Forecast with Observation -- z200 (20N-90N)



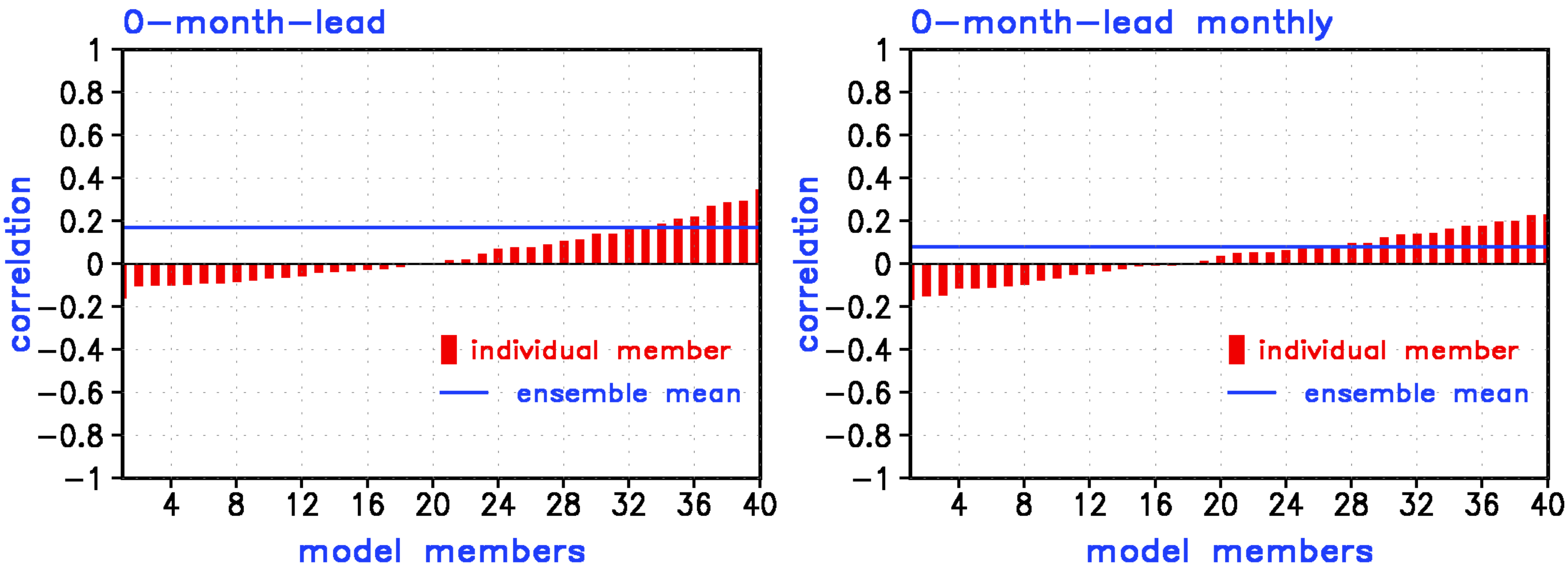
Observed & CFSv2 Forecast Ensemble Average Anomalies
MAM2017 z200(m) 40 runs/worst 4 runs/best 4 runs
0-month-lead



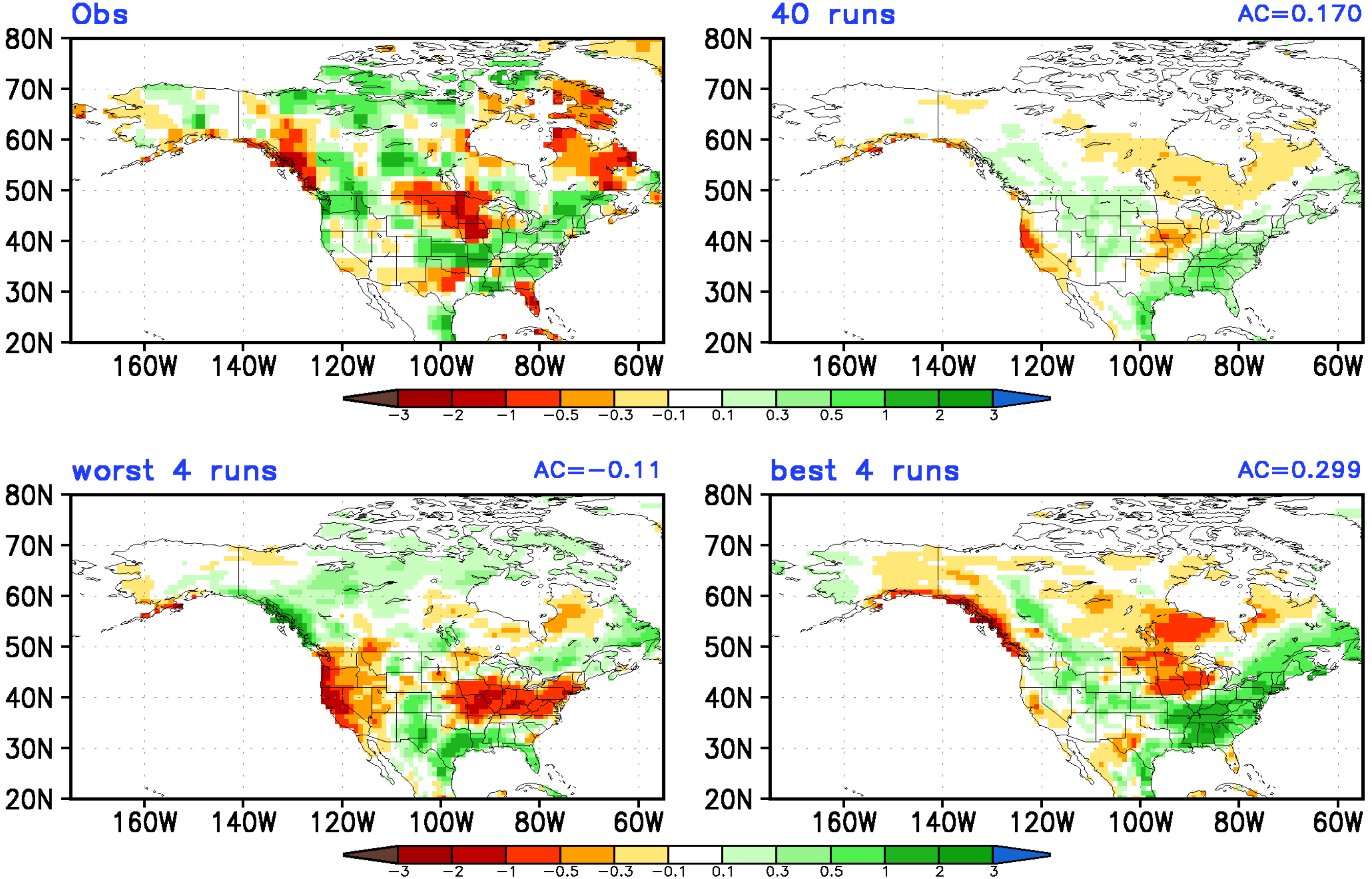
Observed & CFSv2 Forecast Ensemble Average Anomalies
MAM2017 z200(m) 40 runs/worst 4 runs/best 4 runs
0–month–lead monthly



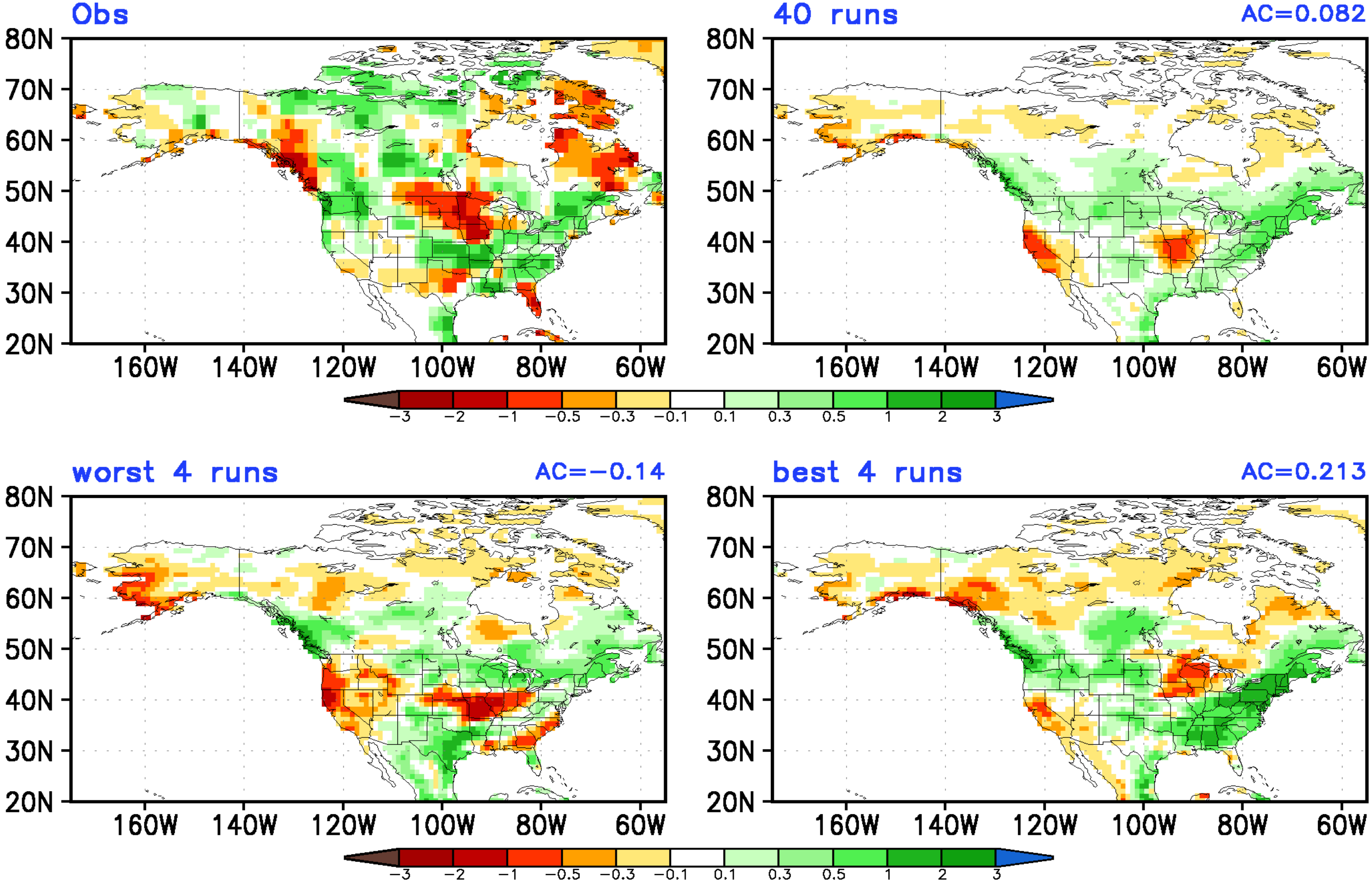
MAM2017 Anomaly Correlation for Individual CFSv2 Forecast with Observation -- Prec (NA)



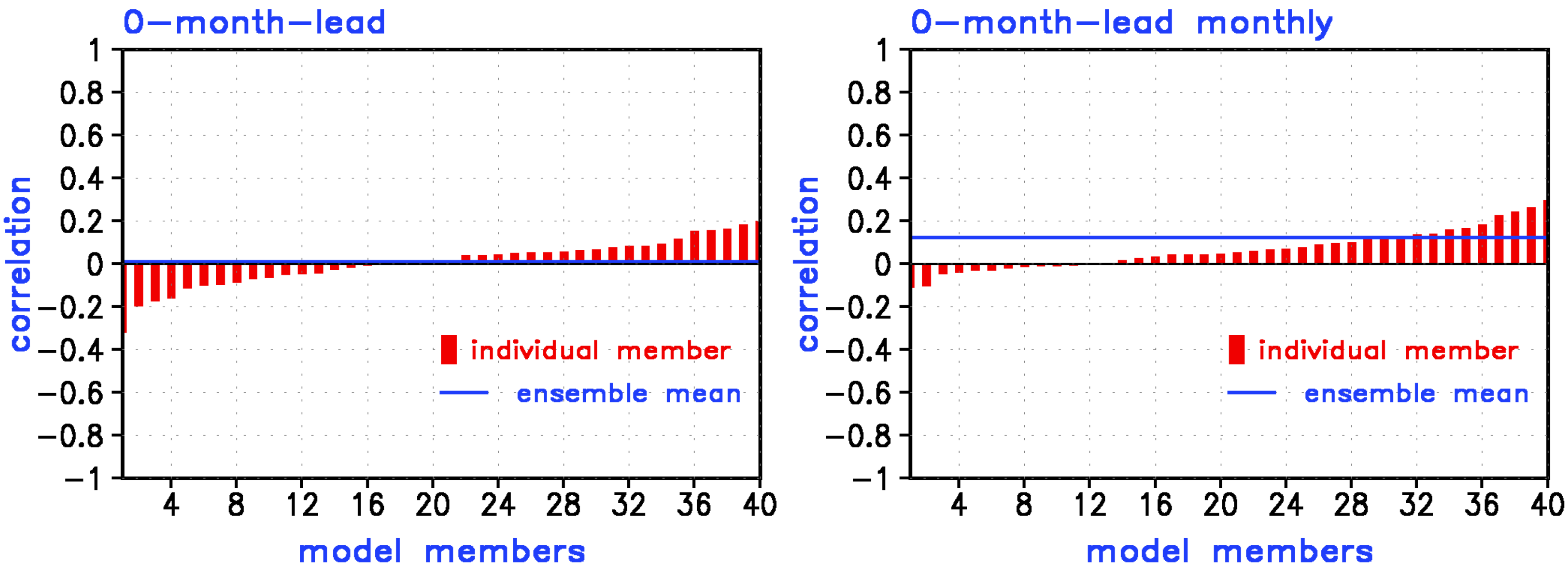
Observed & CFSv2 Forecast Ensemble Average Anomalies
MAM2017 Prec(mm/day) 40 runs/worst 4 runs/best 4 runs
0–month–lead



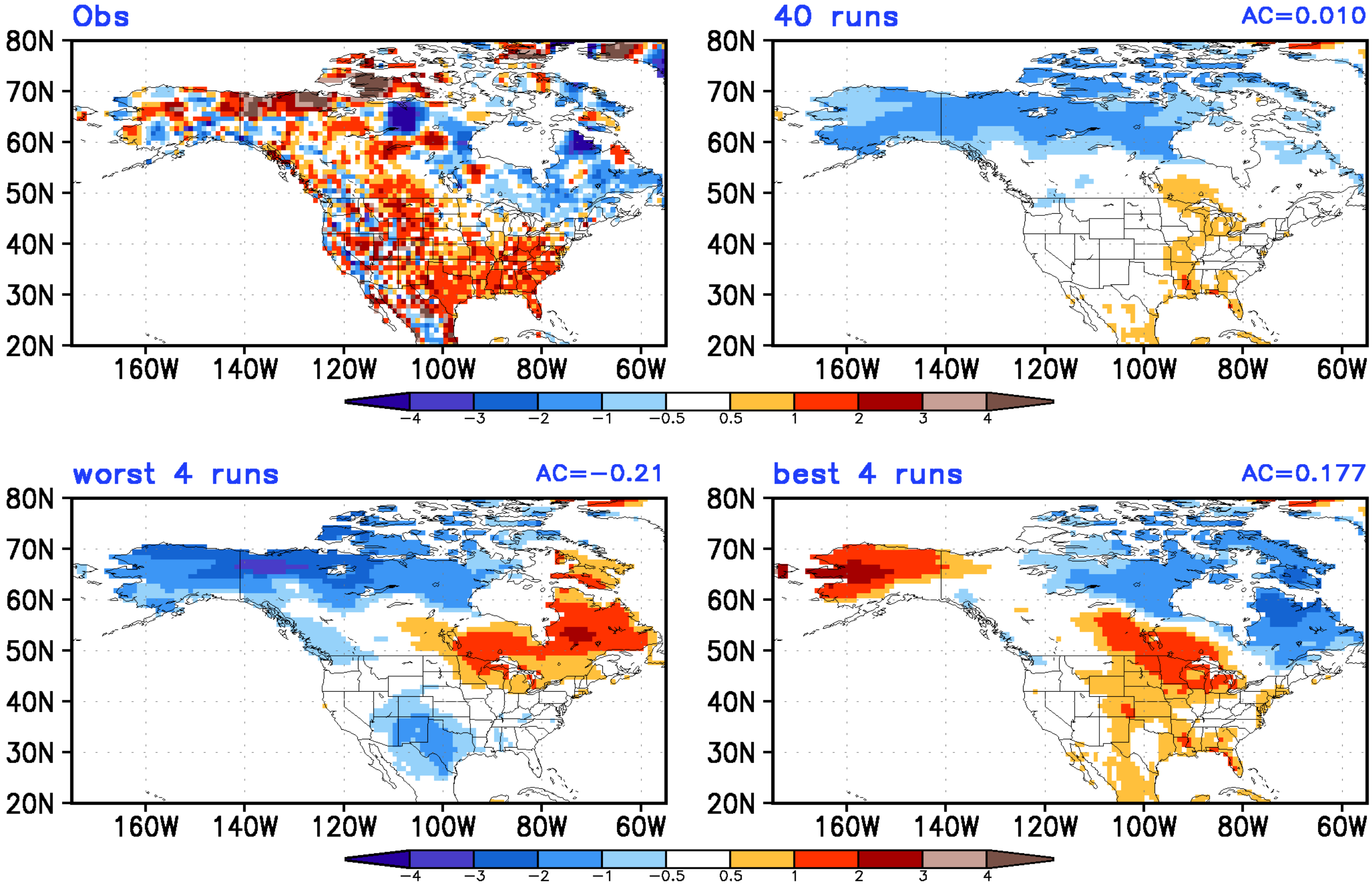
Observed & CFSv2 Forecast Ensemble Average Anomalies
MAM2017 Prec(mm/day) 40 runs/worst 4 runs/best 4 runs
0-month-lead monthly



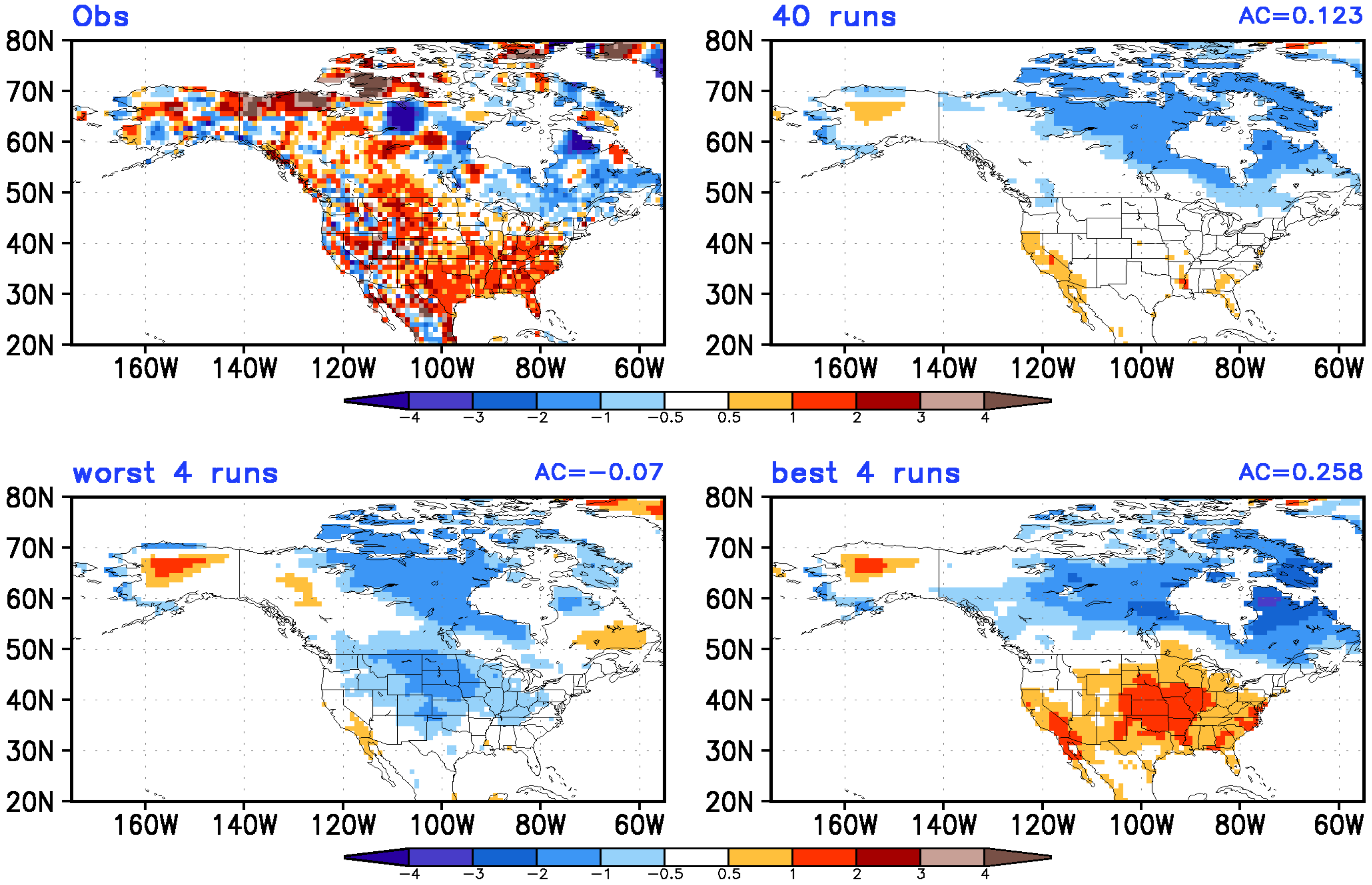
MAM2017 Anomaly Correlation for Individual CFSv2 Forecast with Observation -- T2m (NA)



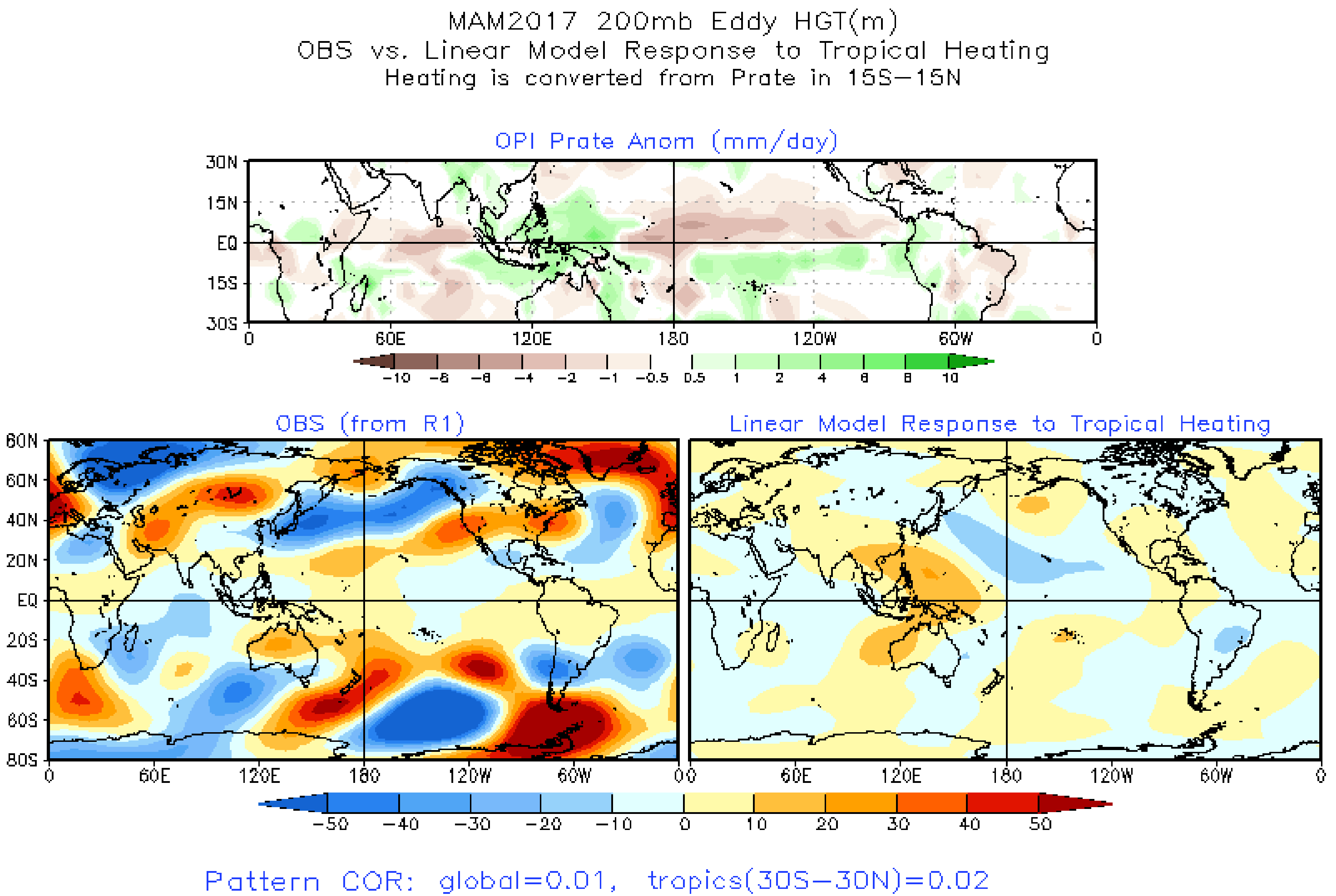
Observed & CFSv2 Forecast Ensemble Average Anomalies MAM2017 T2m(K) 40 runs/worst 4 runs/best 4 runs 0-month-lead



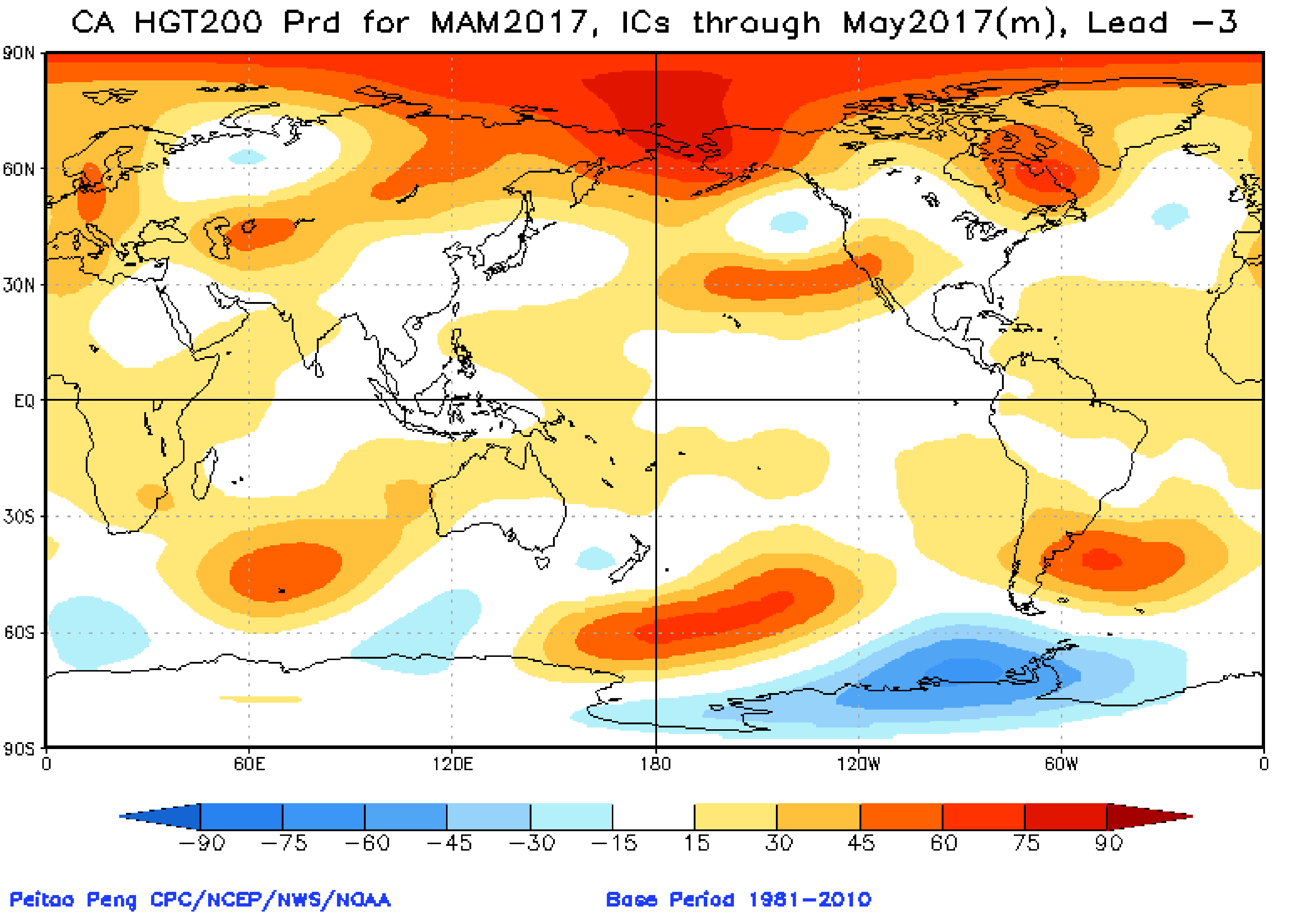
Observed & CFSv2 Forecast Ensemble Average Anomalies
MAM2017 T2m(K) 40 runs/worst 4 runs/best 4 runs
0–month–lead monthly

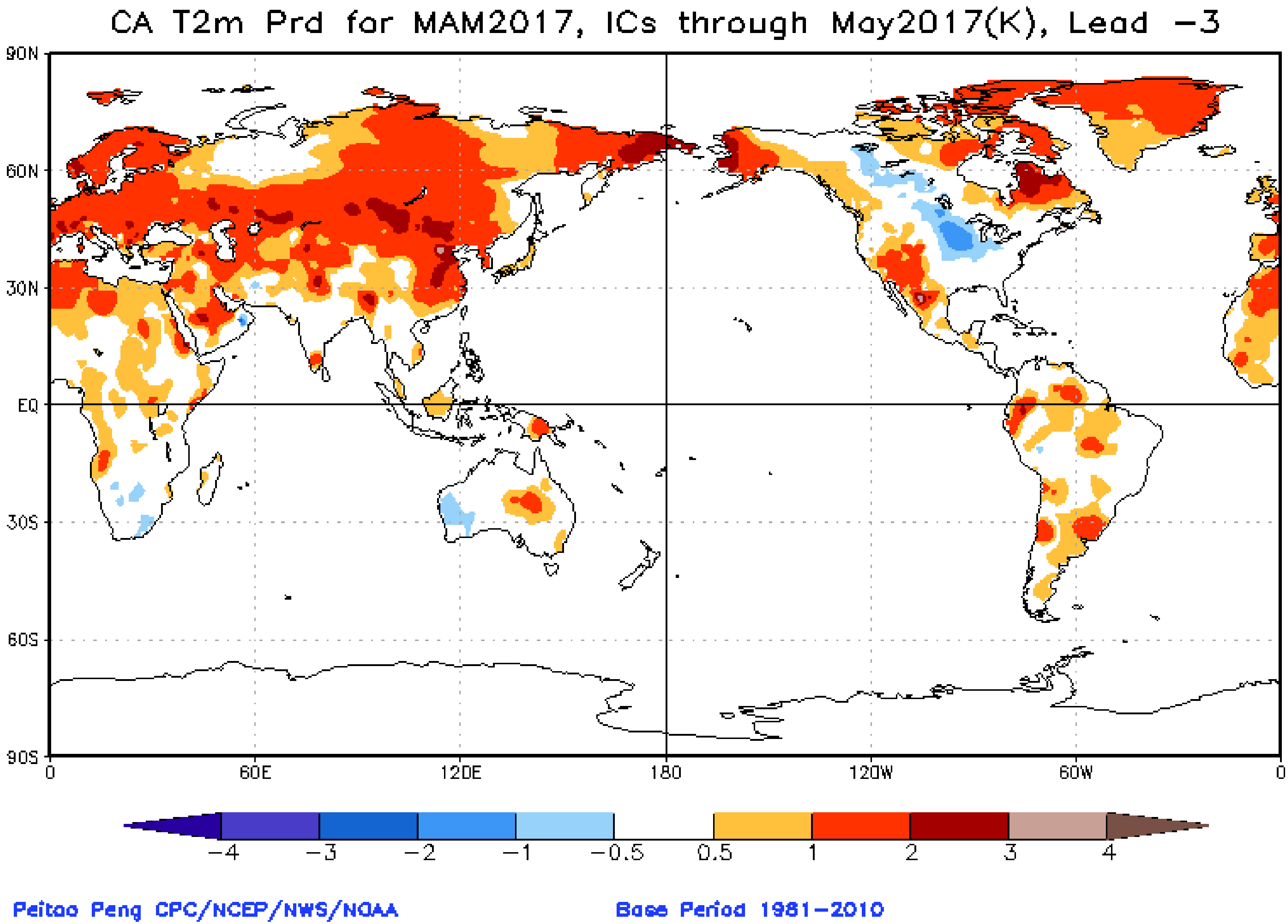


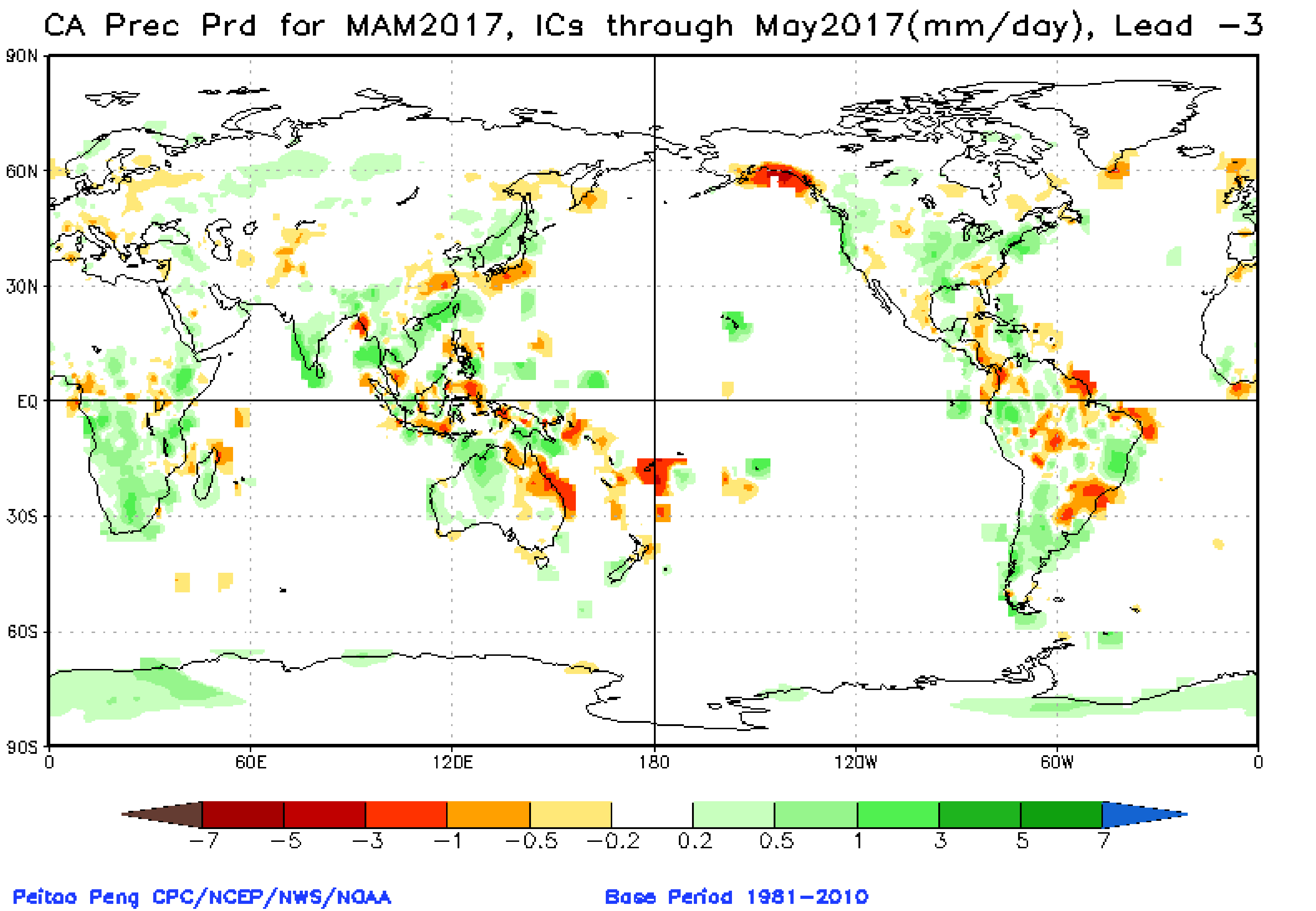
200mb Height from Linear Model


MAM2017 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=0.01, tropics(30S–30N)=0.02

Seasonal Forecasts from the Constructed Analog Model


CA HGT200 Prd for MAM2017, ICs through May2017(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 MAM2017, ICs through May2017(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 MAM2017, ICs through May2017(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

Seasonal Forecasts from WMO Lead Center for Long-Range Forecast Multi-Model Ensemble (LC-LRFMME)

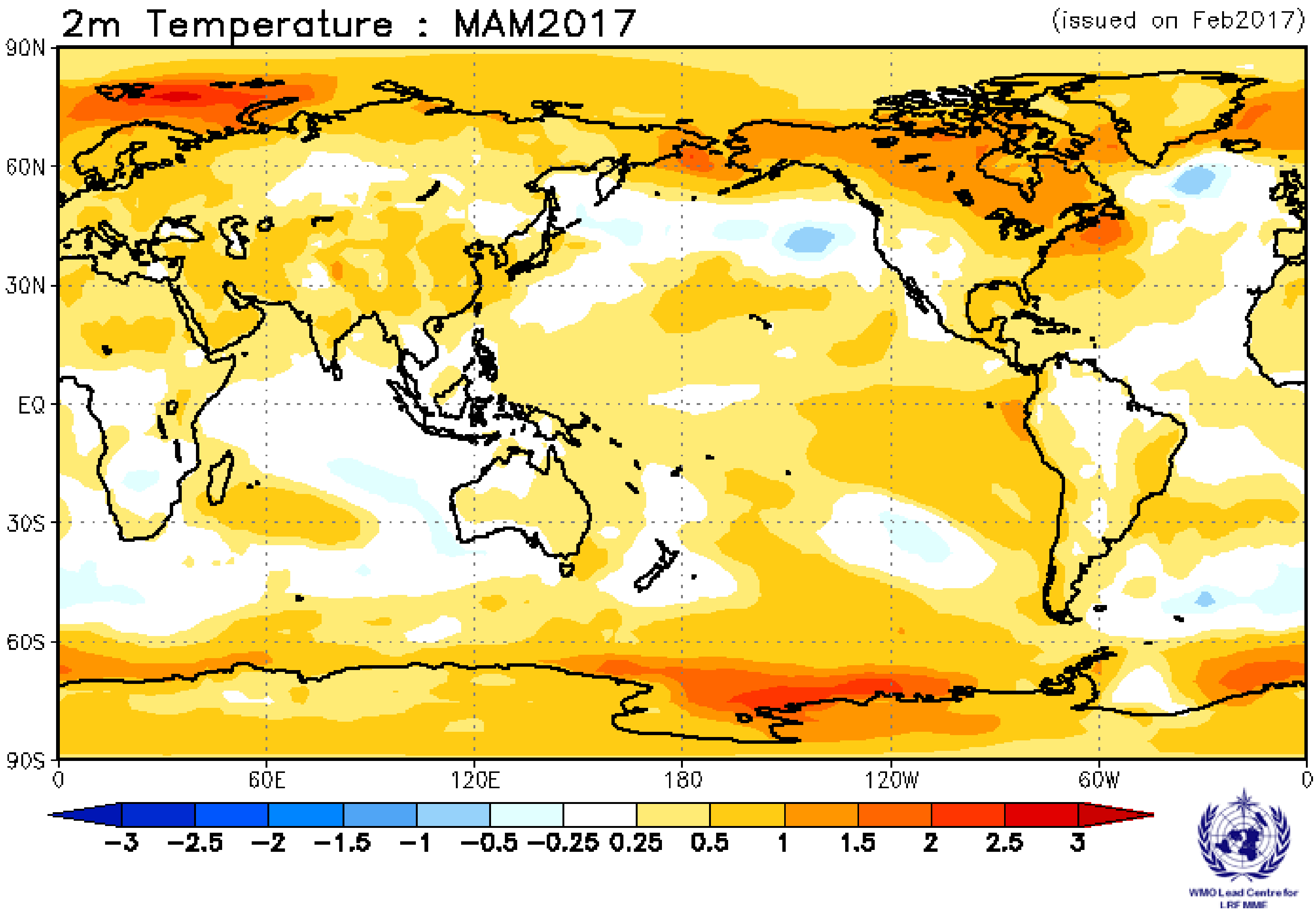
https://www.wmolc.org/

- LC-LRFMME seasonal forecast are based on forecasts provided by WMO recognized Global Producing Centers (GPCs) for Long-Range Forecasts to the LC-LRFMME. Contribution of all GPCs is acknowledged.
- Seasonal forecasts from GPCs are merged into a multi-model ensemble forecast.
- LC-LRFMME forecasts are based on GPC seasonal forecast systems run during the first week of the month for the next season. For example, forecasts runs in first week of January for the seasonal mean of February-March-April.
- Forecasts in slides 41-44 are from the Lead Center.

- *For more information see visit Lead Center website; also see Graham, R., and Co-authors, 2011: New perspectives for GPCs, their role in the GFCS and a proposed contribution to a 'World Climate Watch'. Climate Research, **47**, 47-55.*

Simple Composite Map

GPC_Seoul/GPC_Washington/GPC_Toulouse/GPC_Tokyo/GPC_Montreal/GPC_Melbourne/GPC_Exeter/GPC_ECMWF
GPC_Beijing/GPC_Moscow/GPC_Pretoria/GPC_CPTEC

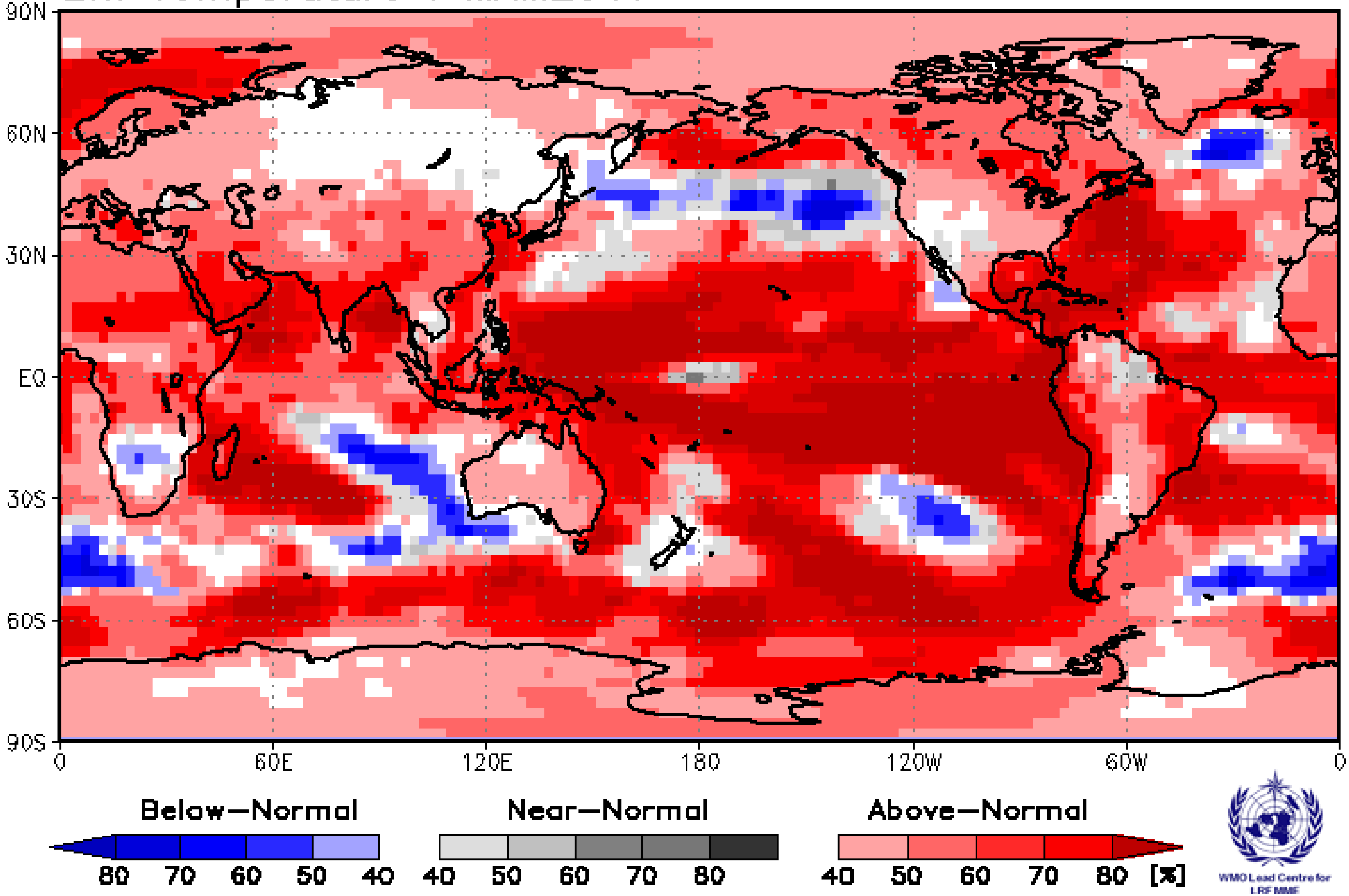


Probabilistic Multi-Model Ensemble Forecast

/GPC_seoul/GPC_washington/GPC_tokyo/GPC_exeter/GPC_moscow/GPC_beijing
/GPC_melbourne/GPC_cptec/GPC_pretoria/GPC_montreal/GPC_ecmwf

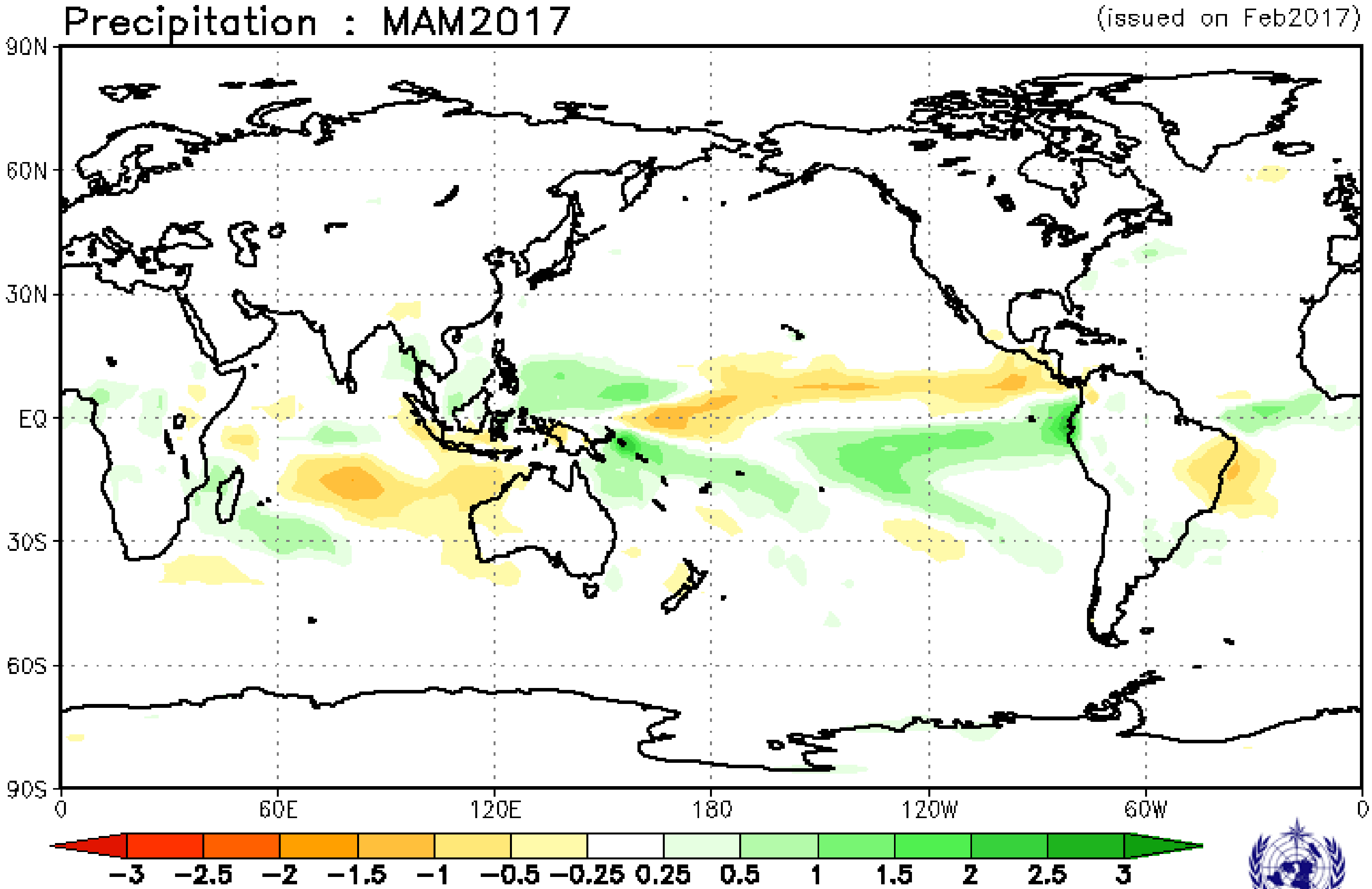
2m Temperature : MAM2017

(issued on Feb2017)

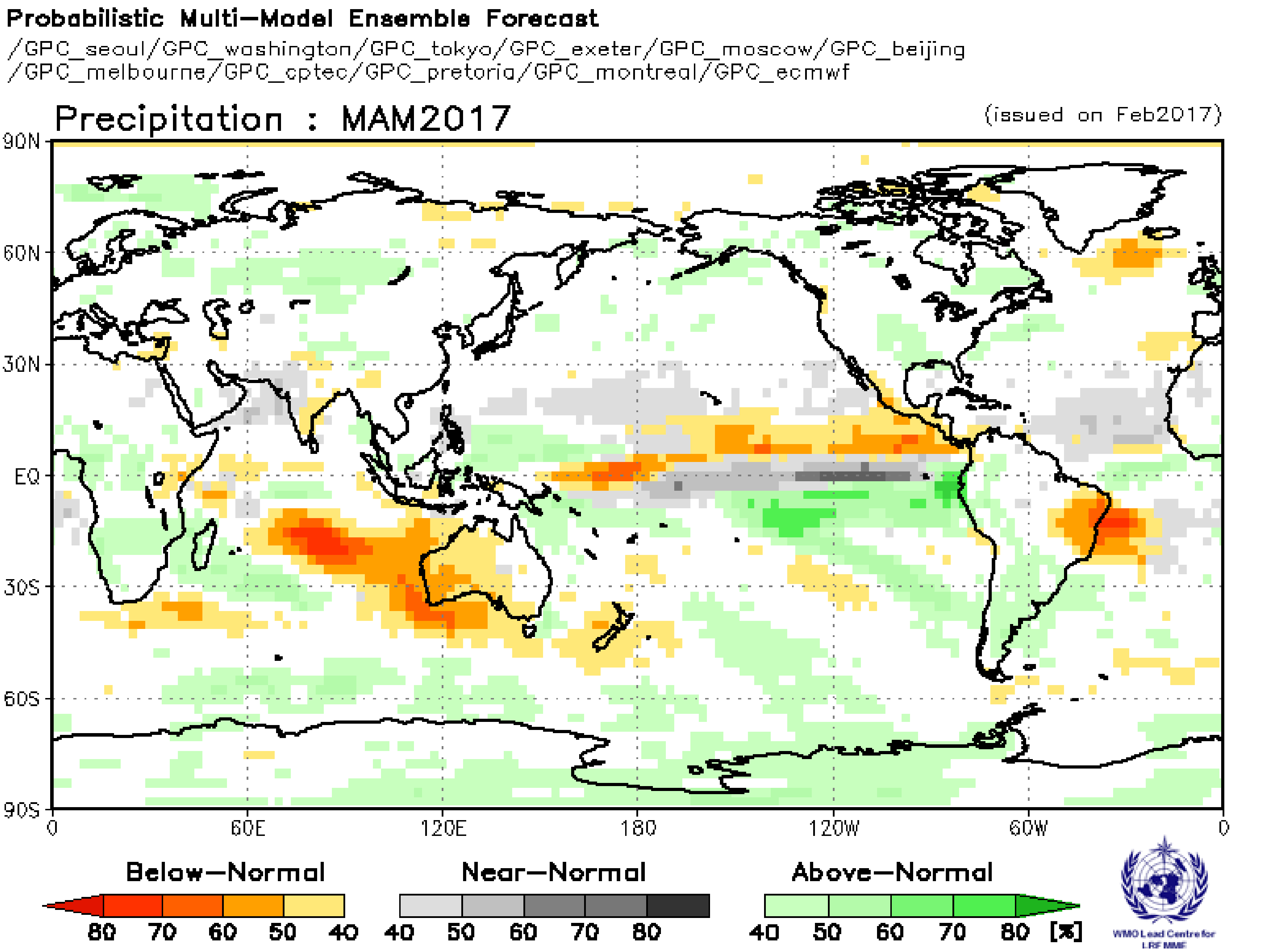


Simple Composite Map

GPC_Seoul/GPC_Washington/GPC_Toulouse/GPC_Tokyo/GPC_Montreal/GPC_Melbourne/GPC_Exeter/GPC_ECMWF
GPC_Beijing/GPC_Moscow/GPC_Pretoria/GPC_CPTEC



WMO Lead Centre for LRF MME


Probabilistic Multi-Model Ensemble Forecast
/GPC_seoul/GPC_washington/GPC_tokyo/GPC_exeter/GPC_moscow/GPC_beijing
/GPC_melbourne/GPC_cptec/GPC_pretoria/GPC_montreal/GPC_ecmwf
Precipitation : MAM2017
(issued on Feb2017)
90N
60N
30N
EQ
30S
60S
90S
0
60E
120E
180
120W
60W
0
Below-Normal
Near-Normal
Above-Normal
80 70 60 50 40
40 50 60 70 80
40 50 60 70 80 [%]
WMO Lead Centre for LRF MME

Summary

- The observed equatorial SST MAM2017 anomalies were weak except relatively large positive anomalies near the west coastal areas of SA; the height anomaly simulated in linear model based on the tropical heating didn’t capture features in the observation;
- CFSv2 forecasted the large scale pattern of SST anomaly, and the forecast skill was improved 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 CFSv2 forecasts didn’t capture well the anomalies of z200, Prec, and T2m; overall correlation skills were low for the global and NA regions;
- For the individual members, the PNA z200, NA Prec and T2m correlation skills were low and had large variations between members; about half of members showing negative correlation skills for the CFSv2 NA Prec and T2m, and AMIP PNA z200;
- The Constructed Analog model looked like forecsted better anomaly patterns of PNA z200 and west US Prec than that from CFSv2;
- CFSv2 forecasts showed considerable differences in T2m & Prec from the ensemble means of NMME and GPC-MME, i.e., large variations among dynamical models;

References

Fan, Y., and Dool H. van den Dool (2008), A global monthly land surface air temperature analysis for 1948-present. J. Geophys. Res., 113, D01103. doi:10.1029/2007JD008470.

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.

Reynolds, R. W. et al (2007), Daily high resolution-blended analyses for sea surface temperature. J. Clim., 20, 5473-5496. doi:10.1175/2007JCLI1824.1.

Saha, S. et al (2010), The NCEP climate forecast system reanalysis. Bull. Amer. Meteor. Soc., 91, 1015-1057. doi:10.1175/2010BAMS3001.1.

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Xie, P, and P. A. Arkin (1997), Global precipitation: A 17-year monthly analysis based on gauge observations, satellite estimates, and numerical model outputs. Bull. Amer. Meteor. Soc., 78, 2539-2558. doi: http://dx.doi.org/10.1175/1520-0477(1997)078%3C2539:GPAYMA%3E2.0.CO;2