# Attribution of Seasonal Climate Anomalies October-November-December 2019

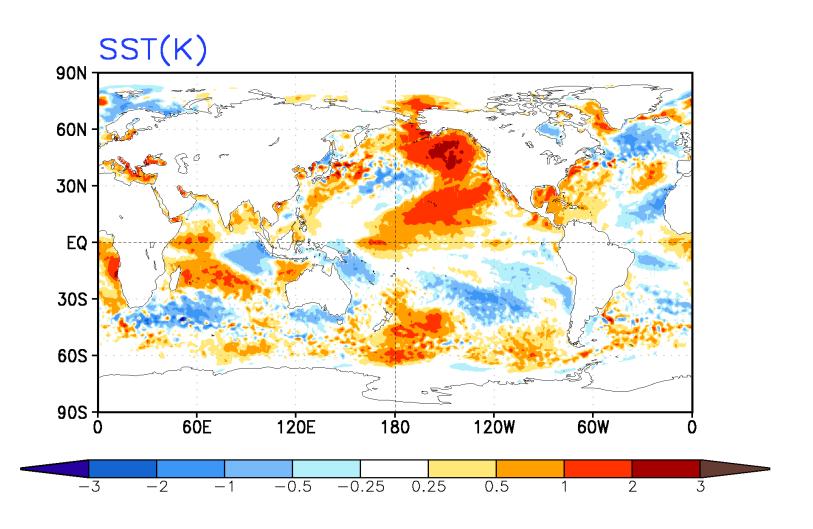
# Summary of October-November-December 2019 Observed Conditions and Outlooks

- The sea surface temperature (SST) anomalies in equatorial Pacific Ocean were weak; Indian Ocean Dipole (IOD) continued to be in a strong positive phase with negative (positive) SST anomalies in the eastern (western) Indian Ocean; SST anomalies throughout the NE Pacific continued to be strongly positive (Slide 4).
- Consistent with the positive phase of the IOD, drier than normal precipitation was observed over the region extending from Indonesian Archipelago to SE. equatorial Indian Ocean (Slide 5).
- Drier than normal precipitation over the region from the Indonesian Archipelago to E. equatorial Indian Ocean, Australia, equatorial central Pacific, and the E Brazil were predicted well in the CFSv2 (slide 11) and the multi-model ensemble forecasts from the WMO Lead Center (slides 39-40).
- Tropical observed above normal height anomalies were well captured in the CFSv2 simulations and forecasts, while the centers of positive and negative height anomalies over the PNA region were misplaced in the model forecasts that led to misplaced cold surface temperature anomalies over the NA.

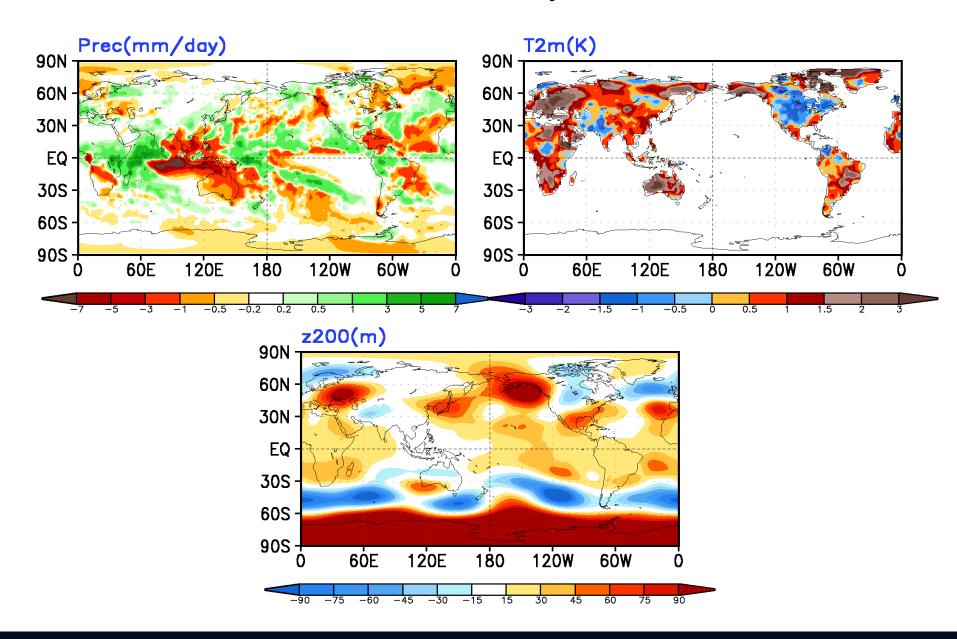
### **Observed Seasonal Anomalies**

Global and North America

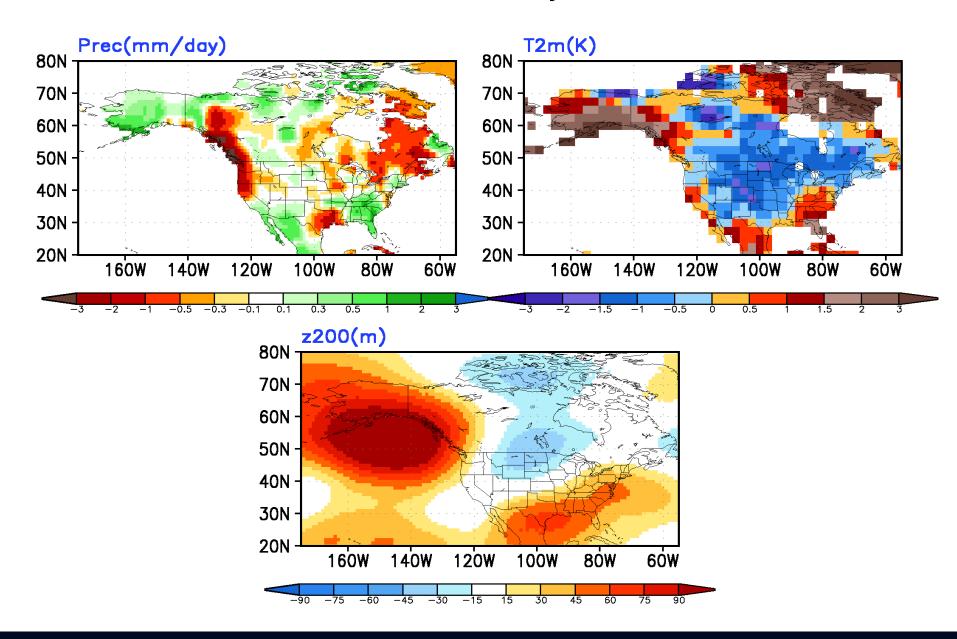
## Observed Anomaly OND2019



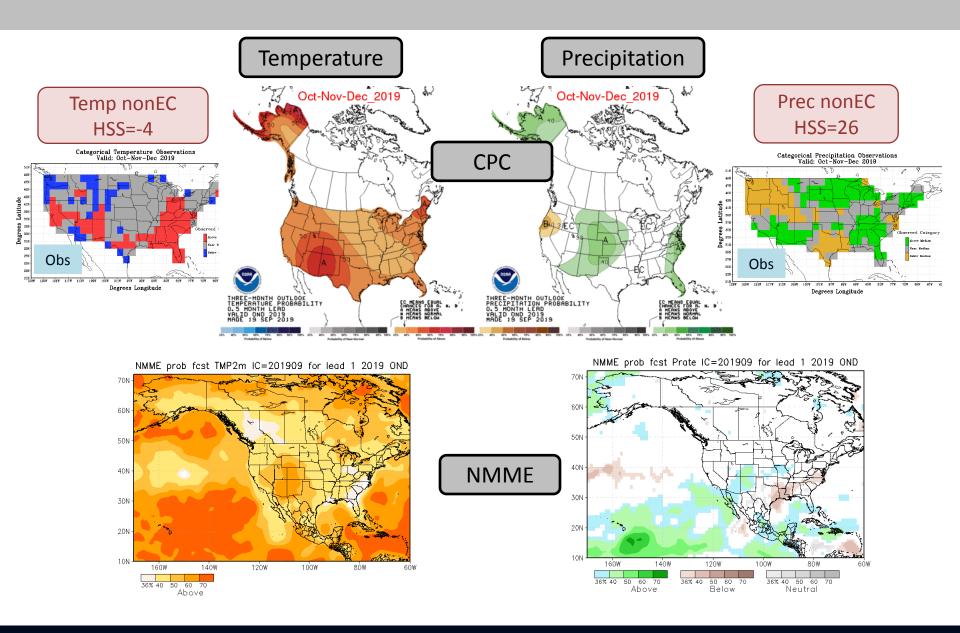
## Observed Anomaly OND2019



### Observed Anomaly OND2019



#### OND2019 CPC Seasonal Outlooks and NMME Forecasts

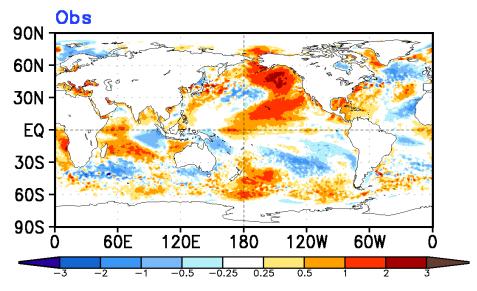


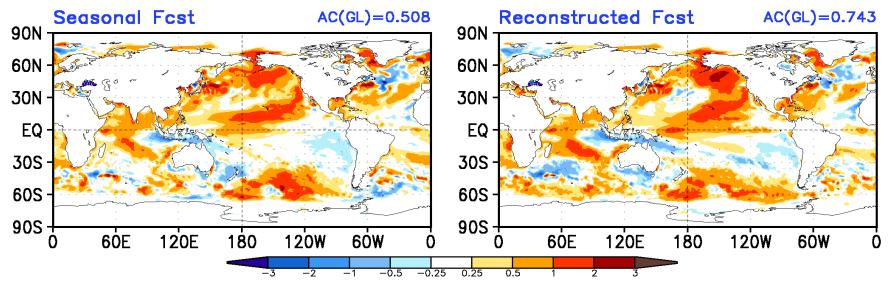
1odel Simulated/Forecast Ensemble Mean Anomalie	<b>2</b> S

### Model Simulated/Forecast Ensemble Average Anomalies

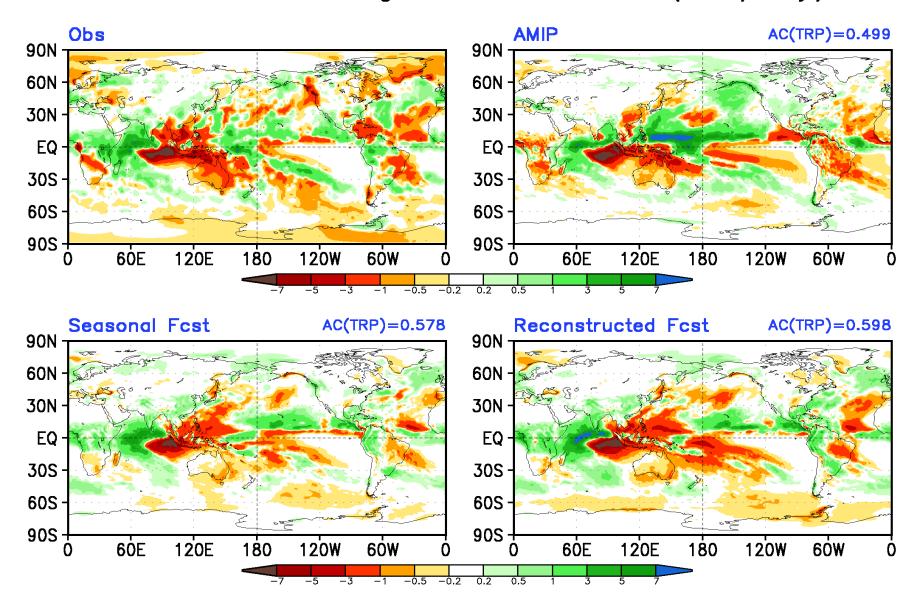
- CFS AMIP simulations forced with observed sea surface temperatures (18 members ensemble)
- CFSv2 real time operational forecasts
  - Seasonal forecast: the seasonal mean forecasts based on 40 members from the latest
     10 days before the target season (0-month-lead). For example, 2016AMJ seasonal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

# OND2019 Observed & Model Simulated/Forecast Ensemble Average Anomalies SST(K)

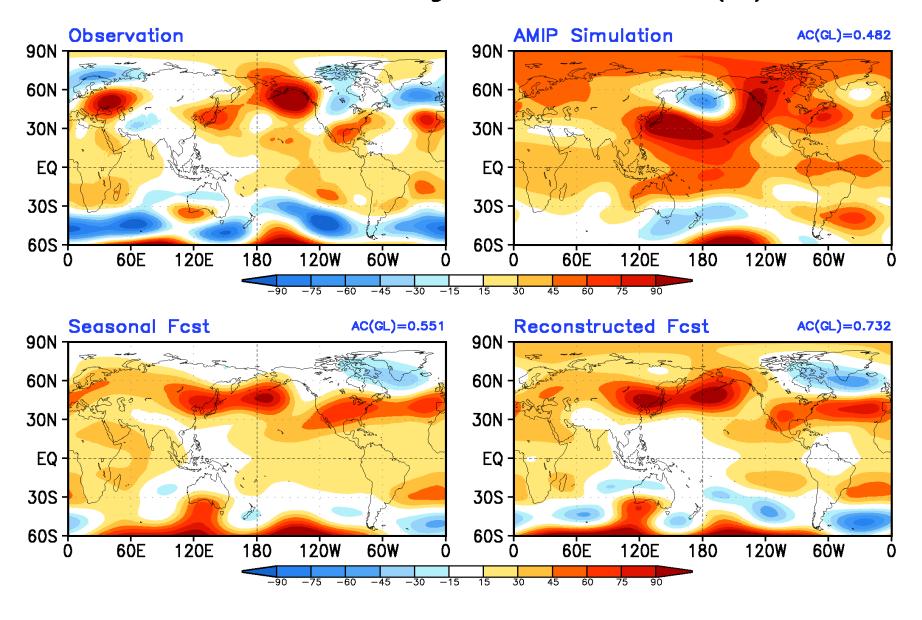




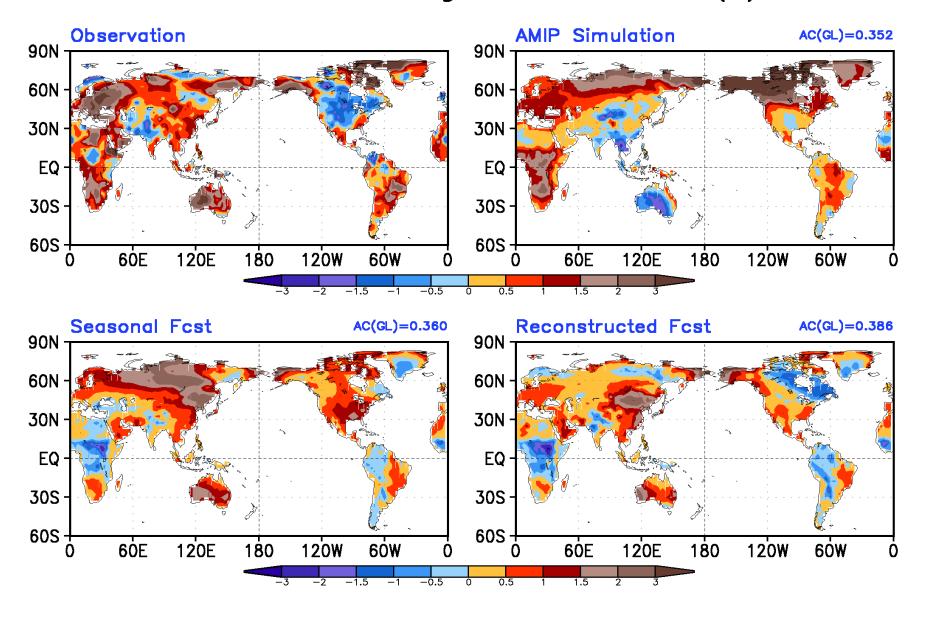
# OND2019 Observed & Model Simulated/Forecast Ensemble Average Anomalies Prec(mm/day)



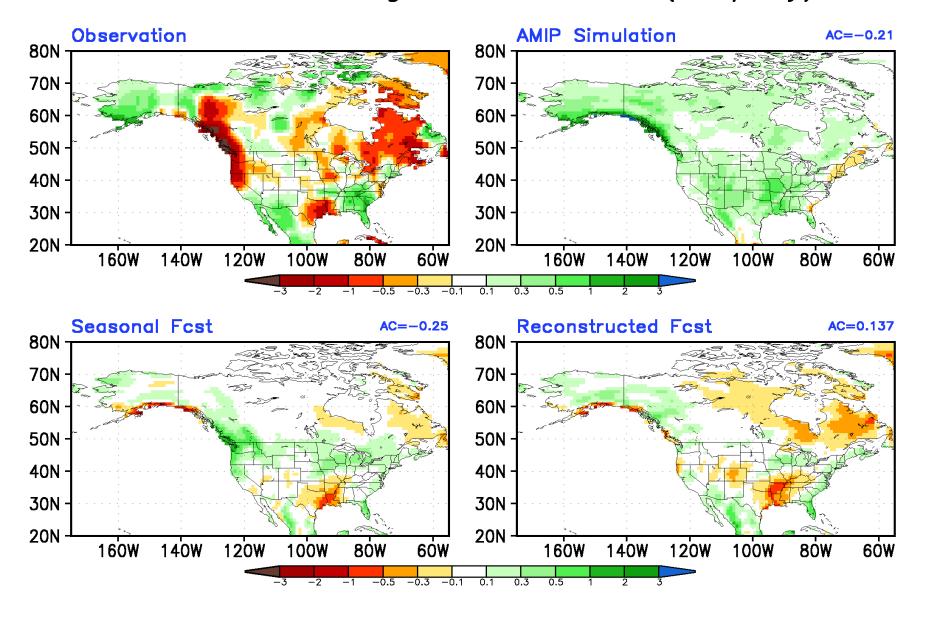
# OND2019 Observed & Model Simulated/Forecast Ensemble Average Anomalies z200(m)



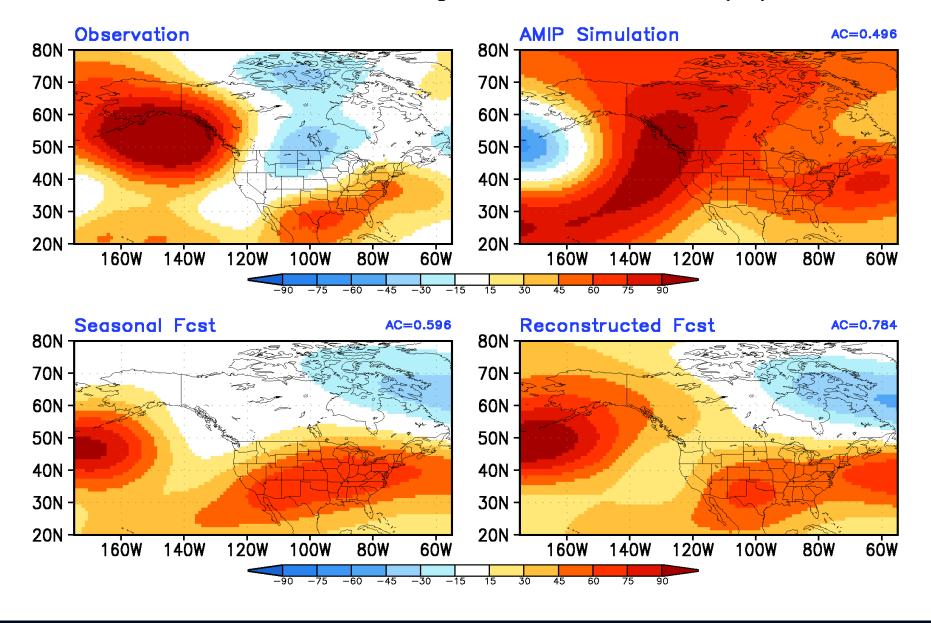
## OND2019 Observed & Model Simulated/Forecast Ensemble Average Anomalies T2m(K)



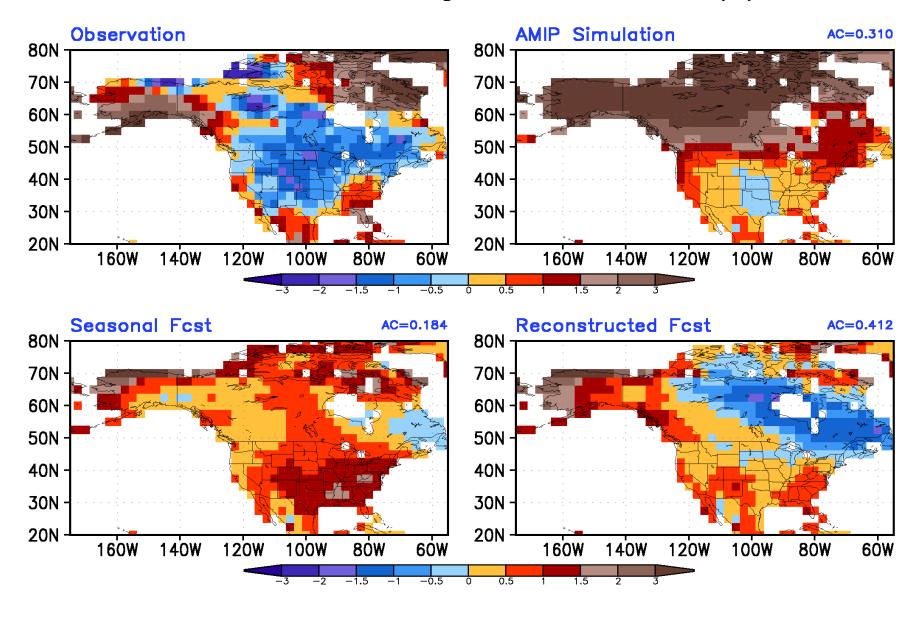
## OND2019 Observed & Model Simulated/Forecast Ensemble Average Anomalies Prec(mm/day)

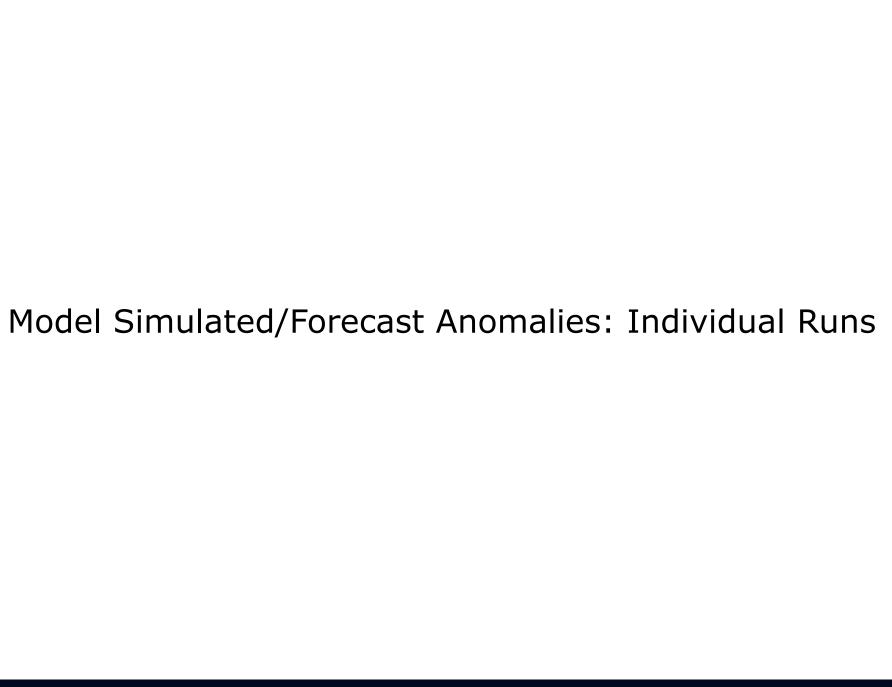


## OND2019 Observed & Model Simulated/Forecast Ensemble Average Anomalies z200(m)



### OND2019 Observed & Model Simulated/Forecast Ensemble Average Anomalies T2m(K)

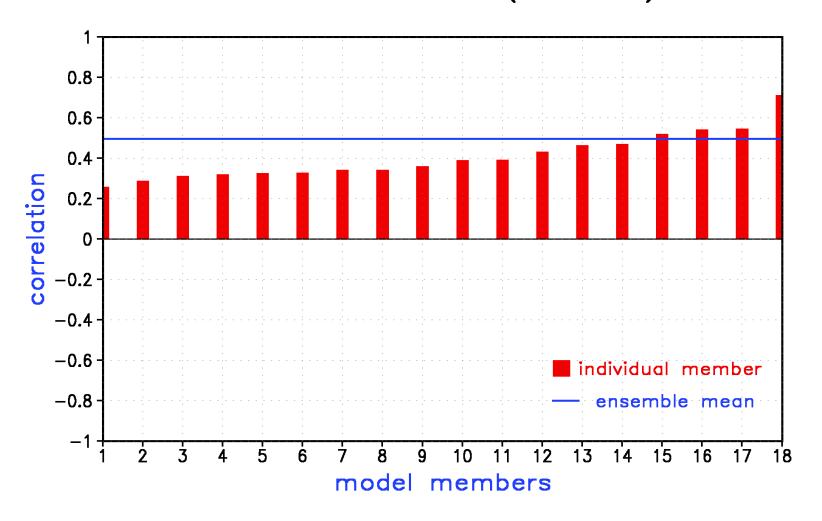




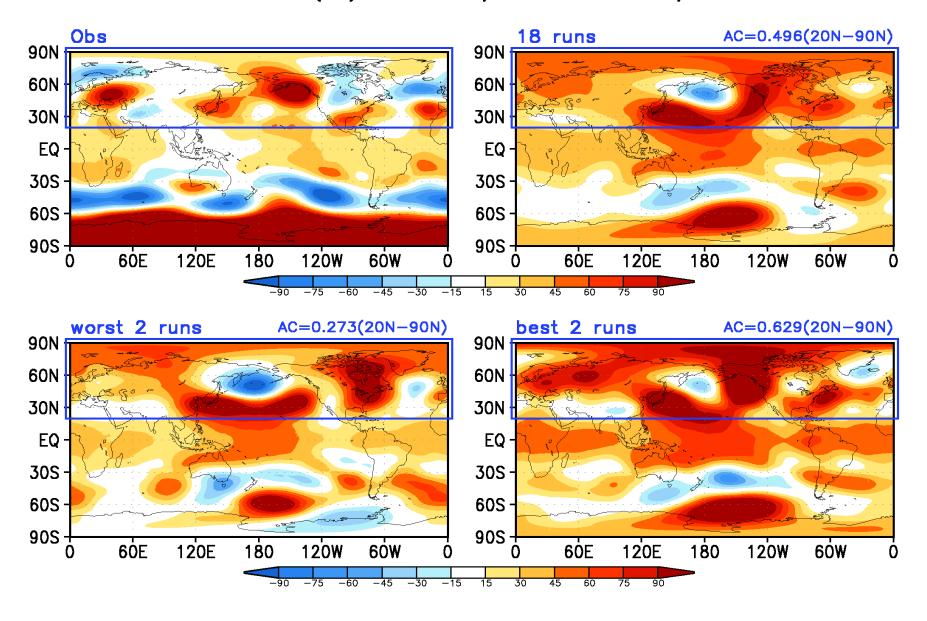
### Model Simulated/Forecast Anomalies: Individual Runs

- 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.

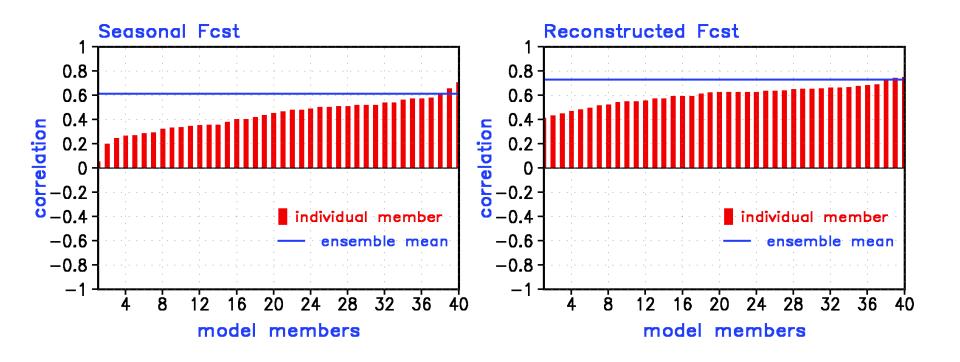
## OND2019 Anomaly Correlation for Individual AMIP Simulation with Observation -- z200(20N-90N)



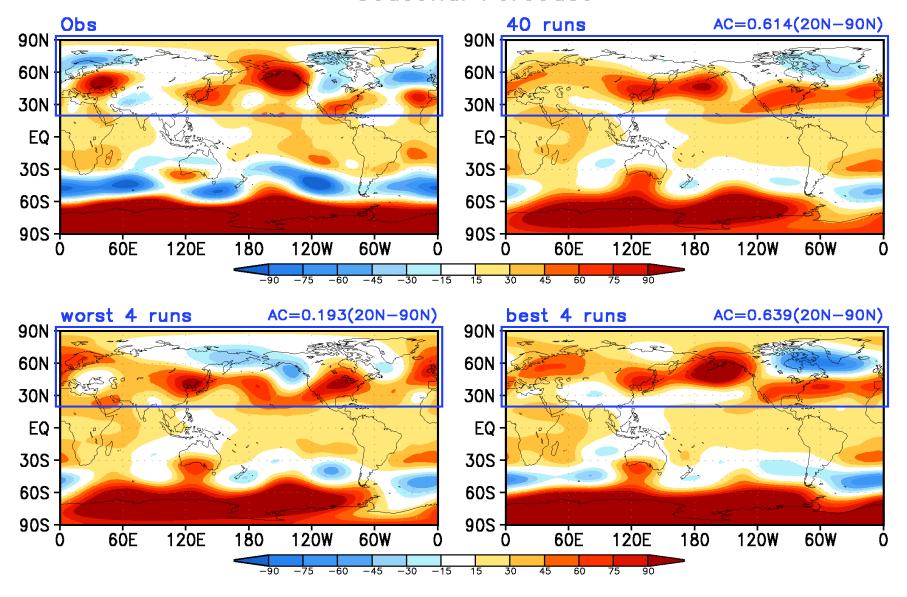
## Observed & AMIP Ensemble Average Anomalies OND2019 z200(m) 18 runs/worst 2 runs/best 2 runs



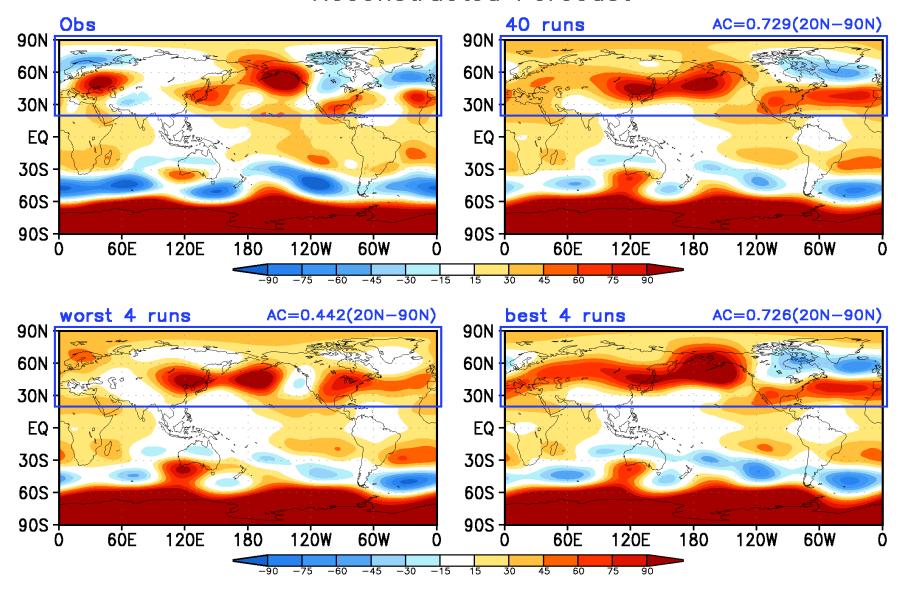
## OND2019 Anomaly Correlation for Individual CFSv2 Forecast with Observation —— z200 (20N—90N)



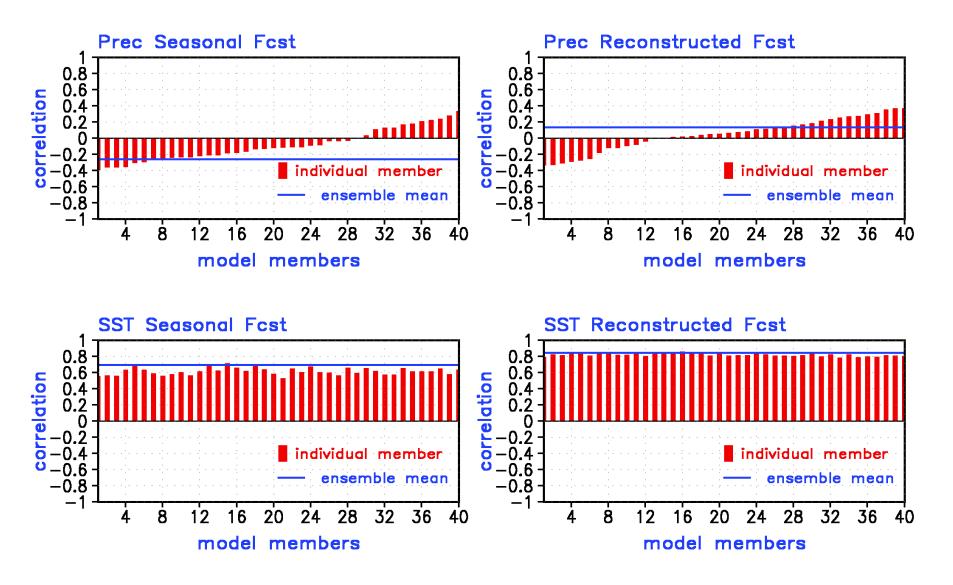
# Observed & CFSv2 Forecast Ensemble Average Anomalies OND2019 z200(m) 40 runs/worst 4 runs/best 4 runs Seasonal Forecast



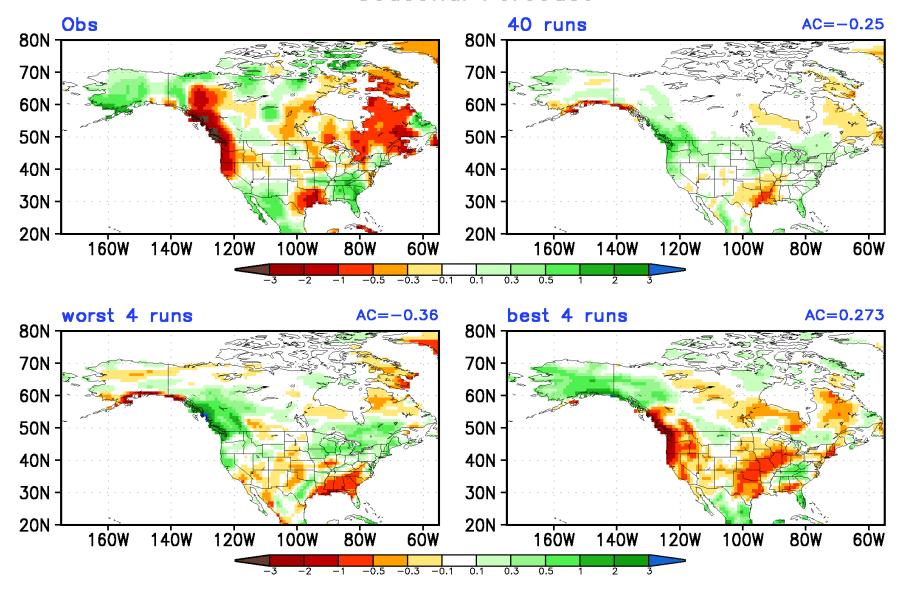
# Observed & CFSv2 Forecast Ensemble Average Anomalies OND2019 z200(m) 40 runs/worst 4 runs/best 4 runs Reconstructed Forecast



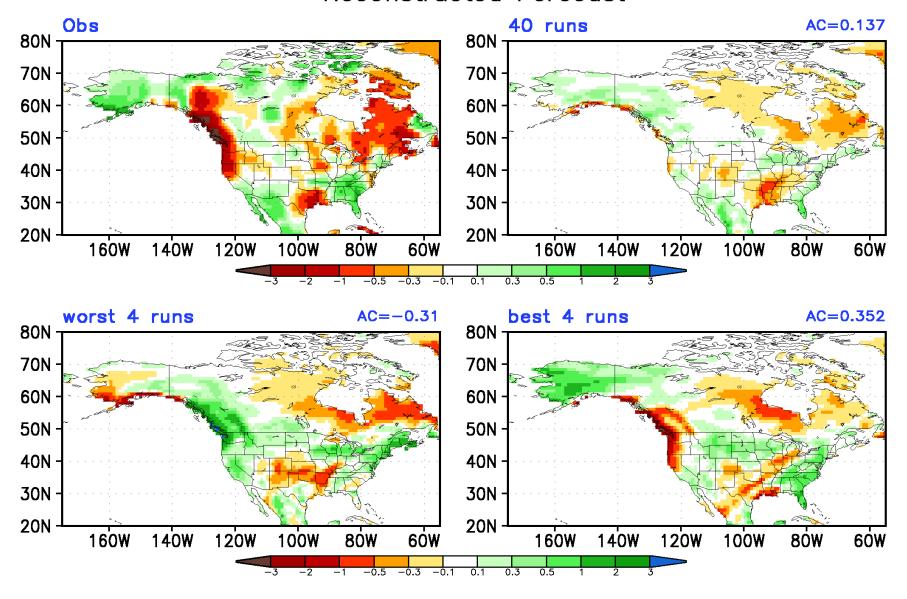
## OND2019 Anomaly Correlation for Individual CFSv2 Forecast with Observation —— Prec(NA)/SST(30S—30N)



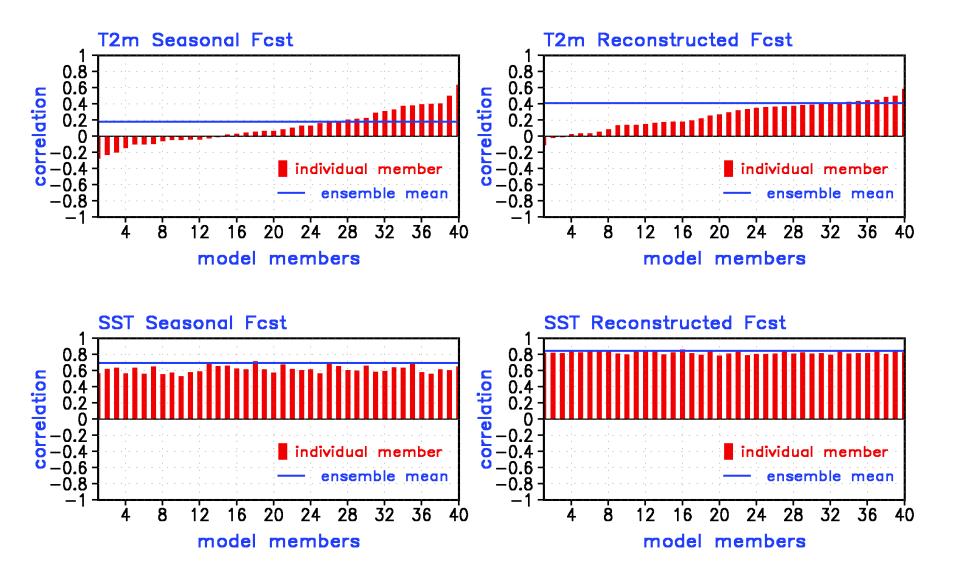
# Observed & CFSv2 Forecast Ensemble Average Anomalies OND2019 Prec(mm/day) 40 runs/worst 4 runs/best 4 runs Seasonal Forecast



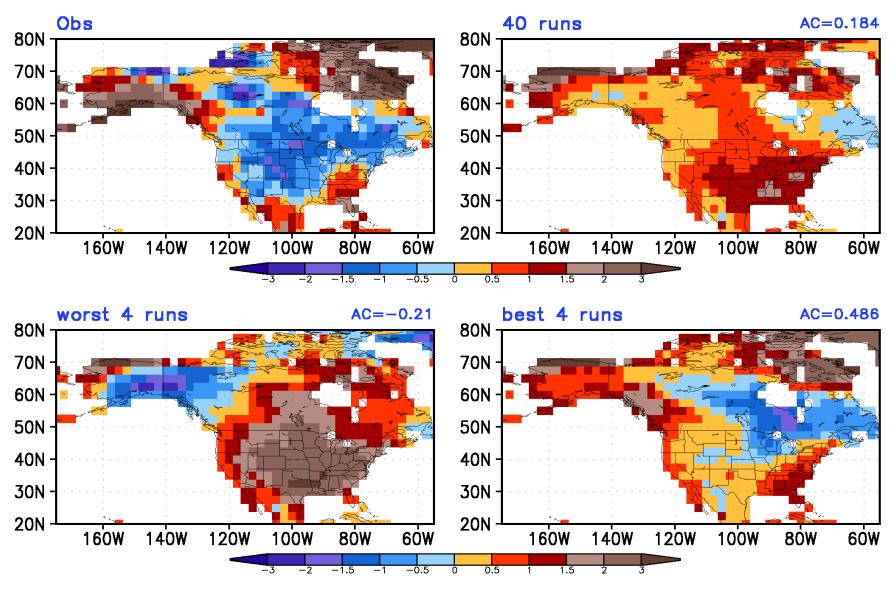
# Observed & CFSv2 Forecast Ensemble Average Anomalies OND2019 Prec(mm/day) 40 runs/worst 4 runs/best 4 runs Reconstructed Forecast



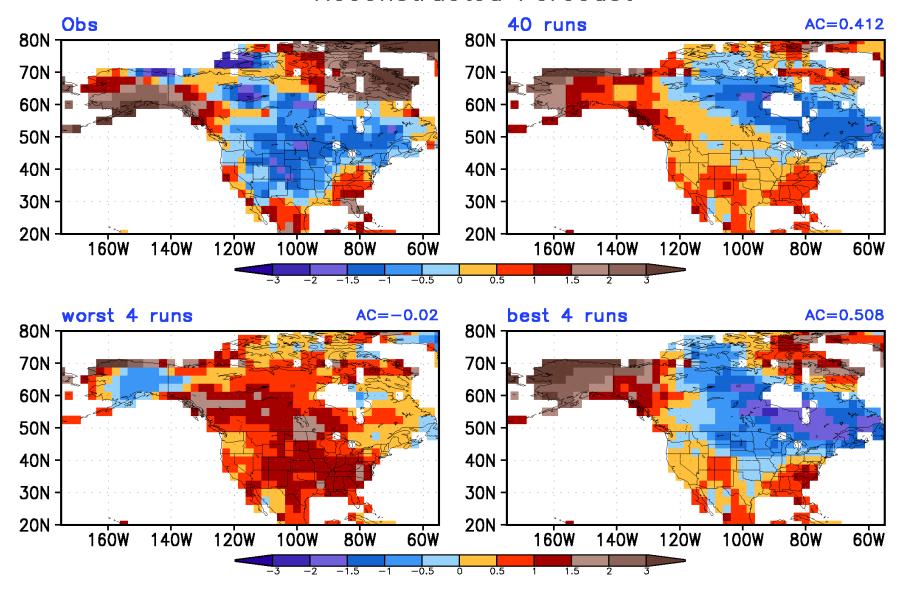
## OND2019 Anomaly Correlation for Individual CFSv2 Forecast with Observation —— T2m(NA)/SST(30S—30N)



# Observed & CFSv2 Forecast Ensemble Average Anomalies OND2019 T2m(K) 40 runs/worst 4 runs/best 4 runs Seasonal Forecast

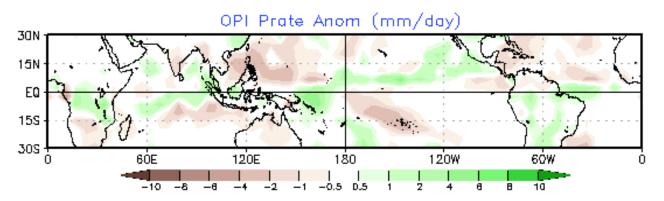


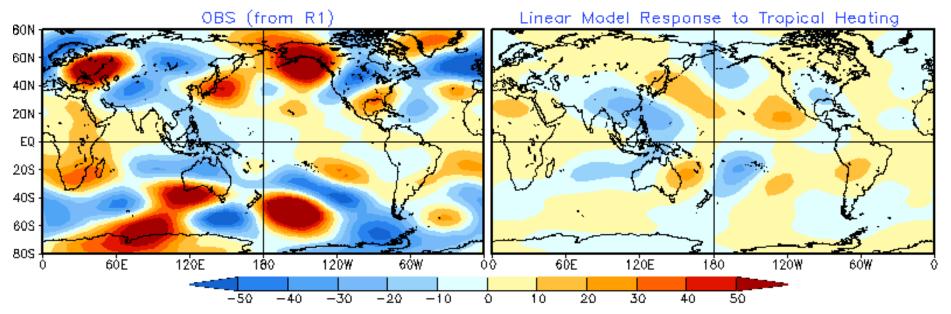
# Observed & CFSv2 Forecast Ensemble Average Anomalies OND2019 T2m(K) 40 runs/worst 4 runs/best 4 runs Reconstructed Forecast



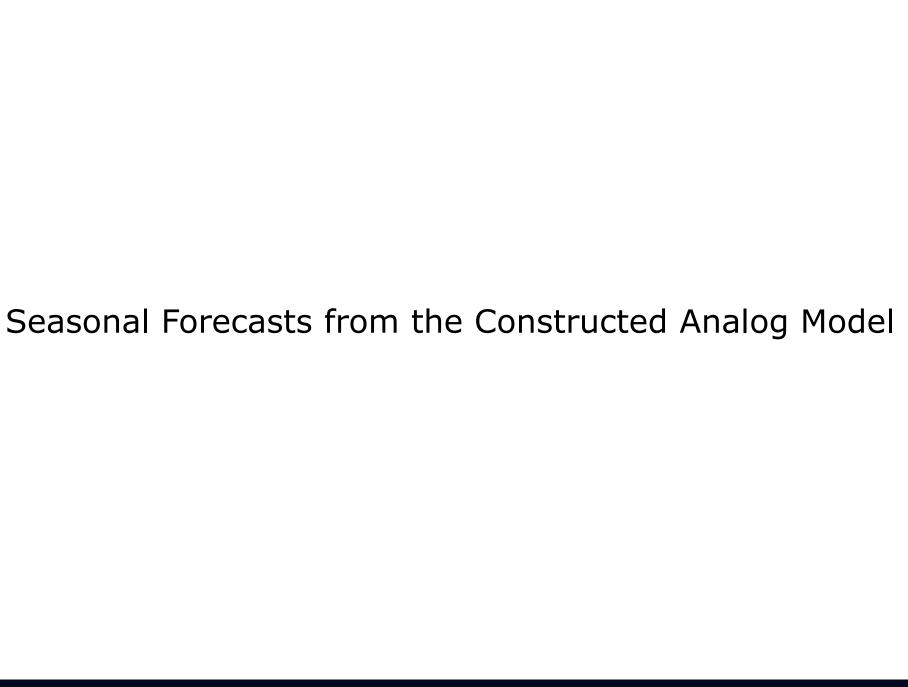
200mb Height from Linear Model

## OND2019 200mb Eddy HGT(m) OBS vs. Linear Model Response to Tropical Heating Heating is converted from Prate in 15S—15N

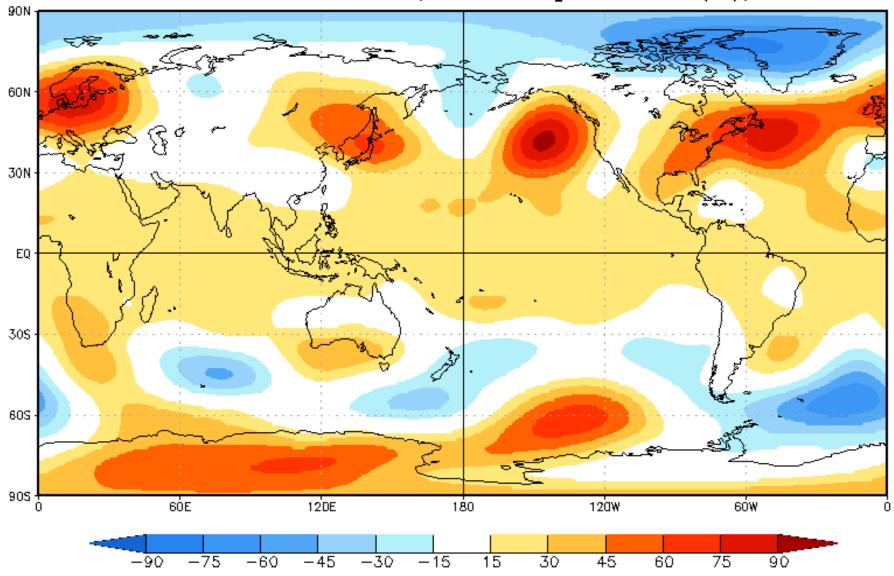




Pattern COR: global=0.15, tropics(30S-30N)=0.38



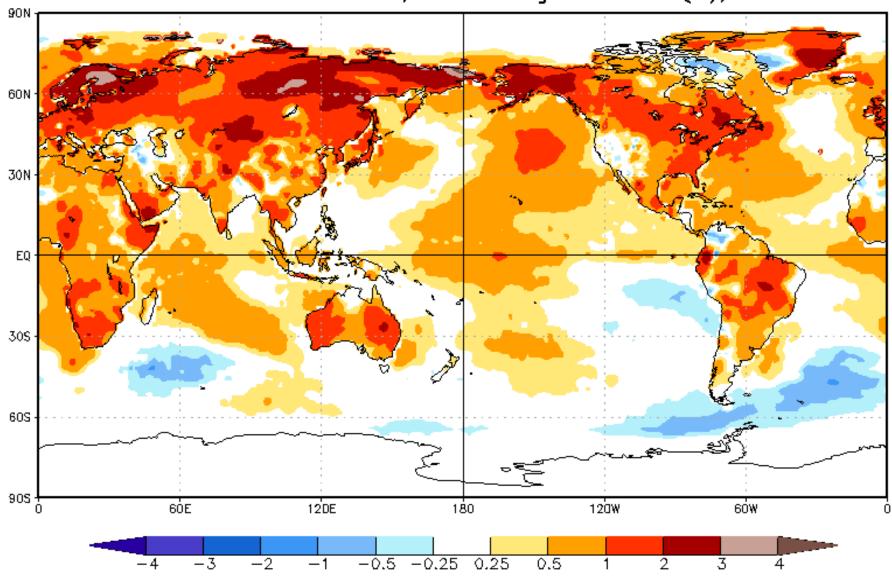
CA HGT200 Prd for OND2019, ICs through Dec2019(m), Lead -3



Peitoo Peng CPC/NCEP/NWS/NGAA

Base Period 1981-2010

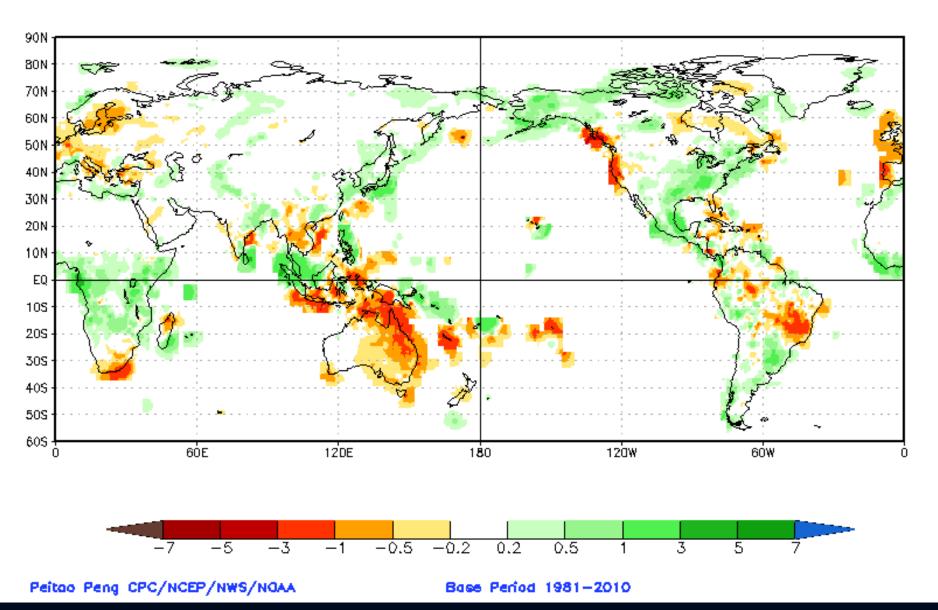
CA T2m Prd for OND2019, ICs through Dec2019(K), Lead -3



Peitoo Peng CPC/NCEP/NWS/NGAA

Base Period 1981-2010

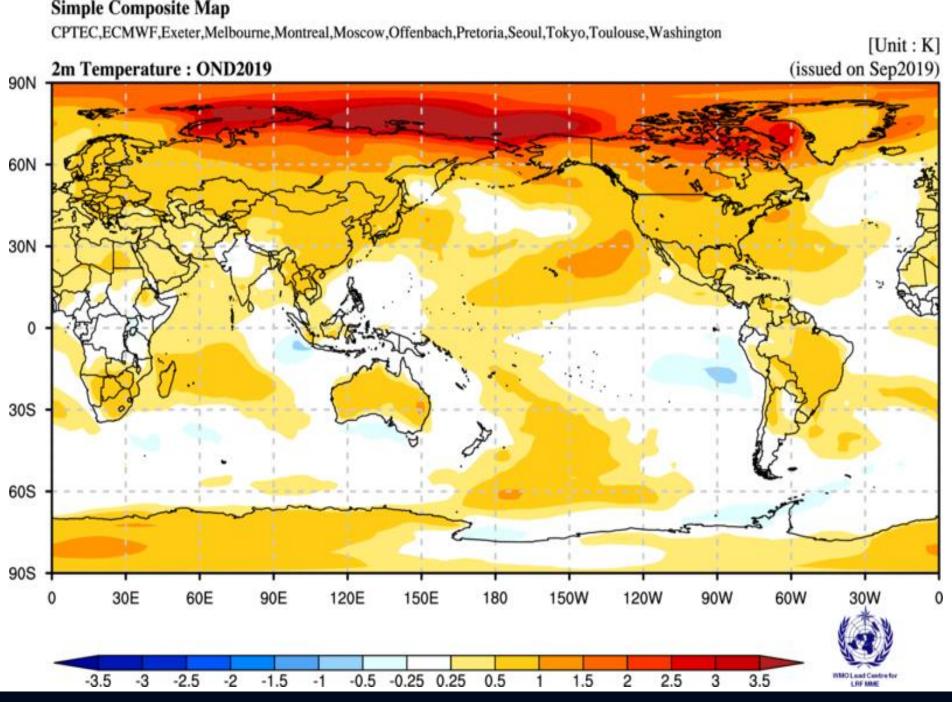
#### CA Prec Prd for OND2019, ICs through Dec2019(mm/day), Lead -3

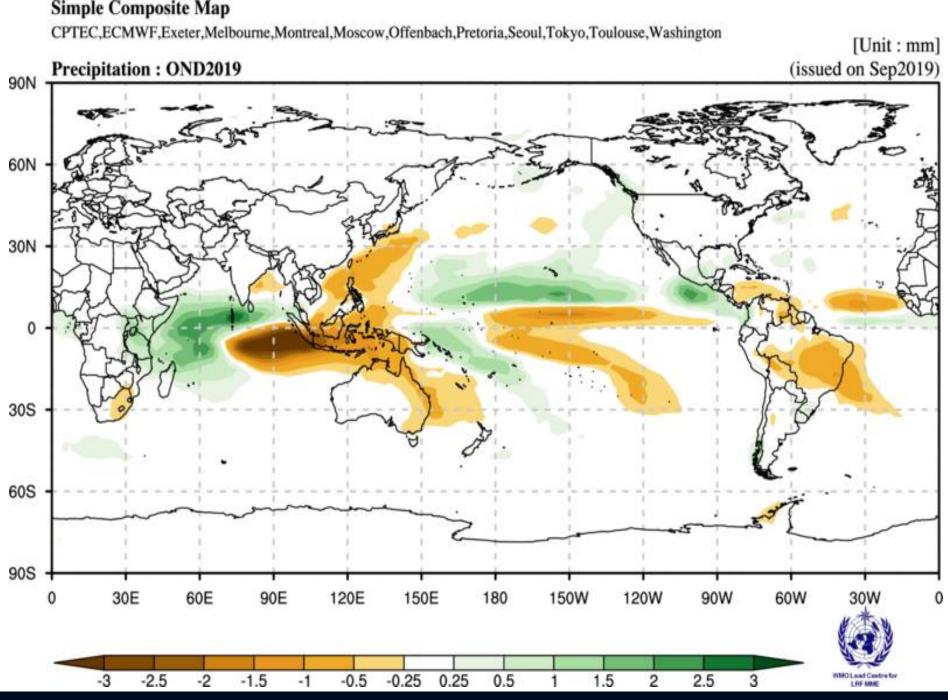


### Seasonal Forecasts from WMO Lead Center for Long-Range Forecast Multi-Model Ensemble (LC-LRFMME)

https://www.wmolc.org/

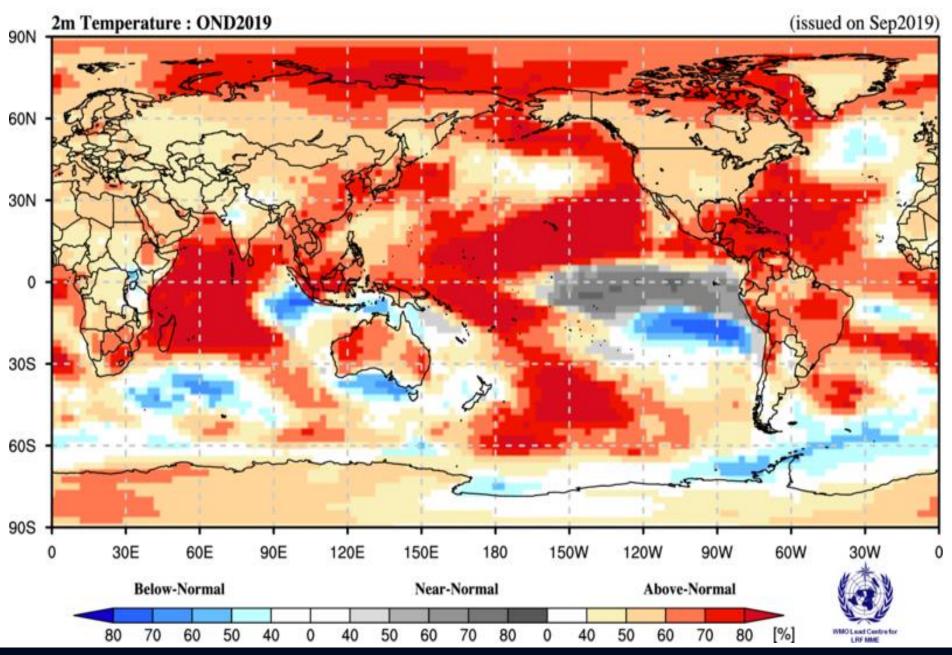
- LC-LRFMME seasonal forecast are based on forecasts provided by WMO recognized Global Producing Centers (GPCs) for Long-Range Forecasts to the LC-LRFMME. Contribution of all GPCs is acknowledged.
- Seasonal forecasts from GPCs are merged into a multi-model ensemble forecast.
- LC-LRFMME forecasts are 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 42-45 are from the Lead Center.
- For latest seasonal outlook guidance see <a href="http://www.wmo.int/pages/prog/wcp/wcasp/LC-LRFMME/index.php">http://www.wmo.int/pages/prog/wcp/wcasp/LC-LRFMME/index.php</a>
- 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.





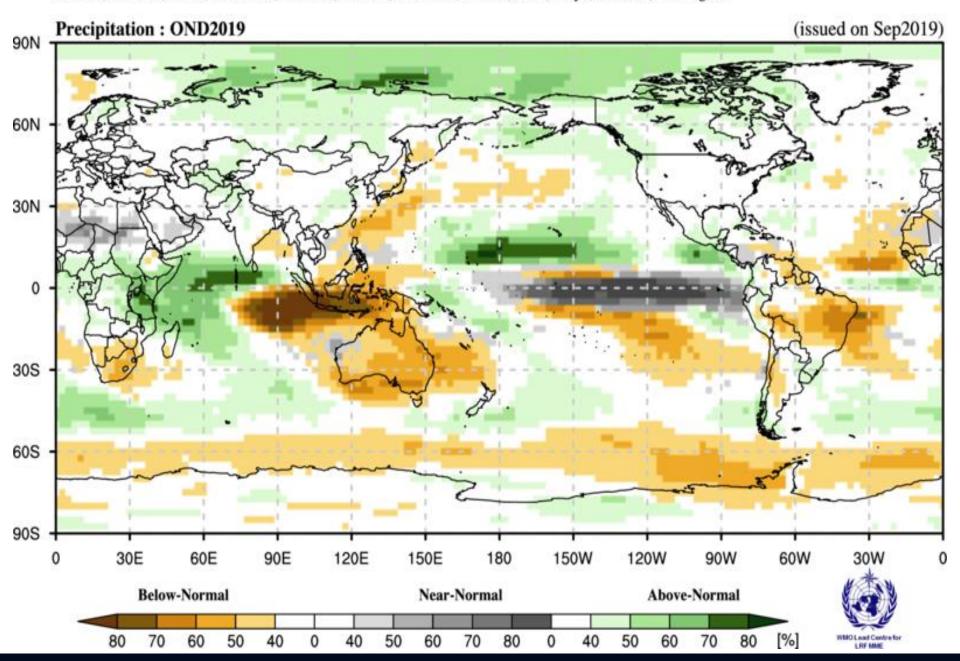
#### Probabilistic Multi-Model Ensemble Forecast

CPTEC,ECMWF,Exeter,Melbourne,Montreal,Moscow,Offenbach,Pretoria,Seoul,Tokyo,Toulouse,Washington



#### Probabilistic Multi-Model Ensemble Forecast

CPTEC,ECMWF,Exeter,Melbourne,Montreal,Moscow,Offenbach,Pretoria,Seoul,Tokyo,Toulouse,Washington



#### 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. <a href="https://doi.org/10.1029/2007JD008470">doi:10.1029/2007JD008470</a>.
- Kumar, A., M. Chen, M. Hoerling, and J. Eischeid (2013), Do extreme climate events require extreme forcings? Geophys. Res. Lett., 40, 3440-3445. <a href="https://doi.org/10.1002/qrl.50657">doi:10.1002/qrl.50657</a>.
- 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.
- Saha, S. et al (2014), The NCEP climate forecast system version 2. J. Clim., 27, 2185-2208. doi:10.1175/JCLI-D-12-00823.1.
- 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: <a href="http://dx.doi.org/10.1175/1520-0477(1997)078%3C2539:GPAYMA%3E2.0.CO;2">http://dx.doi.org/10.1175/1520-0477(1997)078%3C2539:GPAYMA%3E2.0.CO;2</a>



#### 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: 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)
  - <u>Seasonal forecast:</u> 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 from CFSv2 (provided by Dr. Bhaskar Jha/CPC)
  - 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/CPC)
- Seasonal mean anomalies of z200, T2m, and Prec forecasted from the Constructed Analog Model (provided by Dr. Peitao Peng/CPC)