Attribution of Seasonal Climate Anomalies
November-December-January 2019/2020
Summary of November-December-January 2019/2020
Observed Conditions and Outlooks

- The sea surface temperature (SST) anomalies in equatorial Pacific Ocean continued to be weak; Indian Ocean Dipole (IOD) continued to be in a 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).
- Large scale structures of the observed positive height anomalies over the tropical and N. sub-tropical region were well captured in the CFSv2 forecasts, while the centers of positive and negative height anomalies over the northern NA region were misplaced in the model forecasts that led to missed cold surface temperature anomalies over the Alaska and w. Canada.
Observed Seasonal Anomalies

Global and North America
Observed Anomaly NDJ2019/2020

Prec(mm/day)

T2m(K)

z200(m)
OND2019 CPC Seasonal Outlooks and NMME Forecasts

Temperature

Precipitation

Temp nonEC
HSS=77

Prec nonEC
HSS=15

CPC

NMME

Obs

Obs

NMME prob fcst TMP2m IC=201910 for lead 1 2019 NDJ

NMME prob fcst Prate IC=201910 for lead 1 2019 NDJ
Model Simulated/Forecast Ensemble Mean Anomalies
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 March 2016 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 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 April 2016 forecasts from 22-31 March 2016 initial conditions, May 2016 forecasts from 21-30 April 2016 initial conditions, and June 2016 forecasts from 22-31 May 2016 initial conditions.

- Numbers at the panels indicate the spatial anomaly correlation (AC).
NDJ2019/2020 Observed & Model Simulated/Forecast Ensemble Average Anomalies SST(K)

Obs

Seasonal Fcst AC(GL)=0.581

Reconstructed Fcst AC(GL)=0.739
NDJ2019/2020 Observed & Model Simulated/Forecast Ensemble Average Anomalies Prec (mm/day)
NDJ2019/2020 Observed & Model Simulated/Forecast Ensemble Average Anomalies z200(m)

Observation

AMIP Simulation

AC(GL)=0.594

Seasonal Fcst

AC(GL)=0.762

Reconstructed Fcst

AC(GL)=0.761
NDJ2019/2020 Observed & Model Simulated/Forecast Ensemble Average Anomalies T2m(K)

Observation

AMIP Simulation

AC(GL)=0.362

Seasonal Fcst

AC(GL)=0.450

Reconstructed Fcst

AC(GL)=0.466
NDJ2019/2020 Observed & Model Simulated/Forecast Ensemble Average Anomalies z200(m)

Observation

AMIP Simulation, AC=0.530

Seasonal Fcst, AC=0.896

Reconstructed Fcst, AC=0.921
NDJ2019/2020 Observed & Model Simulated/Forecast Ensemble Average Anomalies T2m(K)

Observation

AMIP Simulation  AC=−0.07

Seasonal Fcst  AC=0.023

Reconstructed Fcst  AC=0.092
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.
NDJ2019/2020 Anomaly Correlation for Individual AMIP Simulation with Observation — z200(20N–90N)
Observed & AMIP Ensemble Average Anomalies
NDJ2019/2020 z200(m) 18 runs/worst 2 runs/best 2 runs
NDJ2019/2020 Anomaly Correlation for Individual CFSv2 Forecast with Observation — z200 (20N–90N)
Observed & CFSv2 Forecast Ensemble Average Anomalies
NDJ2019/2020 z200(m) 40 runs/worst 4 runs/best 4 runs
Seasonal Forecast

Acronyms:
- Obs: Observations
- 40 runs: 40 ensemble members
- Worst 4 runs: 4 ensemble members showing the worst performance
- Best 4 runs: 4 ensemble members showing the best performance

The acronyms AC represent the correlation coefficient between the observed anomalies and the forecast anomalies.

- AC = 0.769 (20N-90N) for the 40 runs ensemble
- AC = 0.283 (20N-90N) for the worst 4 runs ensemble
- AC = 0.781 (20N-90N) for the best 4 runs ensemble
Observed & CFSv2 Forecast Ensemble Average Anomalies
NDJ2019/2020 z200(m) 40 runs/worst 4 runs/best 4 runs
Reconstructed Forecast

AC = 0.700(20N–90N)

AC = 0.357(20N–90N)

AC = 0.741(20N–90N)
NDJ2019/2020 Anomaly Correlation for Individual CFSv2 Forecast with Observation -- Prec(NA)/SST(30S–30N)

- Prec Seasonal Fcst
- Prec Reconstructed Fcst
- SST Seasonal Fcst
- SST Reconstructed Fcst

**Correlation vs. Model Members**

- Individual member
- Ensemble mean

**Model Members**

- 4
- 8
- 12
- 16
- 20
- 24
- 28
- 32
- 36
- 40
Observed & CFSv2 Forecast Ensemble Average Anomalies
NDJ2019/2020 Prec(mm/day) 40 runs/worst 4 runs/best 4 runs
Seasonal Forecast

AC = 0.023
AC = -0.36
AC = 0.317
Observed & CFSv2 Forecast Ensemble Average Anomalies
NDJ2019/2020 Prec(mm/day) 40 runs/worst 4 runs/best 4 runs
Reconstructed Forecast

Observed

40 runs

worst 4 runs

best 4 runs

AC=0.117

AC=-0.30

AC=0.361
NDJ2019/2020 Anomaly Correlation for Individual CFSv2 Forecast with Observation -- T2m(NA)/SST(30S–30N)
Observed & CFSv2 Forecast Ensemble Average Anomalies
NDJ2019/2020 T2m(K) 40 runs/worst 4 runs/best 4 runs
Seasonal Forecast

AC=0.023

AC=-0.23

AC=0.254

Climate Prediction Center/NCEP/NWS/NOAA
Observed & CFSv2 Forecast Ensemble Average Anomalies
NDJ2019/2020 T2m(K) 40 runs/worst 4 runs/best 4 runs
Reconstructed Forecast

AC=0.092

AC=-0.20

AC=0.358
200mb Height from Linear Model
NDJ2019 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)**

**OBS (from R1)**
Linear Model Response to Tropical Heating

Pattern COR: global=0.21, tropics(30S–30N)=0.44
Seasonal Forecasts from the Constructed Analog Model
CA HGT200 Prd for NDJ2019/2020, ICs through Jan2020(m), Lead -3
CA Prec Prd for NDJ2019/2020, ICs through Jan2020 (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 http://www.wmo.int/pages/prog/wcp/wcasp/LC-LRFMME/index.php

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

2m Temperature: NDJ2019
(issued on Oct2019)
Precipitation: NDJ2019
(issued on Oct2019)
References


Background & Methodology
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.
• 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.
• 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)
  – Seasonal forecast: 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)