

A New GFSv15 based Climate Model Dataset and Its Application to Understanding Climate Variability, and Predictability

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Summary

- NOAA Climate Prediction Center (CPC) has generated a large 100-member ensemble of AMIP simulations from 1979-present using the GFSv15 with FV3 dynamical core.
- These simulations are forced with the observed evolution of sea surface temperatures (SSTs) and are in support of CPC's efforts to attribute observed seasonal climate anomalies to external forcings.
- The goal of this analysis is to document the performance of these simulations in replicating observed climate variability and trends, together with an assessment of climate predictability.

Outline

- 1) Simulation of observed trends
- 2) Simulation of US climate response to three strong El Niño events
- 3) Assessment of US climate predictability
- 4) Simulation of extreme events—2022 summer South Asia flooding

Data and method

- **Model data**

- 1) 100-member FV3_GFS AMIP simulations.
- 2) 30-member GFSv2 (the atmospheric component of CFSv2) AMIP simulations (the previous version of CPC AMIP simulations).

- **Observational data**

NCEP Z200, GHCN_CAMS T2m and GPCC and CMAP precipitation.

- **Method**

All anomalies are computed relative to 1991-2020 base period.

1) Simulation of observed trends

Difference in climatology between JJA and DJF (JJA-DJF)

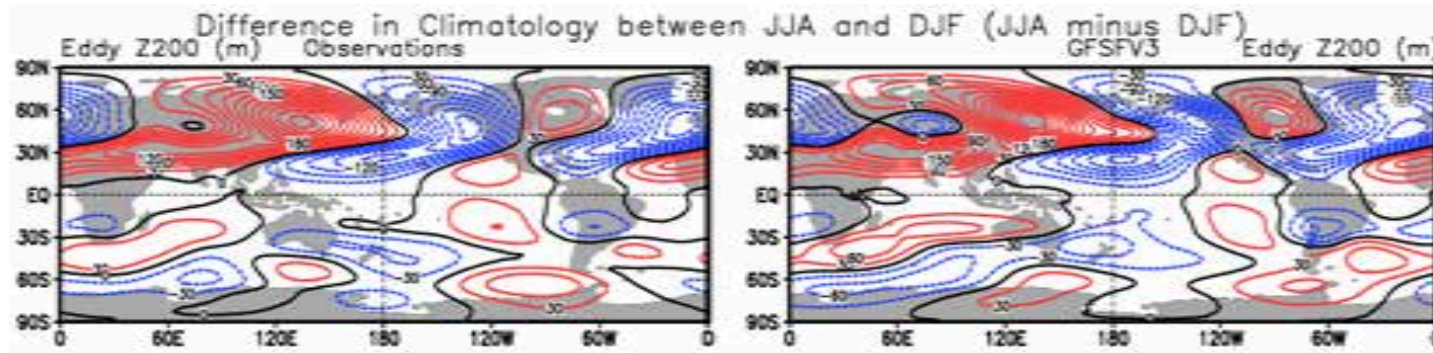
Observation

FV3_GFS

**Global
mean**

**Pattern
Correlation**

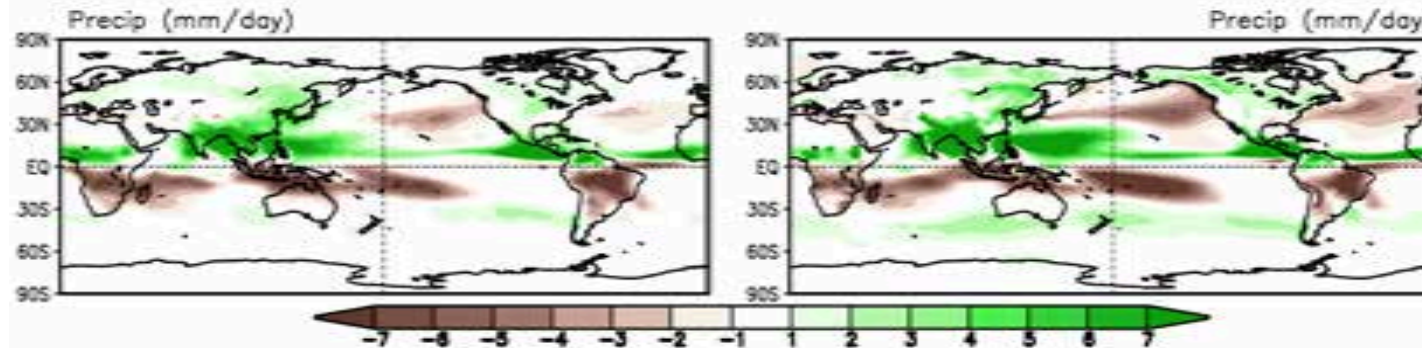
**Eddy
Z200**



**OBS: 0.17
Model: 0.056**

0.94

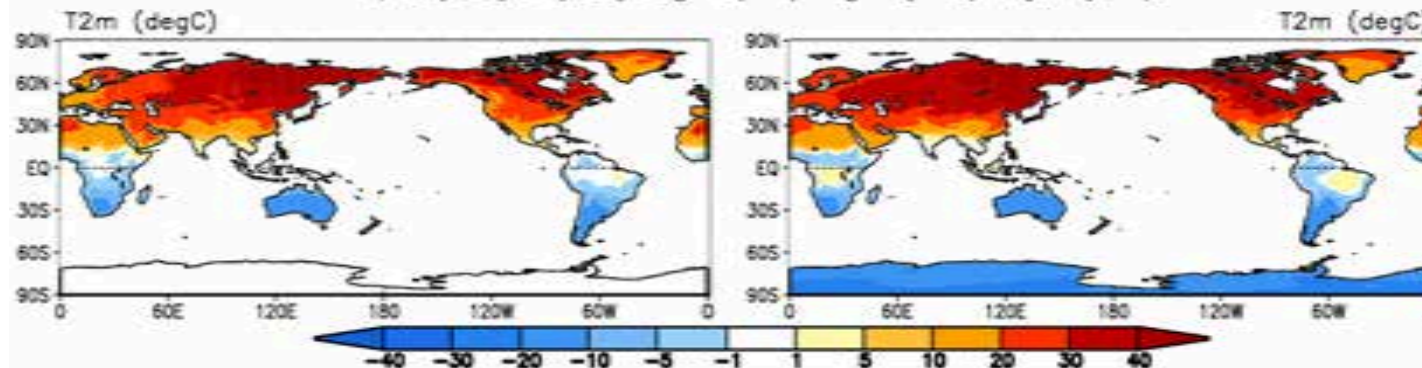
Precip.



**OBS: 0.076
Model: 0.17**

0.82

T2m

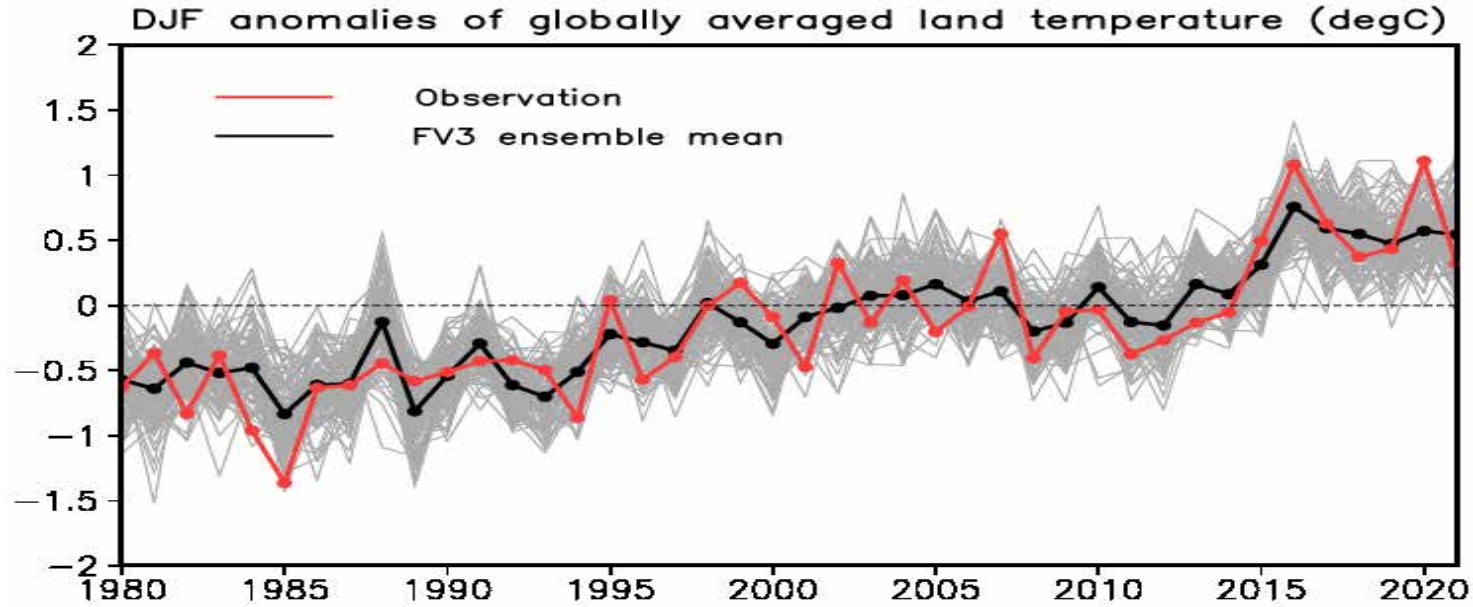


**OBS: 12.95
Model: 12.09**

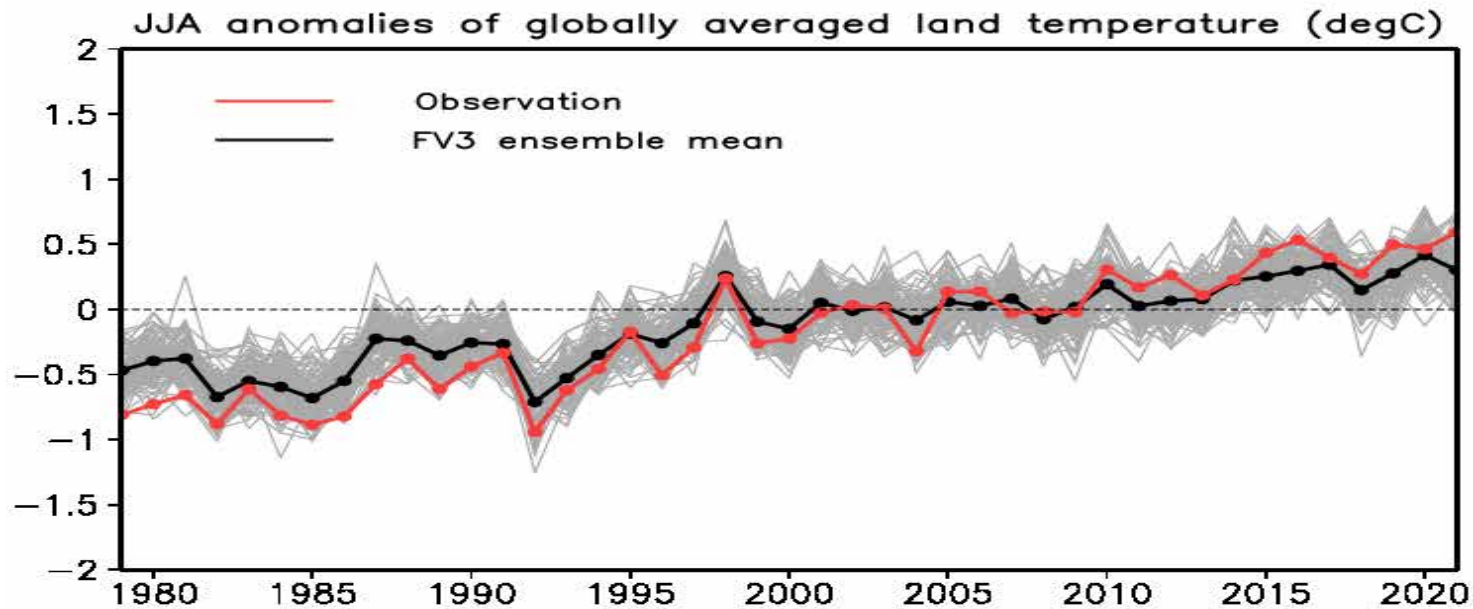
0.98

Time series of T2m over global land

DJF



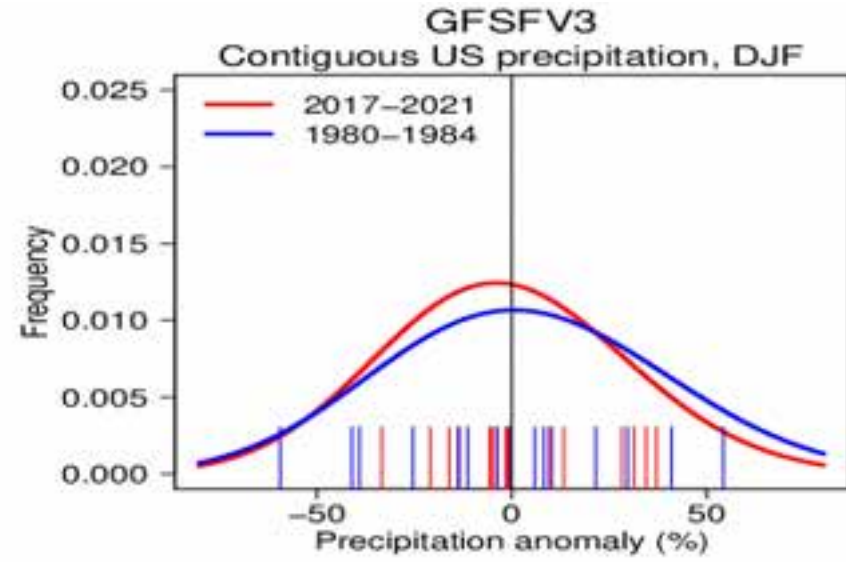
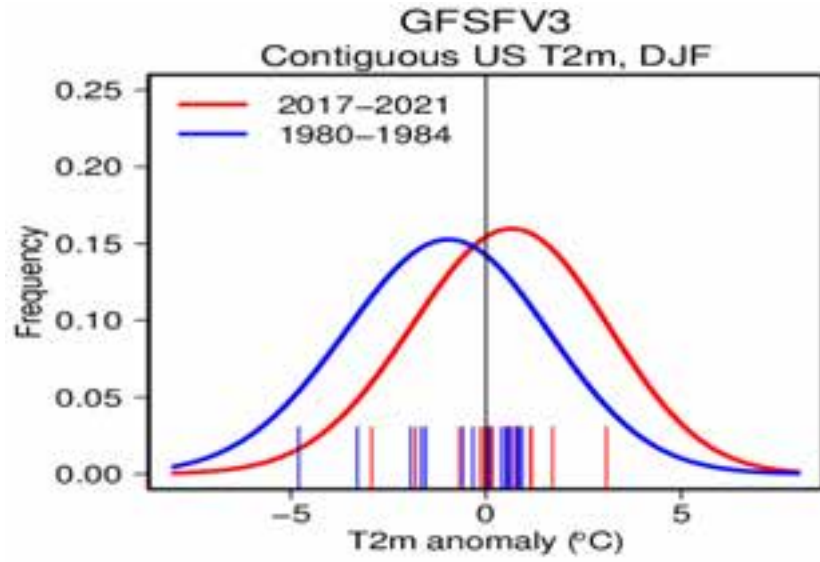
JJA



Contiguous US T2m

Contiguous US precipitation

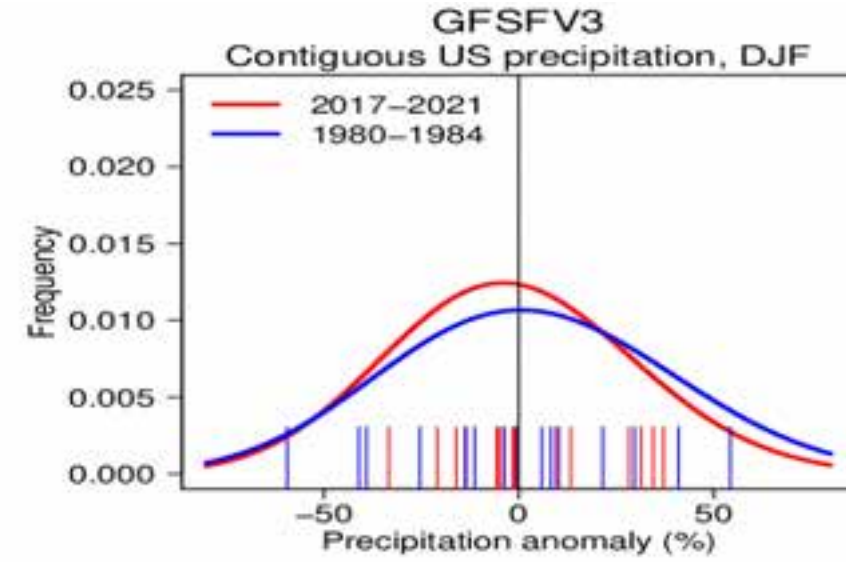
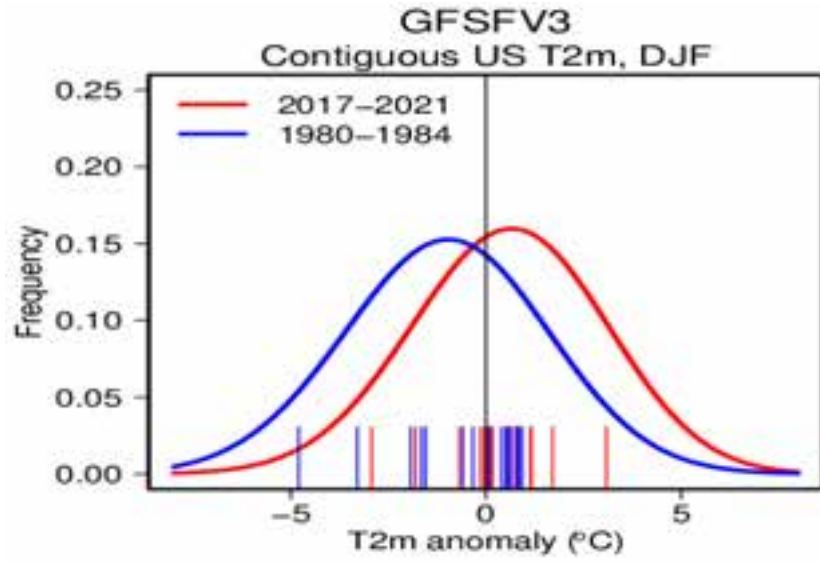
DJF



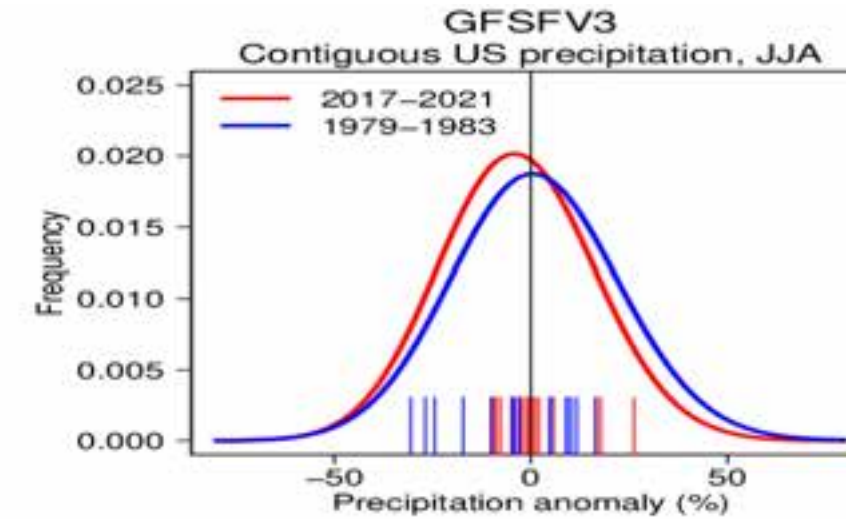
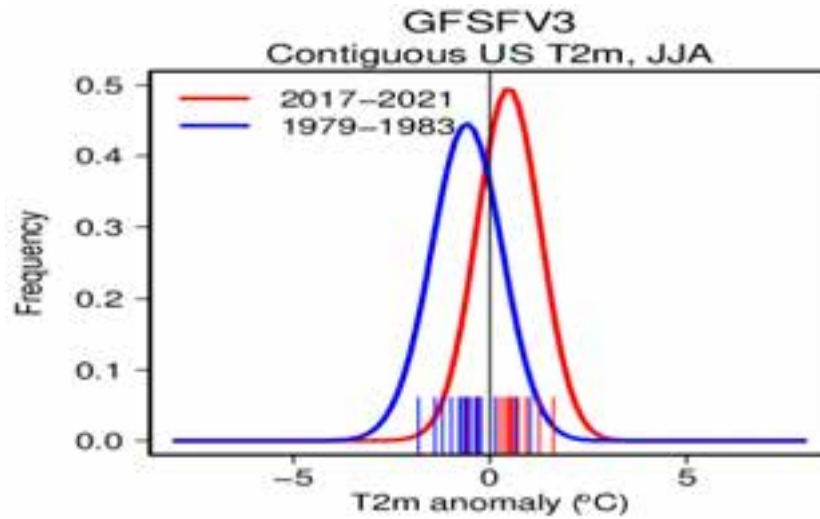
Contiguous US T2m

Contiguous US precipitation

DJF



JJA



2) Simulation of US climate response to three strong El Niño events

Observation **GFSv2** ensemble mean **GFSFV3** ensemble mean

Observation

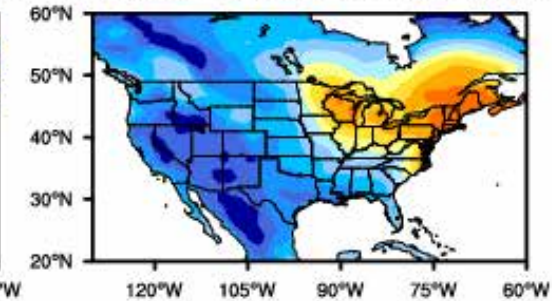
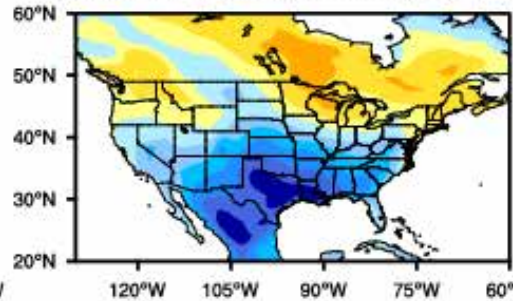
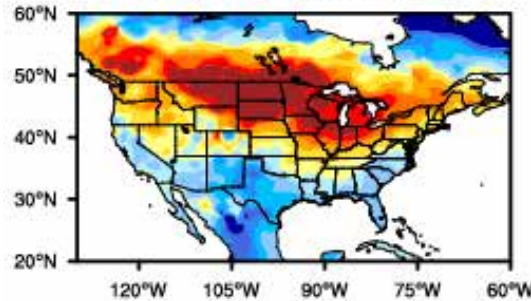
GFSv2 ensemble mean

GFSFV3 ensemble mean

T2m, 1982/83 El Nino

T2m, 1982/83 El Nino (AC: 0.47)

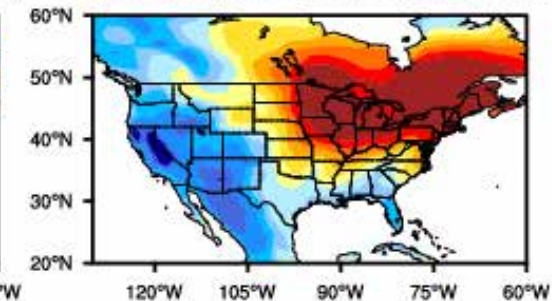
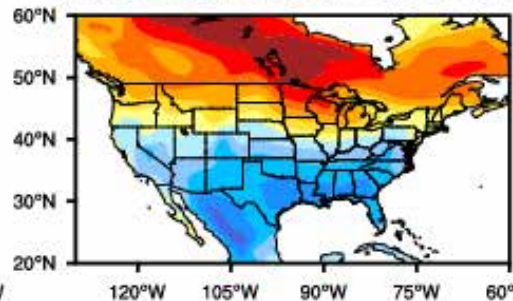
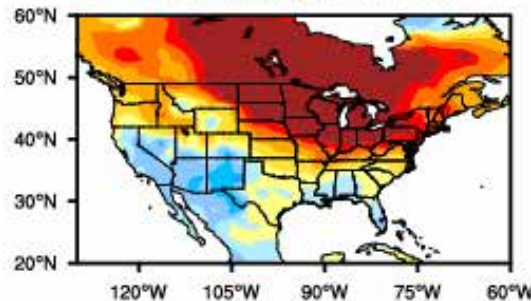
T2m, 1982/83 El Nino (AC: 0.43)



T2m, 1997/98 El Nino

T2m, 1997/98 El Nino (AC: 0.75)

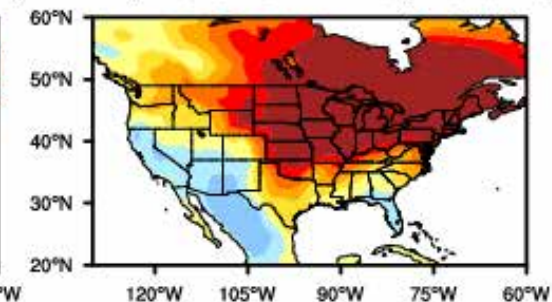
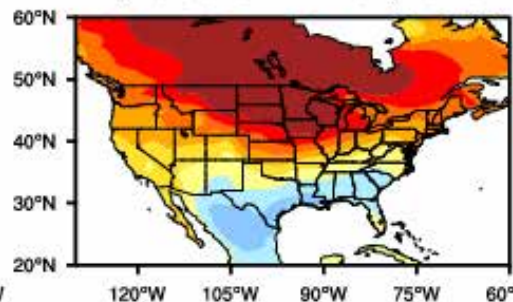
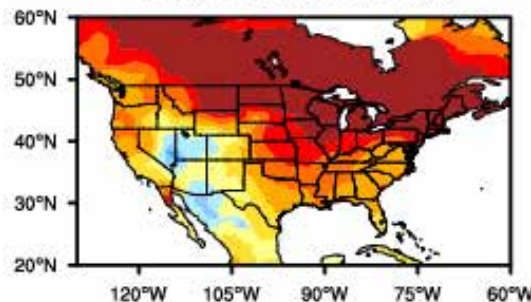
T2m, 1997/98 El Nino (AC: 0.73)



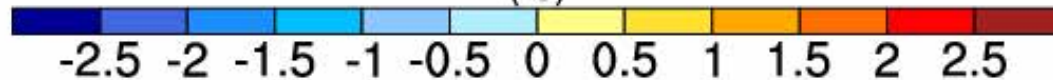
T2m, 2015/16 El Nino

T2m, 2015/16 El Nino (AC: 0.72)

T2m, 2015/16 El Nino (AC: 0.76)



(°C)



**1982/83
DJF**

**1997/98
DJF**

**2015/16
DJF**

Observation **GFSv2** ensemble mean **GFSFV3** ensemble mean

Observation

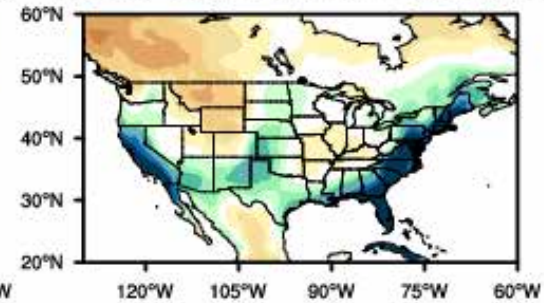
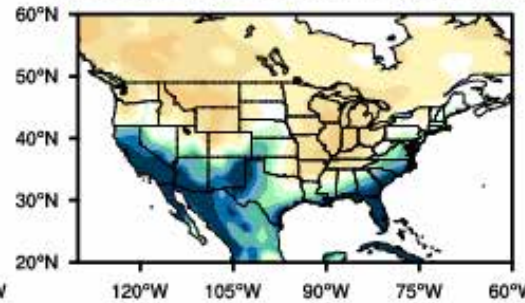
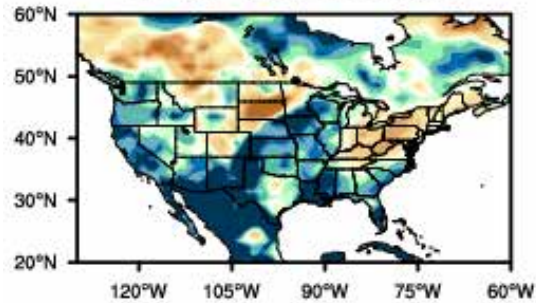
GFSv2 ensemble mean

GFSFV3 ensemble mean

Precip, 1982/83 El Nino

Precip, 1982/83 El Nino (AC: 0.49)

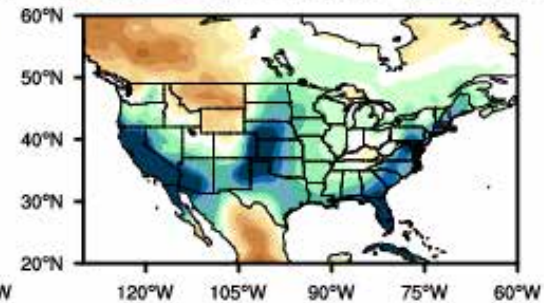
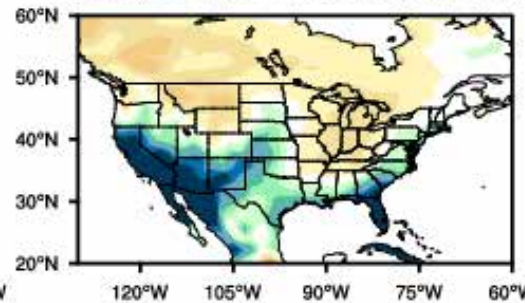
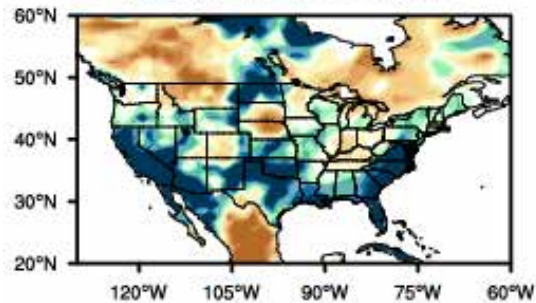
Precip, 1982/83 El Nino (AC: 0.43)



Precip, 1997/98 El Nino

Precip, 1997/98 El Nino (AC: 0.77)

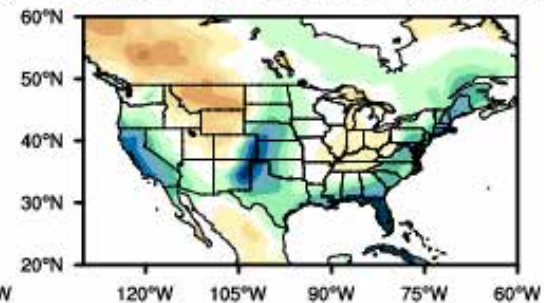
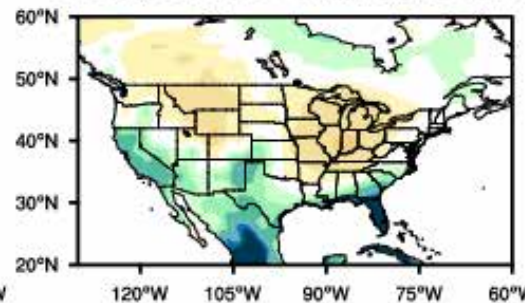
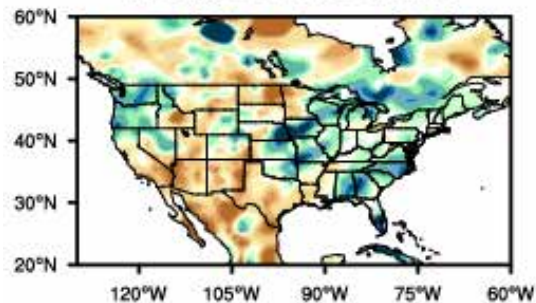
Precip, 1997/98 El Nino (AC: 0.82)



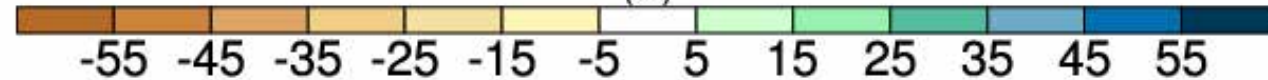
Precip, 2015/16 El Nino

Precip, 2015/16 El Nino (AC: 0.14)

Precip, 2015/16 El Nino (AC: 0.32)



(%)



**1982/83
DJF**

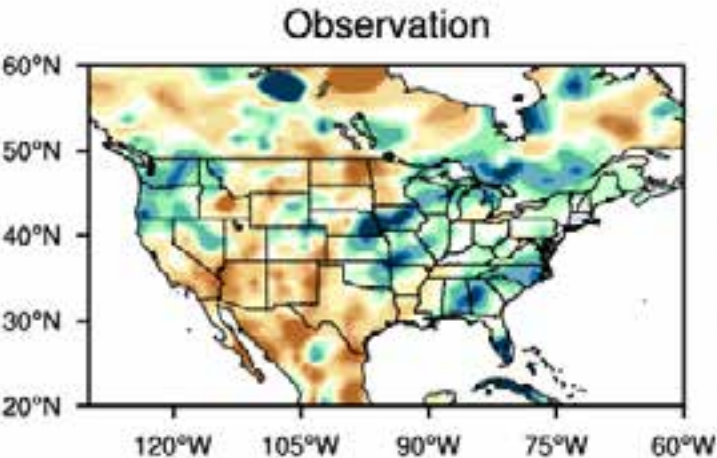
**1997/98
DJF**

**2015/16
DJF**

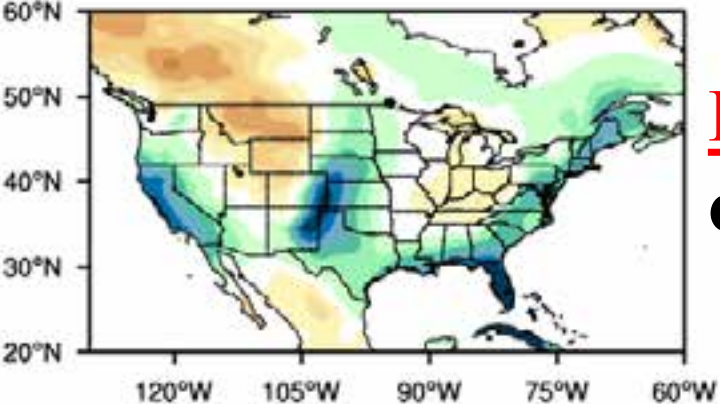
Precipitation anomaly for 2015/16 DJF

Precipitation anomaly for 2015/16

Observation



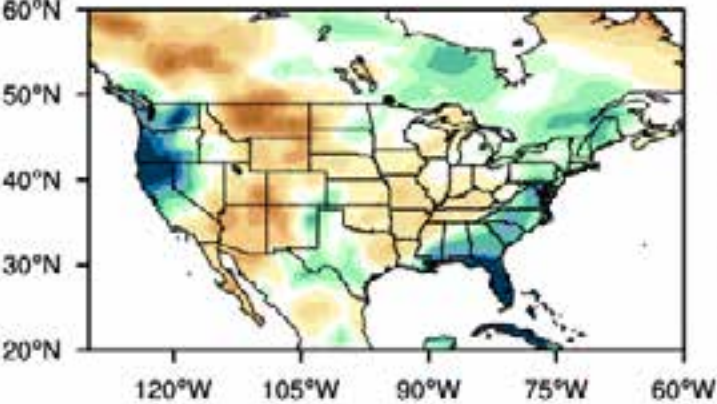
Ensemble mean of GFSFV3 (AC: 0.32)



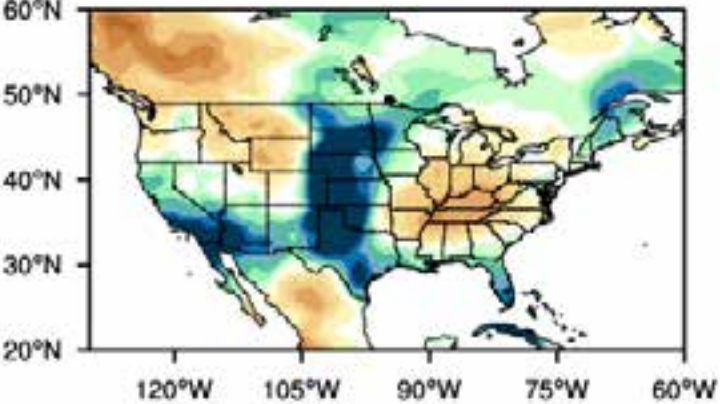
Ensemble mean
of GFSFV3

Composite of
best 4 runs of
GFSFV3

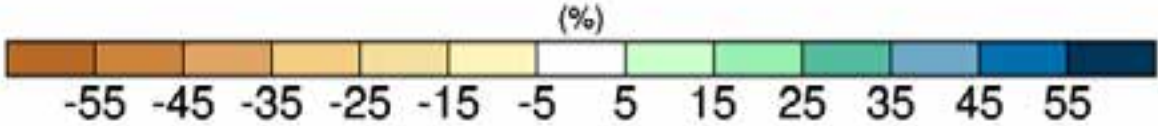
Best 4 runs of GFSFV3 (AC: 0.57)



Worst 4 runs of GFSFV3 (AC: -0.14)



Composite of
worst 4 runs
of GFSFV3



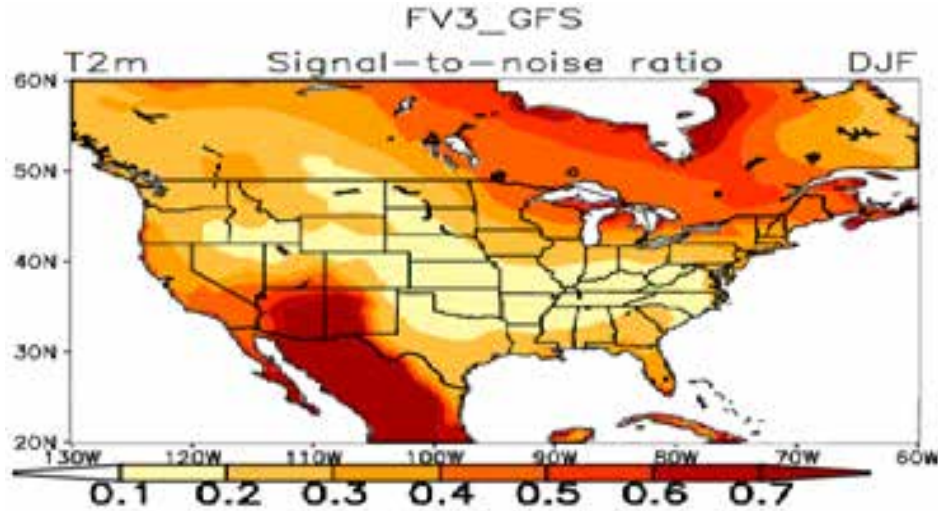
3) Assessment of US climate predictability

- Climate predictability is assessed by quantifying the signal-to-noise ratio (SNR) which is the ratio of predictable and unpredictable components.
- The signal component in the SNR is the variance of ensemble mean but the noise component is the variance of departure in the individual members from the ensemble mean (Kumar and Hoerling 1995).
- Higher SNR value indicates larger predictability.
- The anomaly correlation is defined as the correlation of anomalies between AMIP ensemble means and the observation.

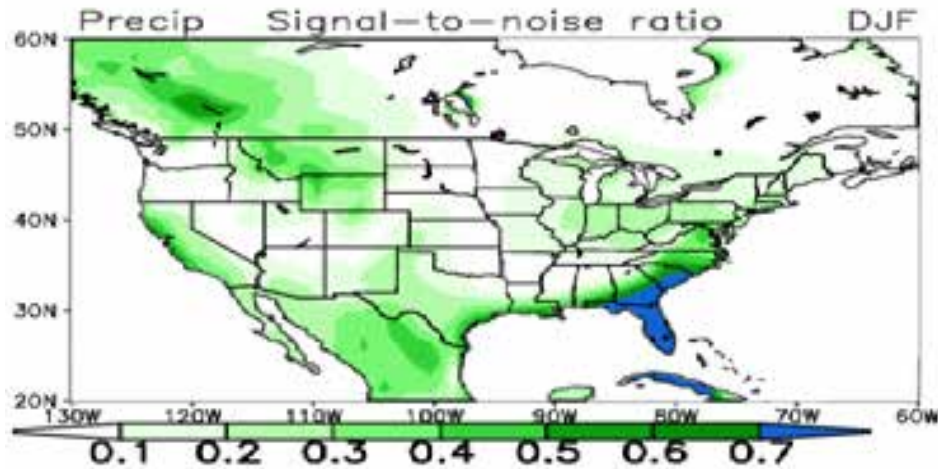
FV3_GFS, DJF

Signal-to-noise ratio

T2m



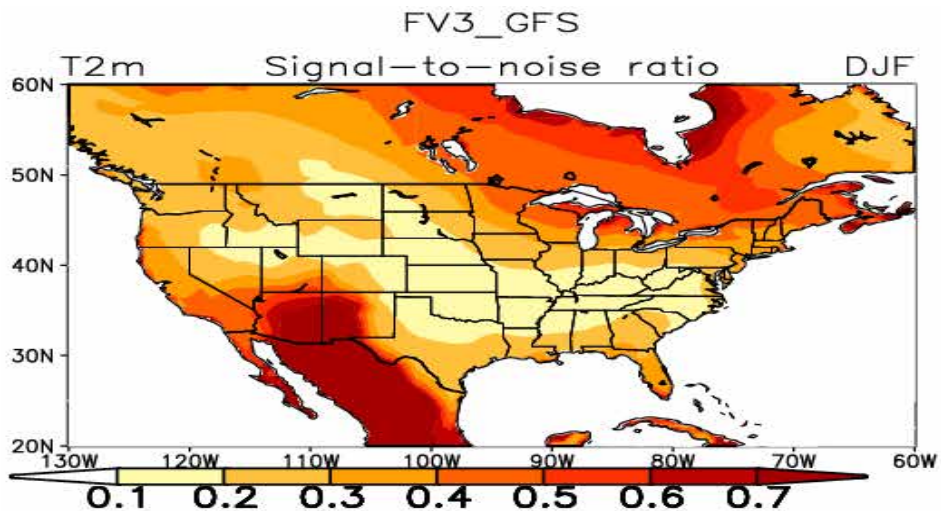
Precip



Higher signal-to noise value indicates larger predictability.

FV3_GFS, DJF

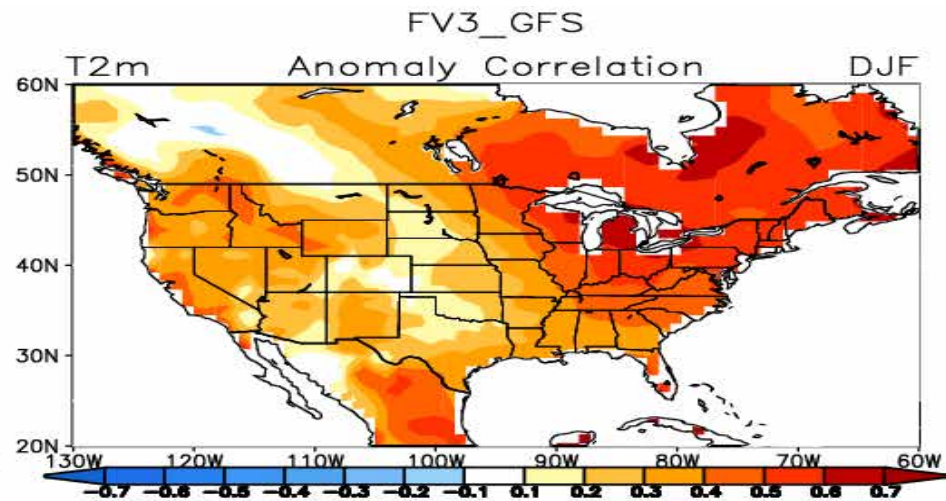
Signal-to-noise ratio



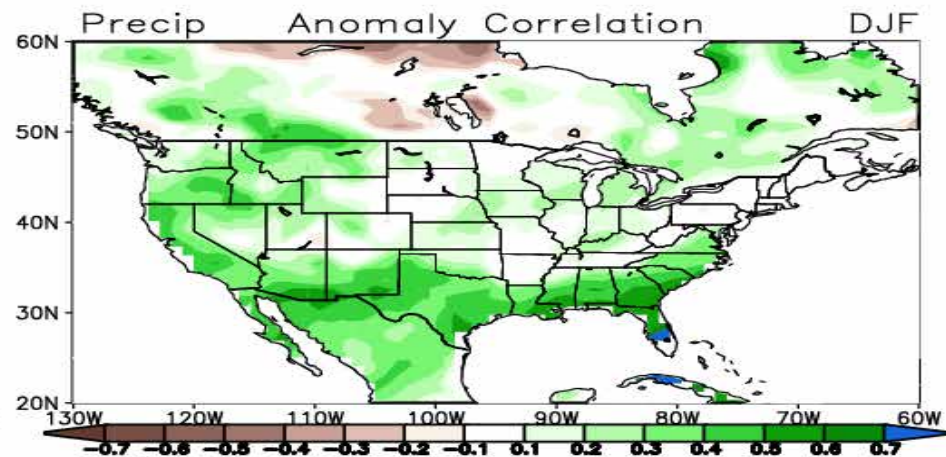
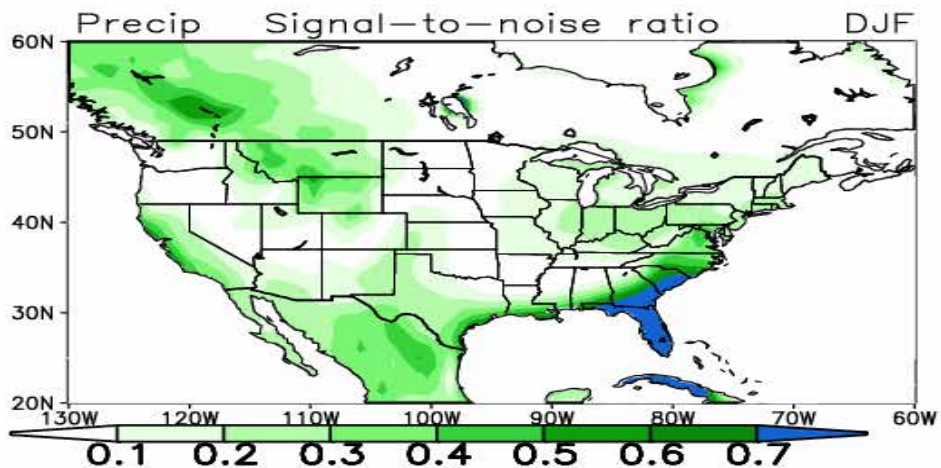
T2m

FV3_GFS, DJF

Anomaly correlation with OBS



Precip



Higher signal-to noise value indicates larger predictability.

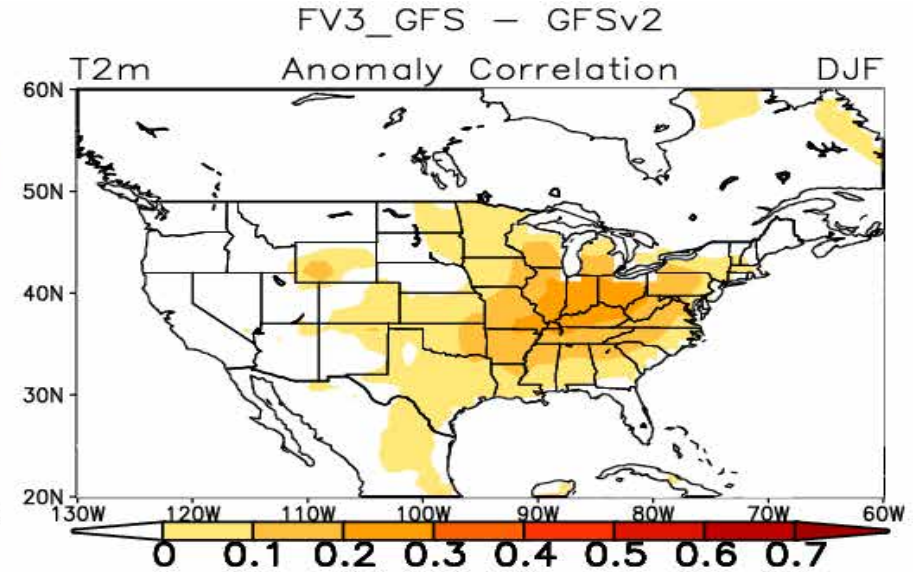
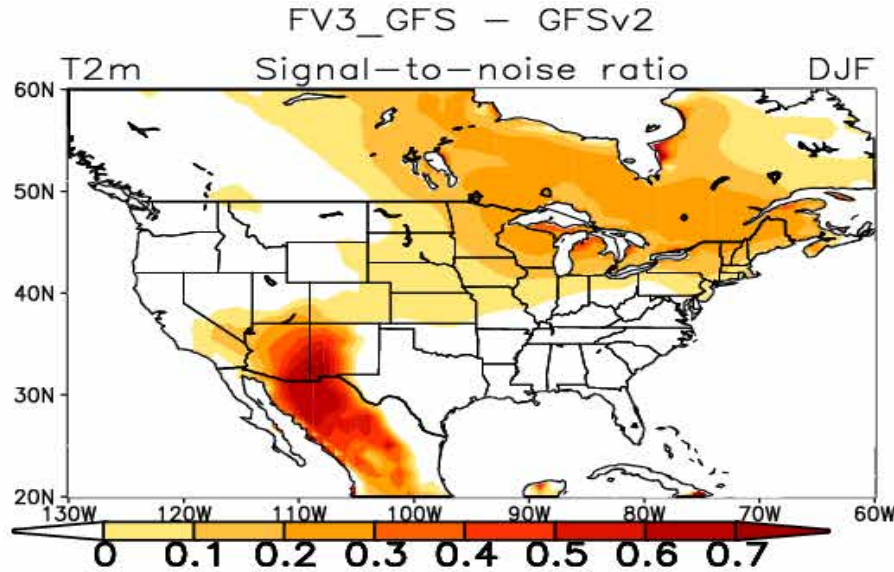
The pattern of anomaly correlation with OBS, generally, follows that of SNR.

FV3_GFS minus GFSv2, DJF

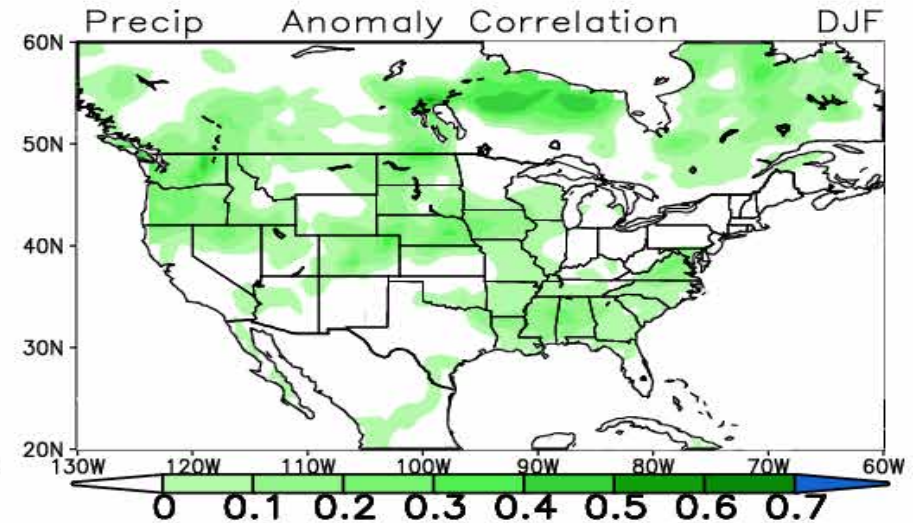
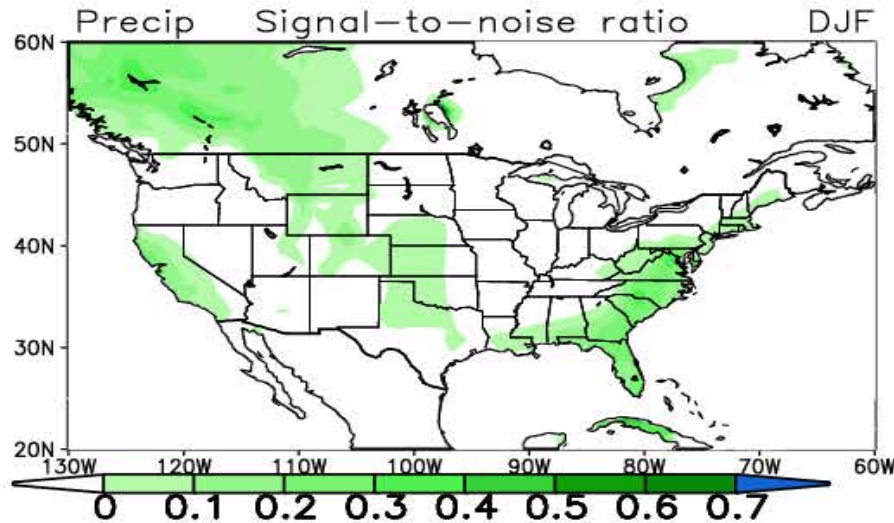
Signal-to-noise ratio

Anomaly correlation with OBS

T2m



Precip

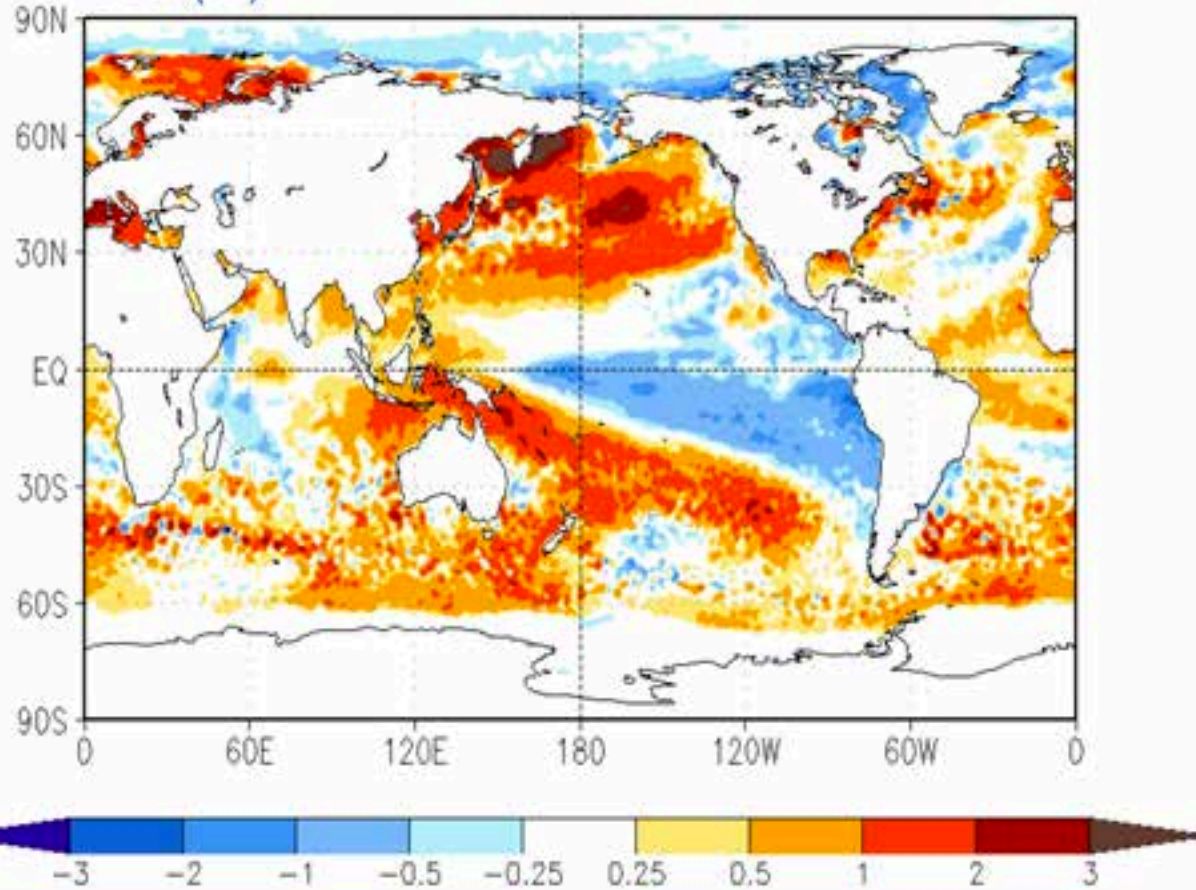


4) Simulation of extreme events—2022 summer South Asia flooding

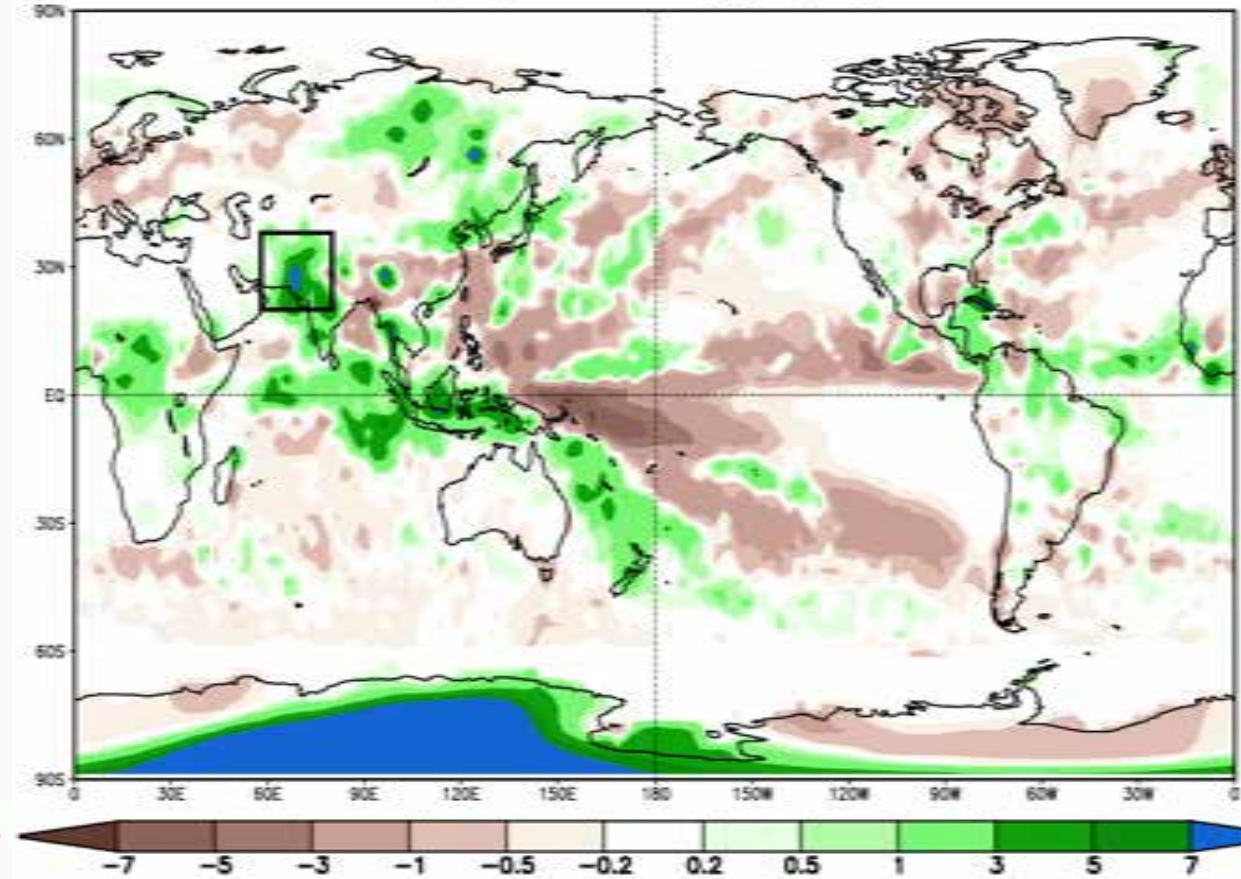
Observed Anomaly JJA2022

Observed Precip. anomaly JJA2022

SST(K)



Observed precipitation anomaly (mm/day), JJA2022

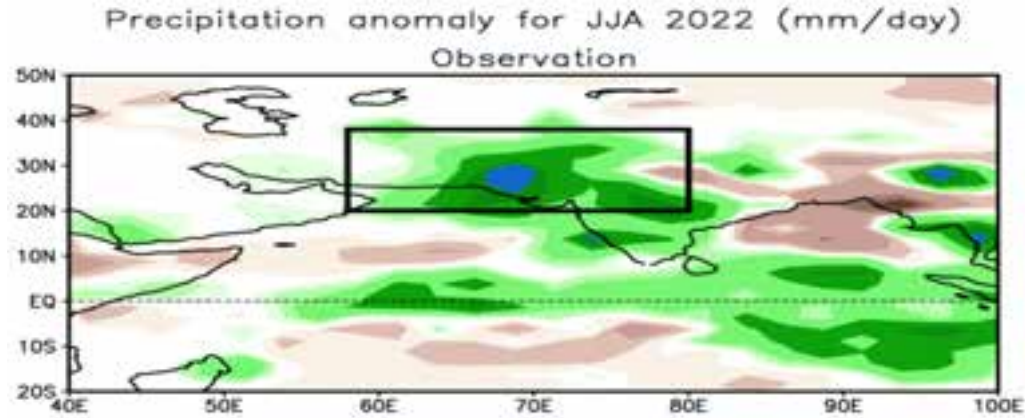


[SST plot is from](https://www.cpc.ncep.noaa.gov/products/people/mchen/AttributionAnalysis/images/Attribution202208.pdf)

<https://www.cpc.ncep.noaa.gov/products/people/mchen/AttributionAnalysis/images/Attribution202208.pdf>

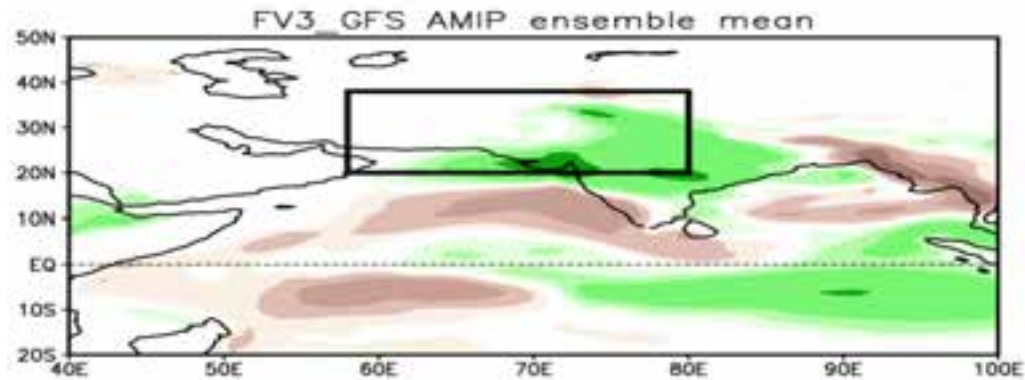
Precipitation anomaly for JJA 2022

Observation



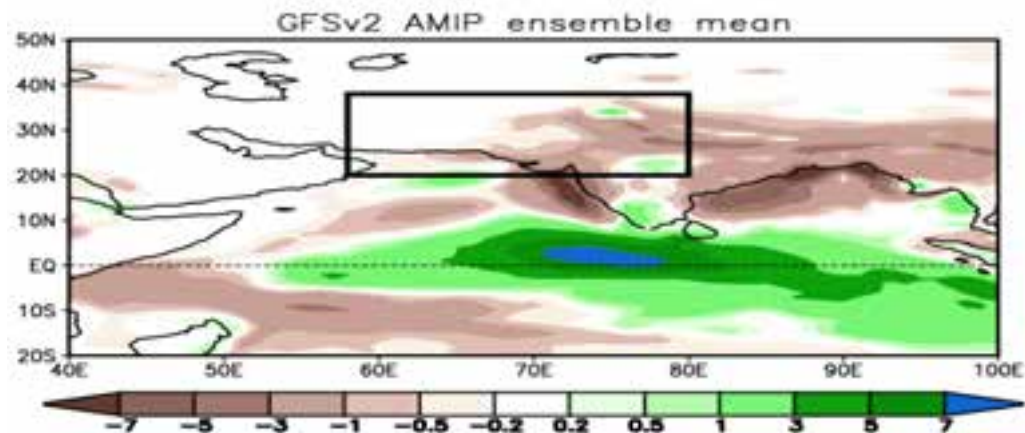
FV3_GFS

AMIP
ensemble mean



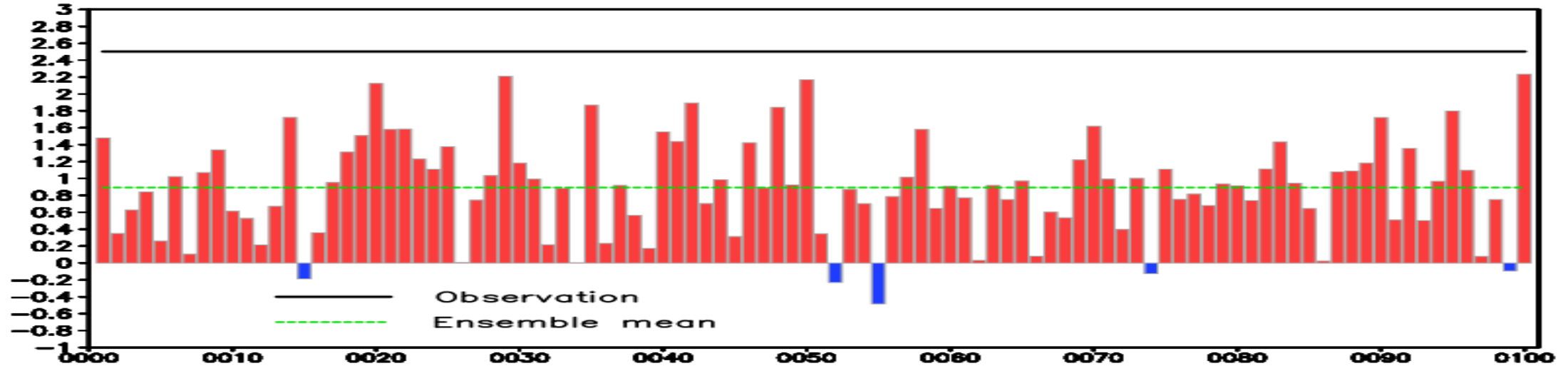
GFSv2

AMIP
ensemble mean



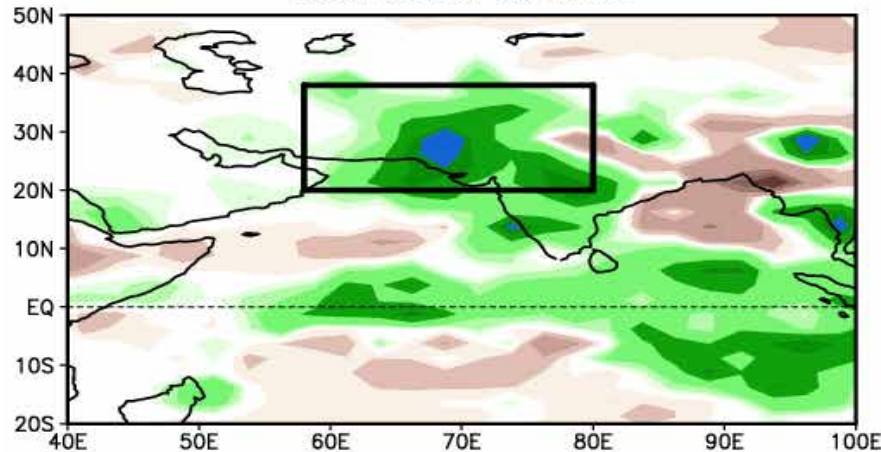
Precipitation anomaly over box region from FV3 individual members

Pakistan precipitation anomaly averaged over (58E–80E, 20N–38N) (mm/day)
JJA2022



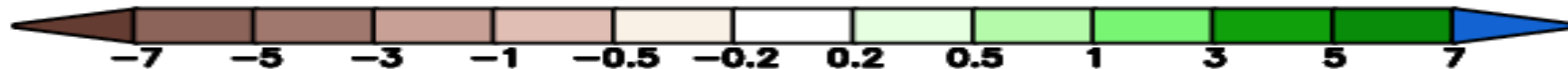
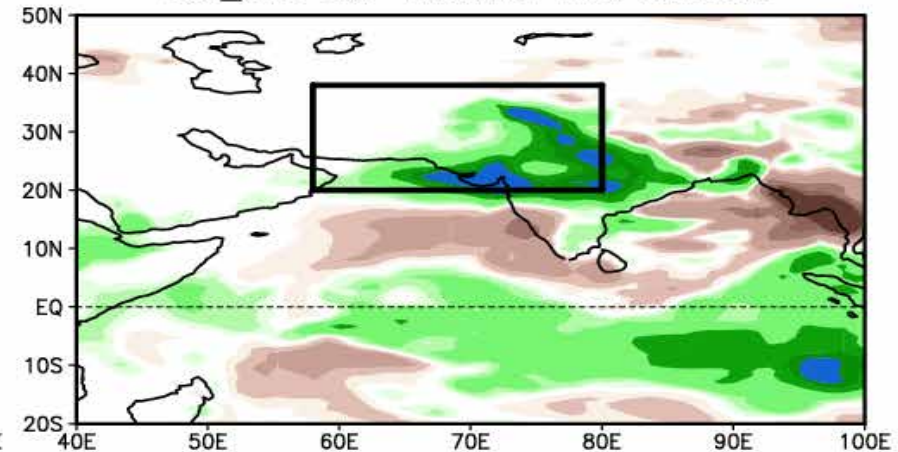
Observation

Observation, JJA2022



FV3 Member 100

FV3_GFS AMIP member 100, JJA2022



Summary

- FV3_GFS model can realistically reproduce the observed climate variability and trends. Compared to old version GFSv2 model, FV3 model has a better simulation of extreme events, such as 2022 summer South Asia flooding.
- Associated with the warming trend over the global land, there is a US warming and drying climate trend.
- Both observations and simulations show a gradual southward shift of stronger warm anomalies from early strong El Nino (1982/83) to recent strong El Nino (2015/16).
- The ensemble AMIP experiments suggest that internal atmospheric noise, rather than a boundary-forced signal, was principally responsible for the failed SCAL rains in 2016.
- The strongest US winter surface temperature predictability is in the northeast while the strongest US winter precipitation predictability is in the southeast.
- The majority of FV3 individual runs produces a wet condition over the South Asia, indicating that the 2022 summer devastating flood over that region could be driven by the SST forcing.