

A seasonal probabilistic forecast model for U.S. regional precipitation based on the tropical Pacific and Atlantic SSTAs

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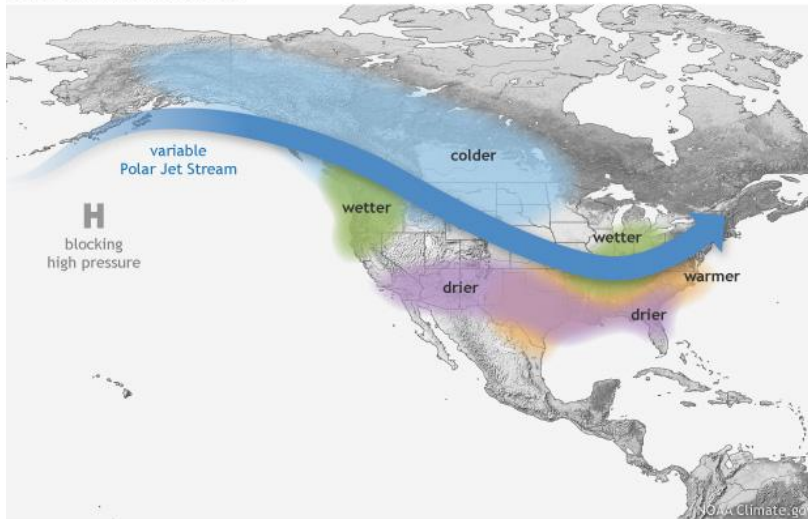
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Major predictors for U.S. rainfall in cold and warm season

WINTER LA NIÑA PATTERN



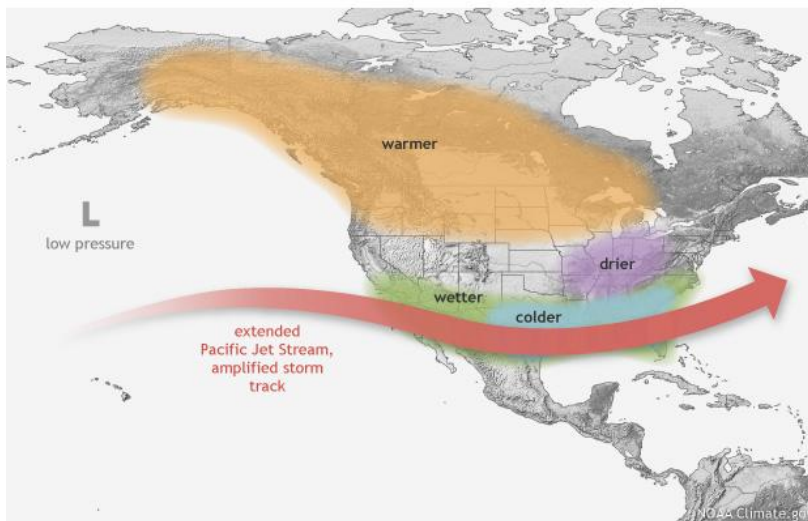
SUMMER



moisture flow
great plains low-level jet
soil moisture
dark green is wettest

Source from Schmitt and Li

WINTER EL NIÑO PATTERN



climate.gov

- **In cold season**

ENSO teleconnection is a major driver to modulate U.S. rainfall.

- **In warm season**

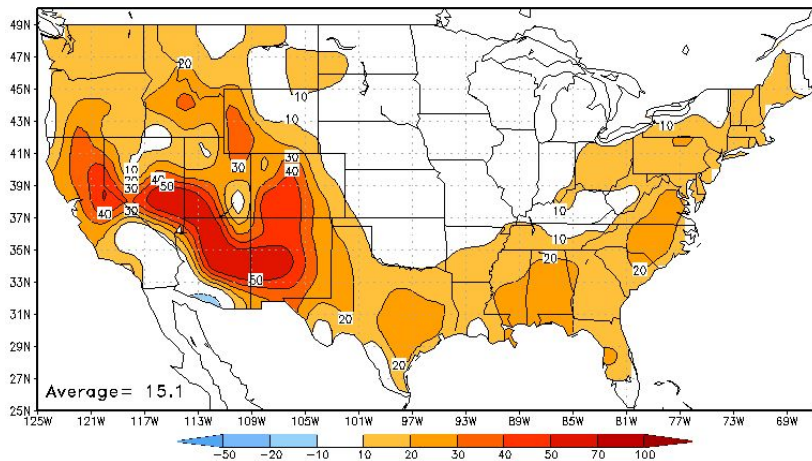
North American low-level jet (NALLJ) is a major factor to modulate U.S. rainfall.

Seasonal prediction skill of U.S. CONUS

2m

Temp.

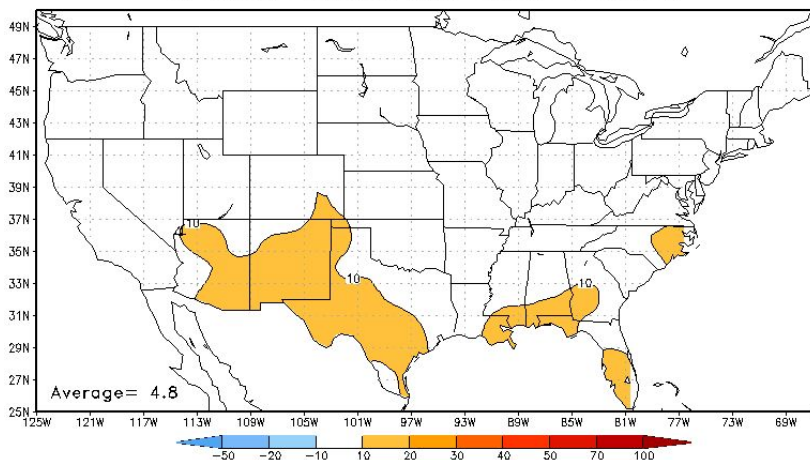
Seasonal (Lead 0.5 Months) Temperature Heidke Skill Score
All Manual Forecasts From 199501 to 202110



- Prediction skills of U.S. temperature is good except for the central U.S.
- However, precipitation prediction skill is not good.
- Interestingly, there is relatively better prediction skill for precipitation in the cold season than in warm season.

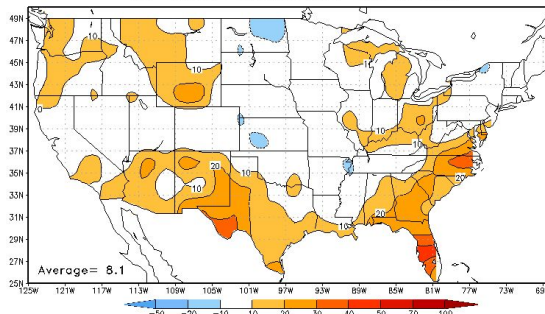
Prec.

Seasonal (Lead 0.5 Months) Precipitation Heidke Skill Score
All Manual Forecasts From 199501 to 202110



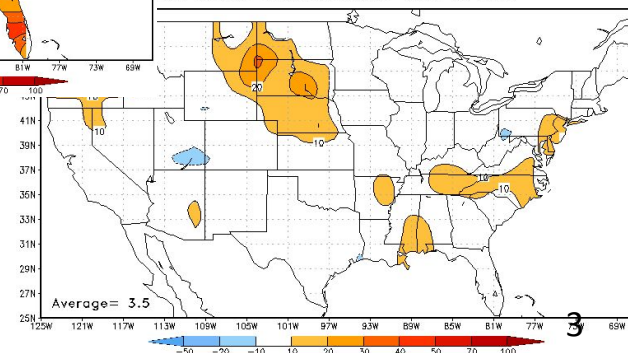
Cold season (DJF)

Seasonal (Lead 0.5 Months) Precipitation Heidke Skill Score
DJF Manual Forecasts From 1995 to 2021



Warm season (JJA)

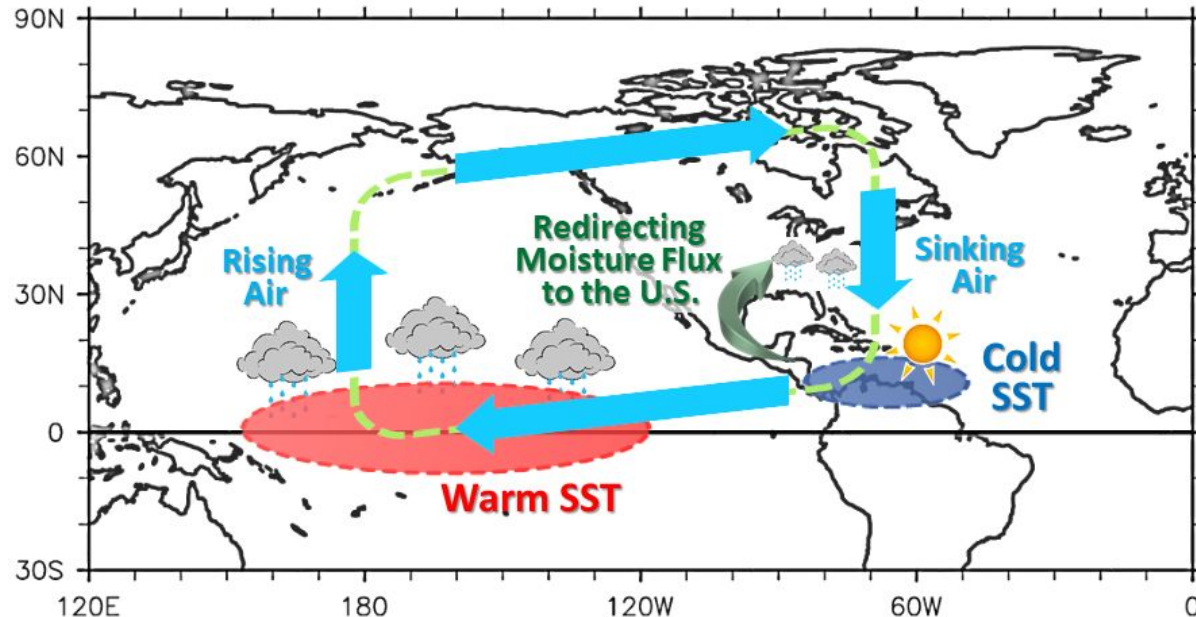
(Lead 0.5 Months) Precipitation Heidke Skill Score
JJA Manual Forecasts From 1995 to 2021



Relationship between U.S. rainfall and interbasin SST

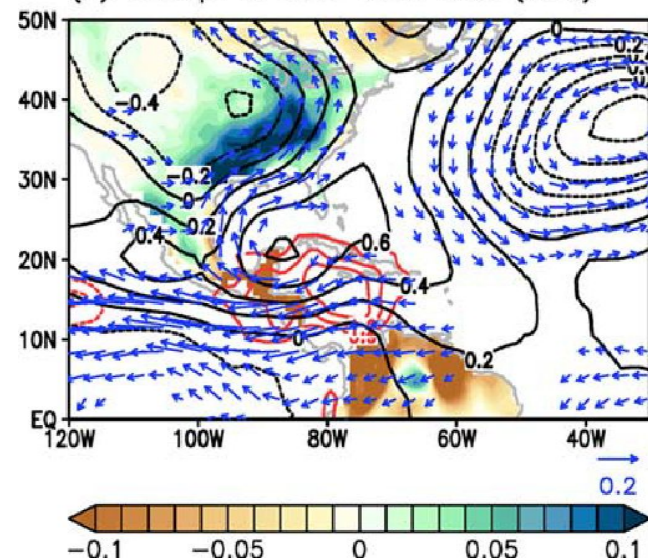
In ASO,

Co-variability of Pacific-Atlantic SST Contrast, tropical rainfall over Caribbean Sea and U.S. Late Summer to Midfall (August – October) Rainfall Variability



Warm SST in Equatorial Pacific (rising air) + Cold SST in Caribbean Sea (sinking air) → Suppressing tropical rainfall over Caribbean Sea → Redirecting Heat & Moisture Fluxes into the U.S. → Increasing U.S. Rainfall

(a) Precip. & GPH–Wind 850 (OBS)

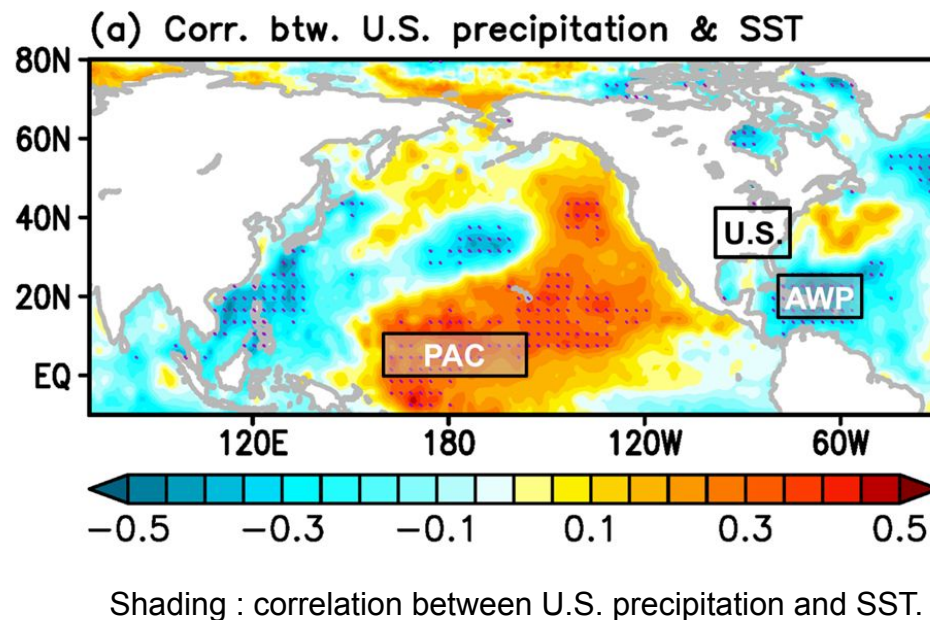
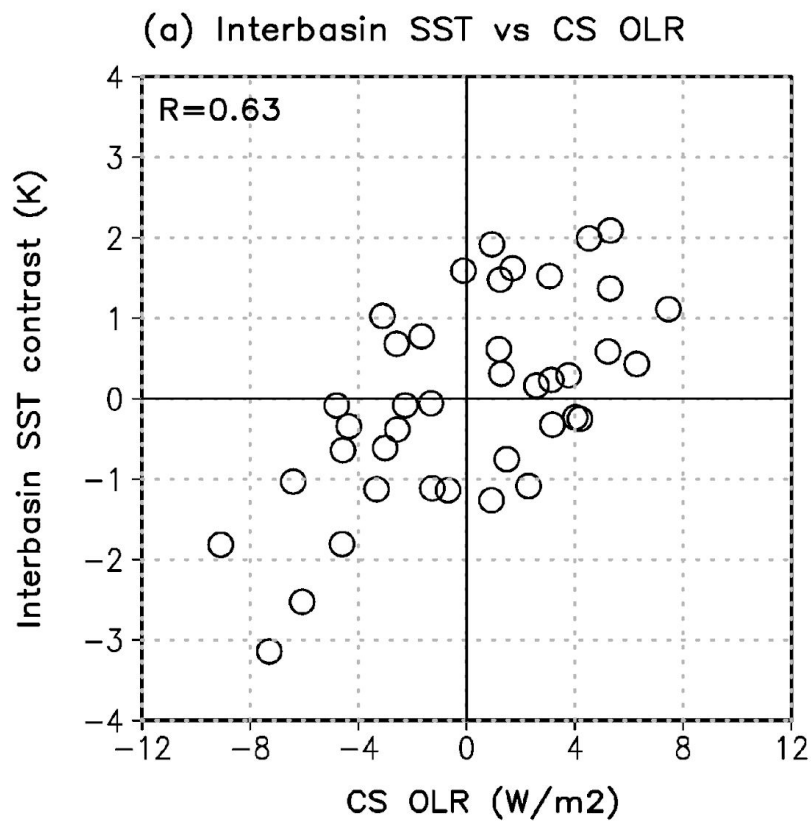


Precipitation (shaded), wind (vectors), and geopotential height at 850 hPa (black contours) regressed onto Caribbean Sea OLR anomalies (red contours)

Kim et al. (2020)

- During ASO, convection activity over Caribbean Sea associated with Pacific-Atlantic interbasin SSTAs contrast modulates the NALLJ which in turn supply moisture flux into the U.S.
- **There is a possible working mechanism to develop seasonal U.S. rainfall prediction model using the interbasin SST**

A potential predictor for warm-season U.S. rainfall



- We developed a hybrid model using predicted SSTAs over the tropical Pacific and tropical Atlantic from NMME.

Data

Observation and atmospheric reanalysis products :

- **SST**: HadISST data
- **Precipitation** : CRU-monthly precipitation data

North American Multi-model Ensembles (NMME)

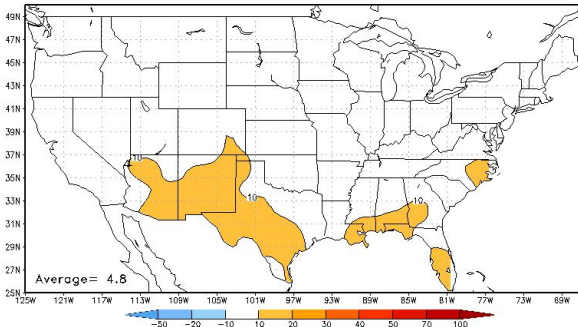
- CCSM4, CESM1, CFSv1, CFSv2, CanCM3, CanCM4, GFDL-CM2
- We focused on 3-month averaged forecast (Seasonal prediction).

Period : 1979-2018 (40 years) for observational analysis, 1982-2010 (29 years) for NMME validation

- All data are detrended to minimize anthropogenic global warming signal.

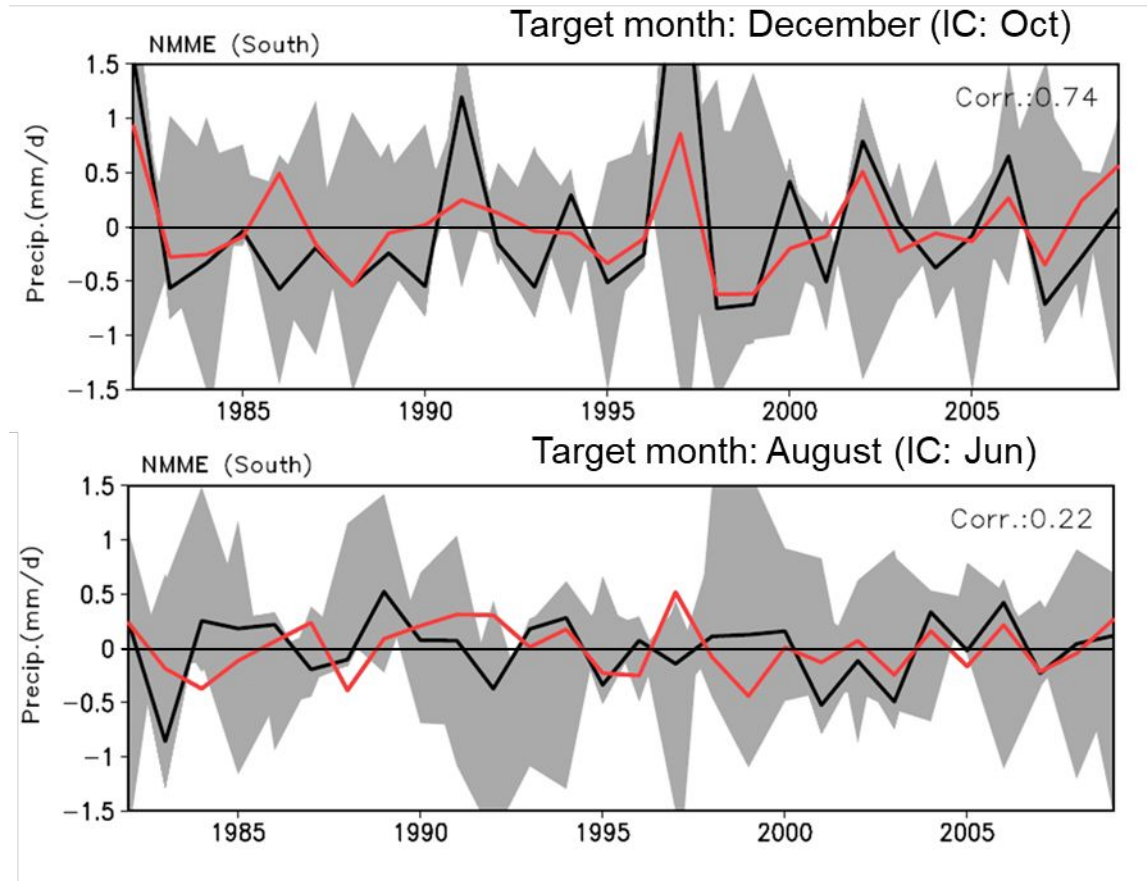
Validation of dynamical U.S. precipitation from NMME

Seasonal (Lead 0.5 Months) Precipitation Heidke Skill Score
All Manual Forecasts From 199501 to 202110



Red: OBS

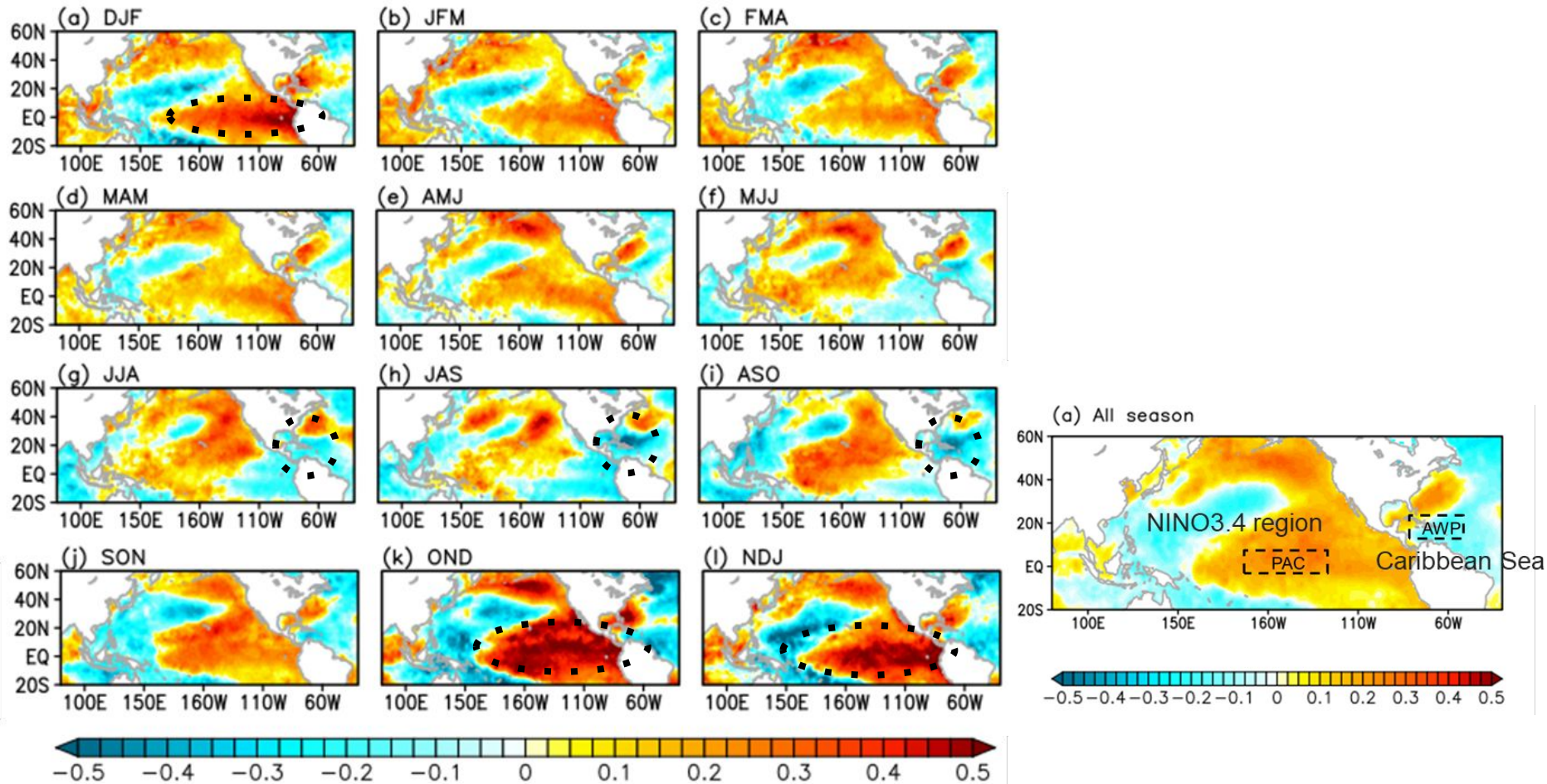
Black : NMME mean



- There is relatively **better prediction skill of precipitation in the cold season than in warm season.**
- It suggests that we have a room to improve prediction skill in warm season using hybrid forecast

Global SSTAs correlated with U.S rainfall

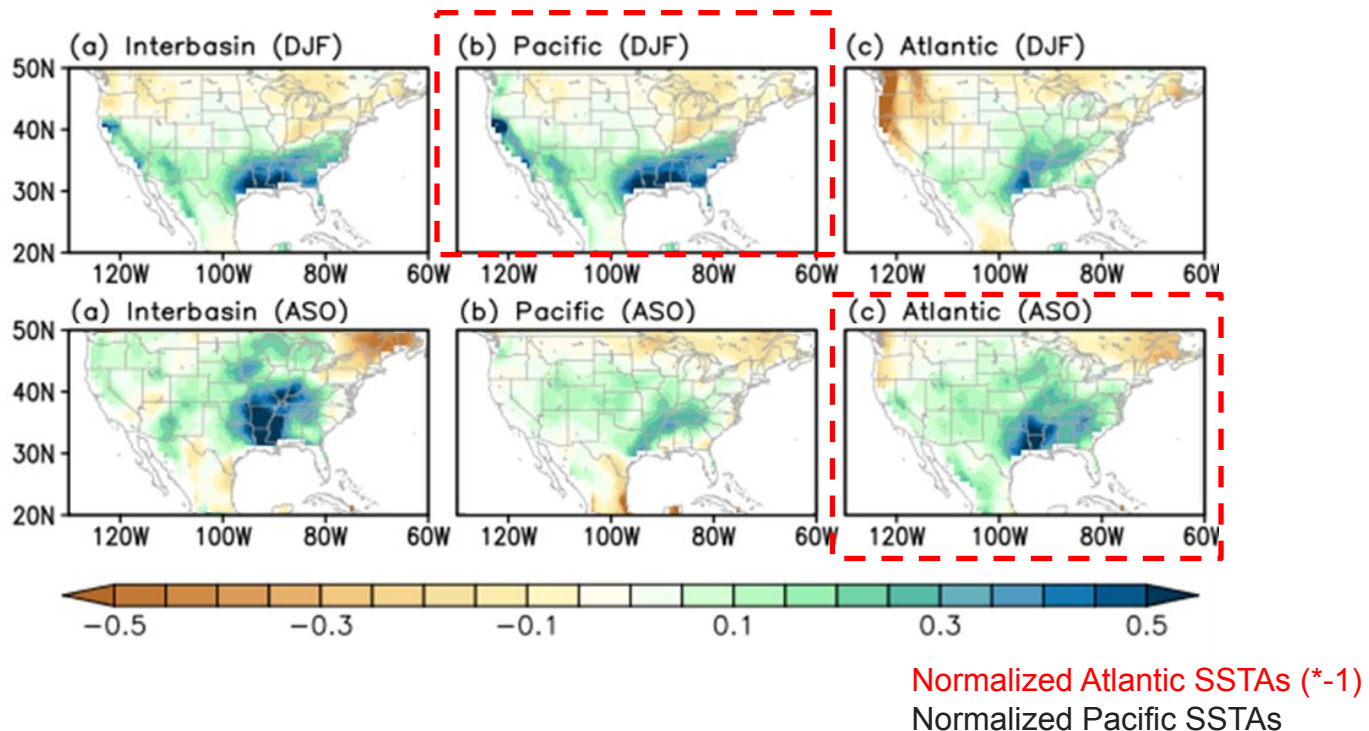
Correlation between global SSTAs and U.S. rainfall (East of Rockies)



- Relationship between global SSTAs and U.S. rainfall largely varies in space and time.
- During boreal cold season, tropical Pacific SSTAs has a strong positive correlation to U.S. rainfall. Conversely, during boreal warm season, Atlantic warm pool has a strong negative correlation to U.S. rainfall.

Partial regression of U.S rainfall to Pacific and Atlantic SSTAs

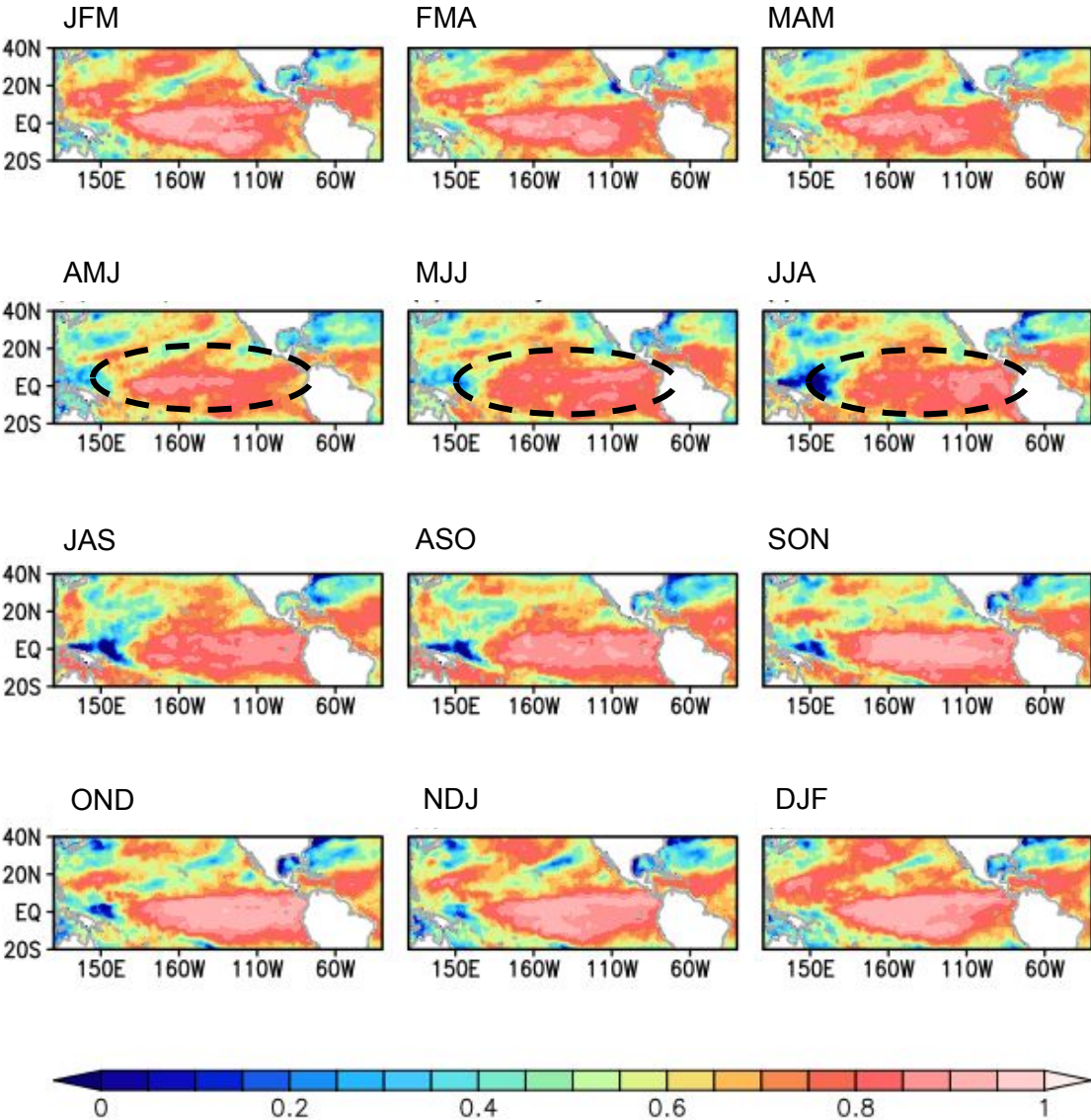
Regression map of U.S. rainfall



- Following similar mechanism in Kim et al. (2020), we developed an interbasin SSTAs index.
- Partial regression maps show that **during boreal cold season, tropical Pacific has strong relationship to U.S rainfall while during boreal warm season, Atlantic warm pool has strong relationship to U.S. rainfall.**

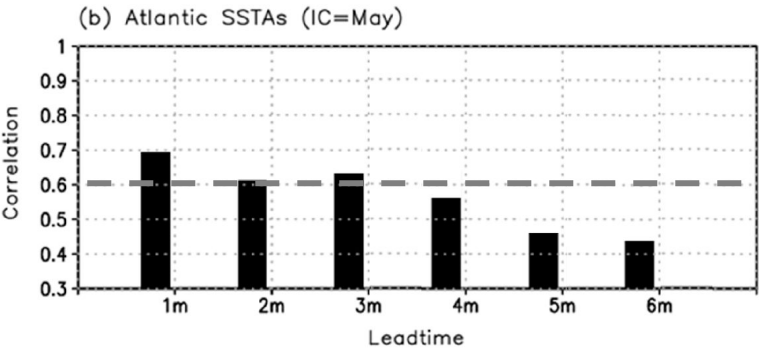
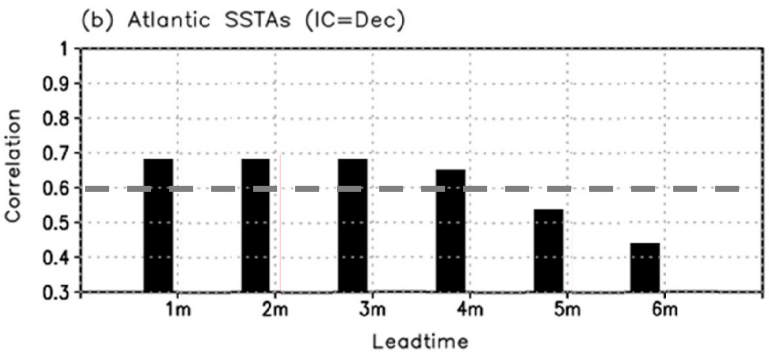
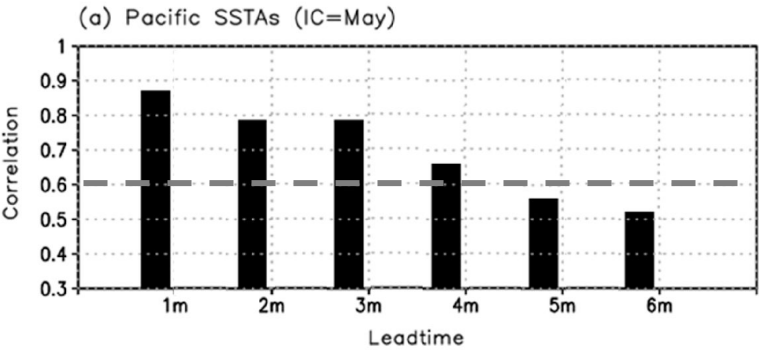
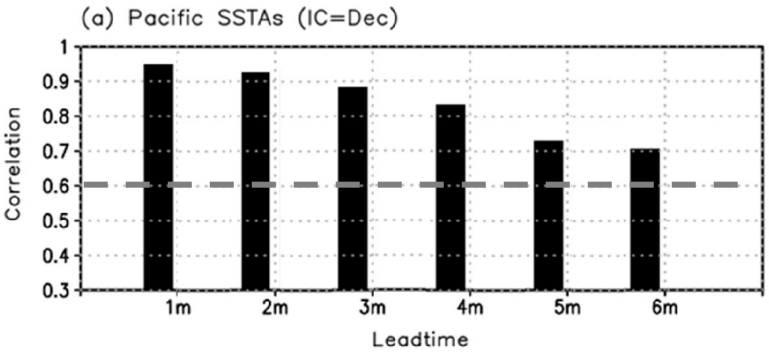
Prediction skill of SSTAs in NMME

NMME (3mon-lead)



- Tropical Pacific SSTAs in NMME has good prediction skill. In tropical Atlantic, there is also reliable prediction skill.
- From Apr to Jun, prediction skill over the tropical Pacific decreases dramatically (i.e., predictability barrier).

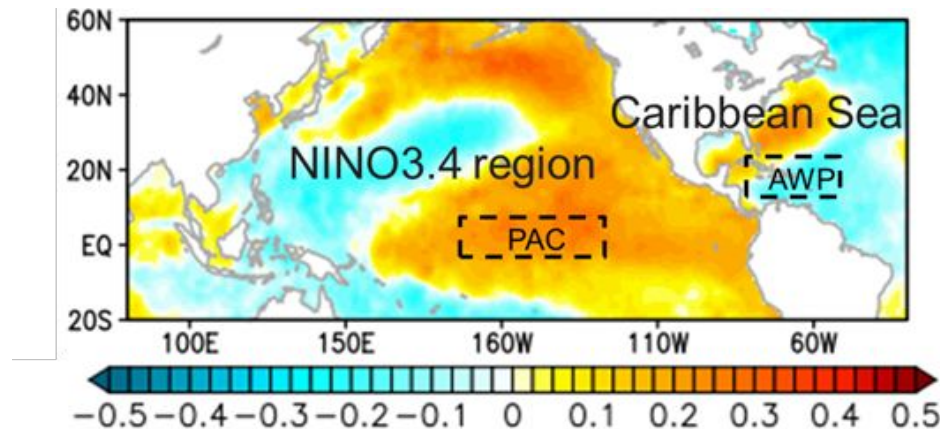
Prediction skill of Pacific/Atlantic SSTAs in NMME



- Consistent with previous slides, **tropical Pacific has better prediction skill than tropical Atlantic** especially during boreal winter.

Multiple regression for reconstruction of U.S. precipitation

- To develop hybrid model, we combined regression coefficient derived from observation and Pacific and Atlantic SST derived from NMME.



- Hybrid model** : reconstructed precipitation derived from multiple regression using regression coefficients from observational precipitation and SST from NMME with ensemble spread.

$$Prec = (a_1 PSST + a_2 ASST) + ens_spread$$

a_1 & a_2 : Multiple regression coefficients

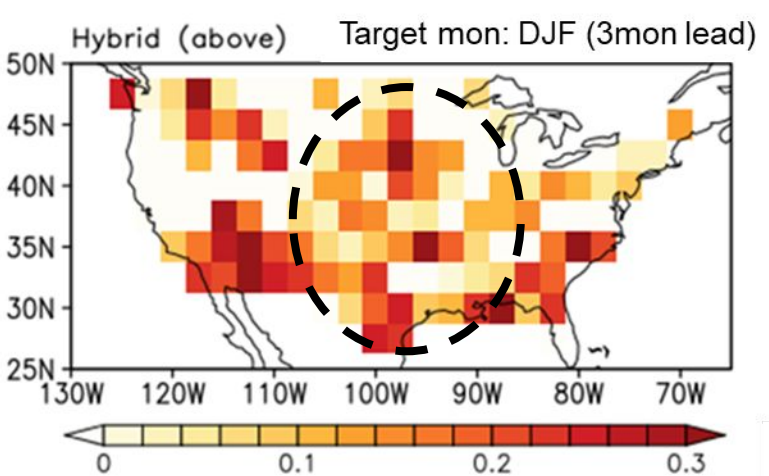
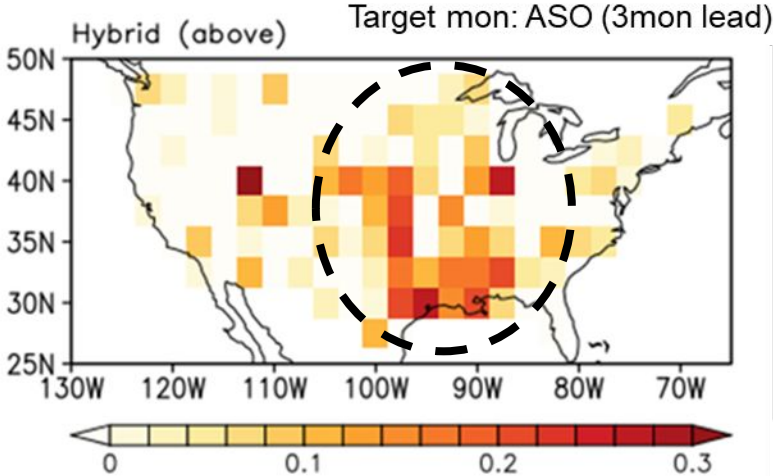
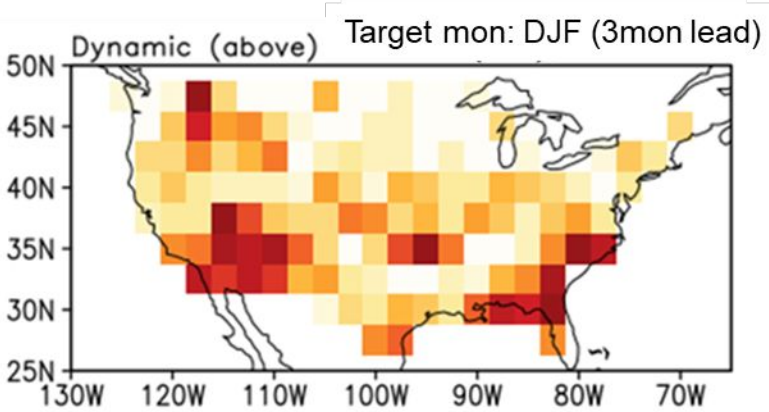
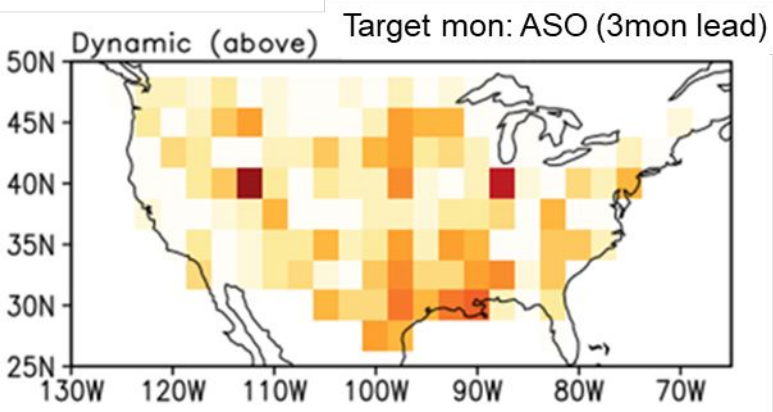
$PSST$: Normalized tropical Pacific SST

$ASST$: Normalized Atlantic warm pool SST

ens_spread : deviation of precipitation in NMME mean

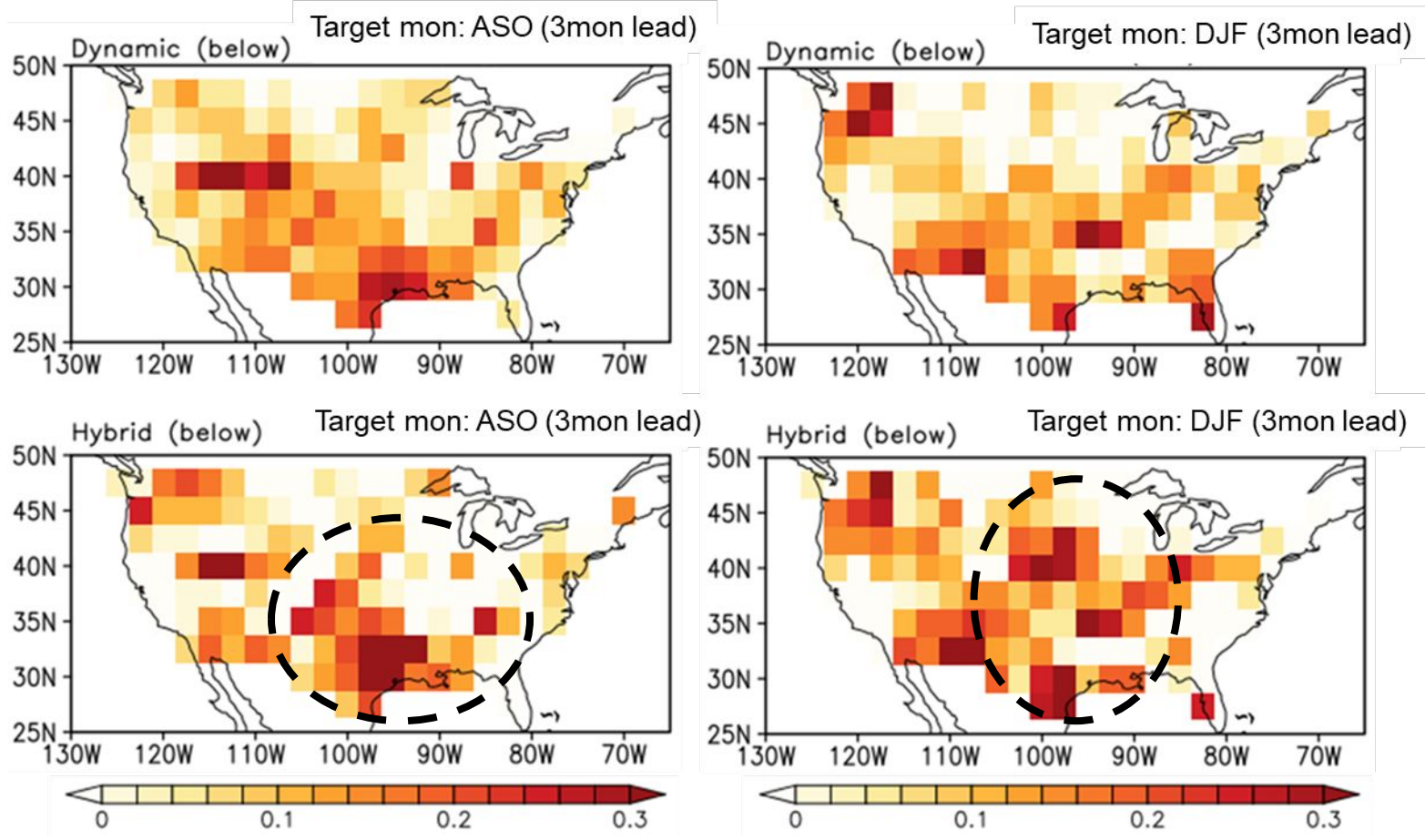
- Dynamic model** : precipitation derived from NMME.

Probabilistic forecast skill (Above normal)



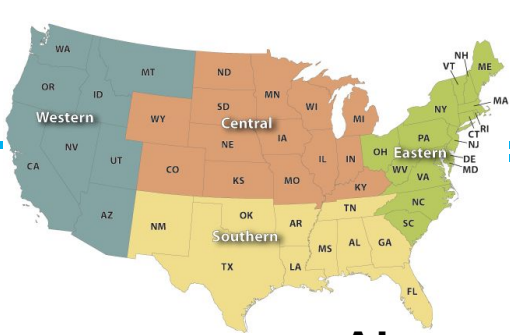
- The hybrid forecast model shows higher brier skill scores over the Southern and Central U.S. than the dynamic forecast.

Probabilistic forecast skill (below normal)



- Same as above normal case, the hybrid model seems to perform better prediction of above- and below-normal cases.

Four NWS divisions



Above normal

ASO

	Dynamical	Hybrid
CONUS	0.019	0.019
Western	0.046	0.044
Central	0.052	0.063
Southern	0.074	0.096
Eastern	0.036	0.031

DJF

	Dynamical	Hybrid
CONUS	0.038	0.041
Western	0.134	0.127
Central	0.060	0.096
Southern	0.115	0.130
Eastern	0.090	0.083

Below normal

ASO

	Dynamical	Hybrid
CONUS	0.035	0.034
Western	0.098	0.101
Central	0.075	0.056
Southern	0.132	0.174
Eastern	0.054	0.046

DJF

	Dynamical	Hybrid
CONUS	0.032	0.042
Western	0.107	0.131
Central	0.061	0.122
Southern	0.121	0.137
Eastern	0.041	0.065

Validation of hybrid and dynamic models for extreme years

- To validate the performance of probabilistic forecast for U.S. precipitation, we explore probabilistic map in some extreme years at each month.

Contiguous U.S. Precipitation
November

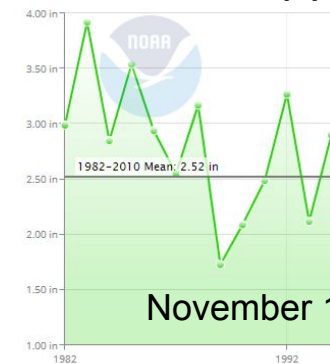
Wet year (cold season)



November 1983

Contiguous U.S. Precipitation
November

Dry year



November

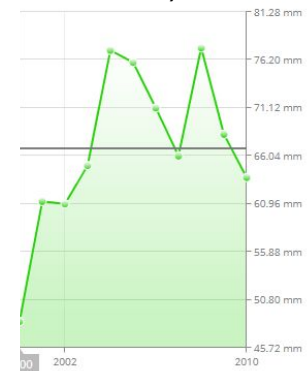
Contiguous U.S. Precipitation
August

Wet year (warm season)



August 2008

Wet year (warm season)



Precip	Probability of Occurrence			Most likely category
	Above	Near	Below	
	80.0%-90.0%	16.7%-06.7%	03.3%	"Above"
	70.0%-80.0%	26.7%-16.7%	03.3%	"Above"
	60.0%-70.0%	33.3%-26.7%	06.7%-03.3%	"Above"
	50.0%-60.0%	33.3%	16.7%-06.7%	"Above"
	40.0%-50.0%	33.3%	26.7%-16.7%	"Above"
	33.3%-40.0%	33.3%	33.3%-26.7%	"Above"
	33.3%-30.0%	33.3%-40.0%	33.3%-30.0%	"Near Normal"
	30.0%-25.0%	40.0%-50.0%	30.0%-25.0%	"Near Normal"
	33.3%-26.7%	33.3%	33.3%-40.0%	"Below"
	26.7%-16.7%	33.3%	40.0%-50.0%	"Below"
	16.7%-06.7%	33.3%	50.0%-60.0%	"Below"
	06.7%-03.3%	33.3%-26.7%	60.0%-70.0%	"Below"
	03.3%	26.7%-16.7%	70.0%-80.0%	"Below"
	03.3%	16.7%-06.7%	80.0%-90.0%	"Below"
	33.3%	33.3%	33.3%	"Equal Chances"

- We followed the probabilistic table provided by CPC which is combined with above, near-, below-normal conditions.

Validation of hybrid and dynamic models for extreme years

Wet year (cold season)

Dry year (cold season)

Wet year (warm season)

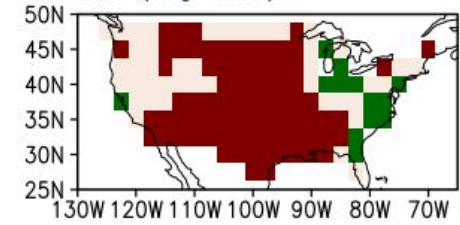
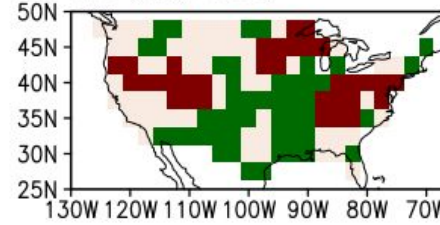
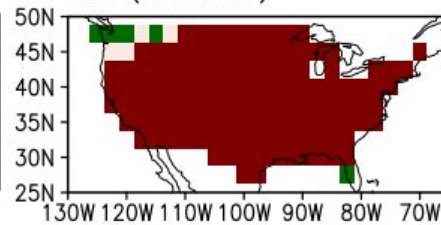
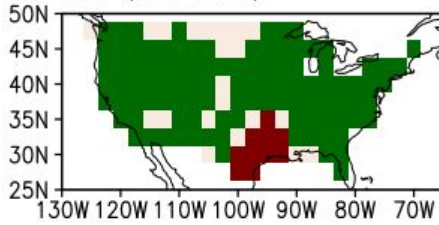
Dry year (warm season)

OBS (Nov 1983)

OBS (Nov 1999)

OBS (Aug 2008)

OBS (Aug 2000)

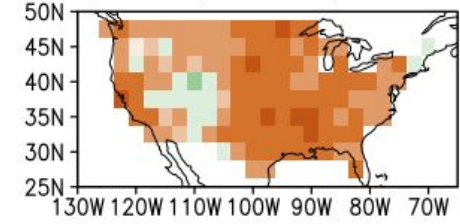
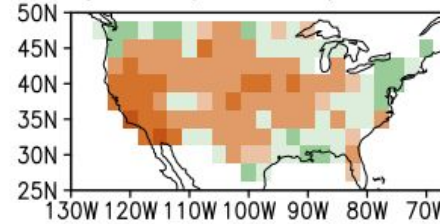
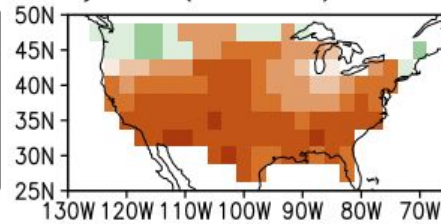
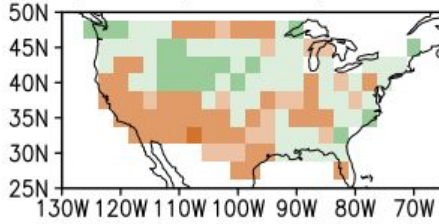


Dynamic (3mon lead)

Dynamic (3mon lead)

Dynamic (3mon lead)

Dynamic (3mon lead)

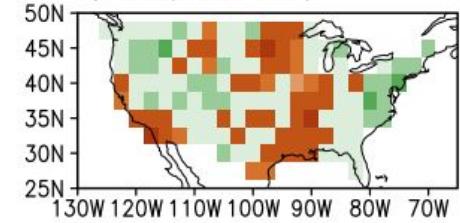
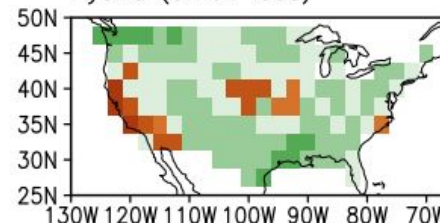
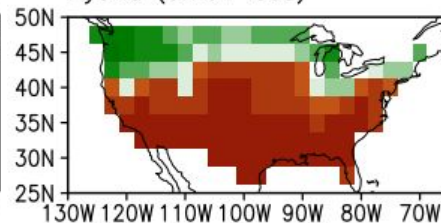
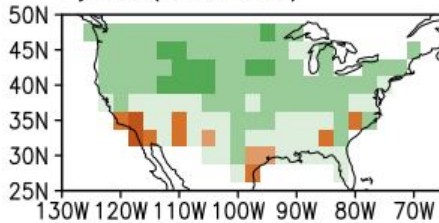


Hybrid (3mon lead)

Hybrid (3mon lead)

Hybrid (3mon lead)

Hybrid (3mon lead)



- The hybrid model seems to perform better at predicting extreme years of U.S. rainfall than the dynamic model.

Summary

- **Prediction skill of cold season U.S. precipitation is reliable in NMME** especially the Southern U.S., whereas prediction skill of **warm season U.S. precipitation is very low.**
- We developed **a hybrid forecast model for U.S. rainfall targeting the warm season**, based on the Pacific-Atlantic interbasin SSTA index derived from NMME.
- The **hybrid forecast model seems to perform better** than the dynamic forecast models, especially in the warm season.
- The **hybrid model shows a potential for better predicting extreme years** than the dynamic forecast models.