Impact of initialized land temperature on sub-seasonal to seasonal prediction (LS4P) – A GEWEX/GASS Initiative

Yongkang Xue[1], T. Yao[2], A. Boone[3], X. Zeng[4], D. Klocke[5], I. Diallo[1], Y. Liu[1], M.-S. Koo[6], H. Lin[7], Z. Lin[8], R. Muncaster[7], S. Saha[9], Y. Takaya[10], H. Zhang[11],M. Zhao[12]

1). UCLA, USA; 2). ITP/CAS, China; 3) Meteo-France; 4). U. Arizona, USA; 5). MPImet, Germany; 6) KIAPS/KMA, Korea; 7). Env. Canada; 8) IAP/CAS, China; 9) IITM, India; 10), MRI/JMA, Japan; 11) NMC/CMA, China; 12), BOM, Australia

International Workshop of First Phase of
GEWEX/GASS LS4P Initiative and TPEMIP
Washington D.C., December 8-9, 2018

YX1

Acknowledgment

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Slide 2

YX1 Yongkang Xue, 12/10/2018

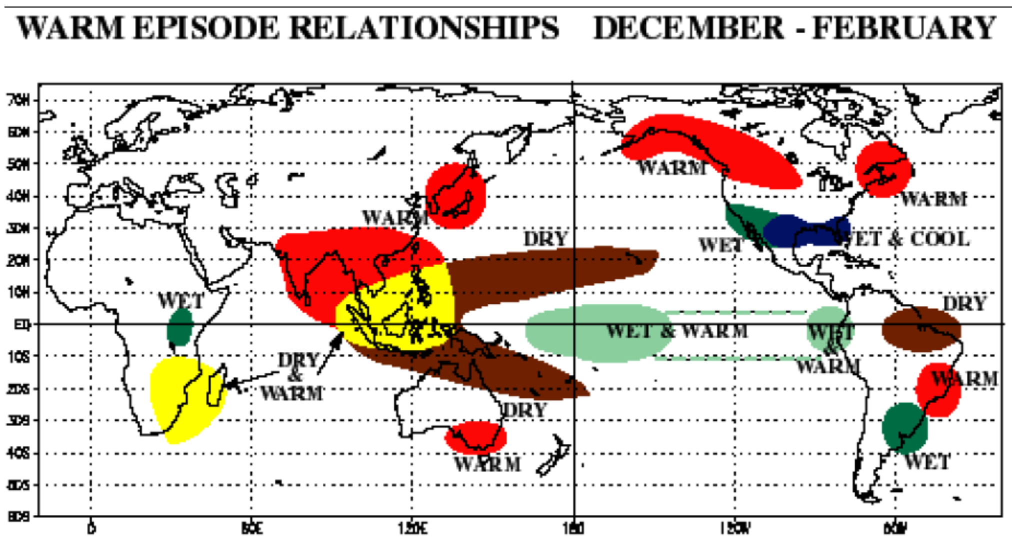
1). Why Land Surface Temperature and Subsurface Temperature?

SST (Focus on N. America)

Based on observed SST, statistically significant correlations above ~0.3 at the $\alpha<0.05$ level between Pacific SST and dry/wet conditions in the U.S. have also been found.

The results from a GCM with a filter that removed time scales shorter than about 6 years showed that specified SST produced low-frequency variations in the U.S. Great Plains precipitation, generally consistent with observations, and that SST fluctuations accounted for about one third of the total low-frequency variability in precipitation (Schubert et al., 2004).

During 2015-2016 one of the strongest El Nino events since 1950 was associated with an extraordinary Californian drought, while a 2016-2017 La Nina event has been associated with record rainfall that effectively ended the 5-year Californian drought, contrary to the expected SST - drought/flood relations. Other factors must be taken into account to complement the SST effects for S2S prediction.



Snow (focus on Third Pole area)

Himalayan Winter Snow and Indian monsoon:

Blanford (1884): Himalayan winter snow cover on rainfall over India.

Walker (1910): an out-of-phase relationship between the May Himalayan snow depth and the Indian rainfall.

Many Data analyses and modeling studies support the snow/monsoon relationship

The Difficulty for the Third Pole snow data application

Bamzai and Shukla (1999): There were only a few years, for which Himalayan winter snow cover anomalies persisted through the spring season

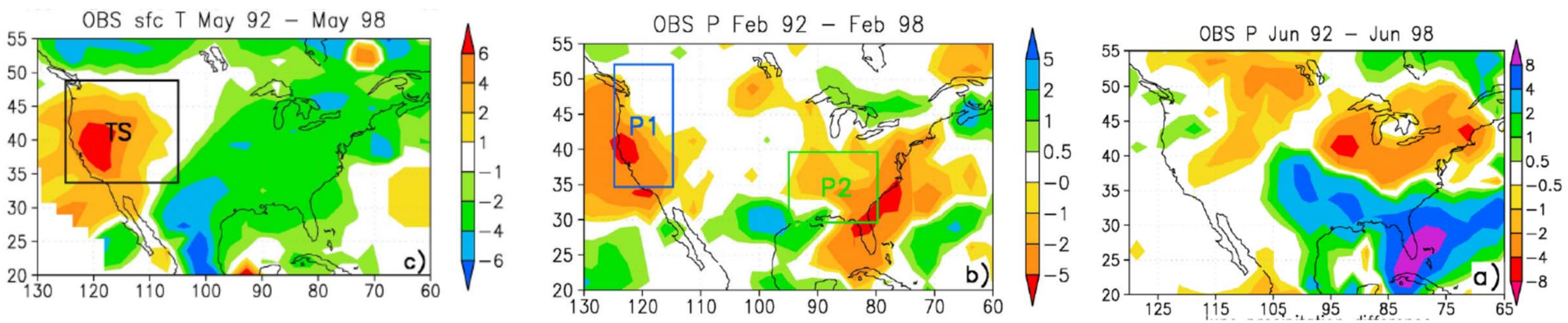
Robock et al. (2003):soil moisture memory is short and cannot be used as a bridge to link the winter snow cover and the subsequent summer monsoon.

Bamzai and Shukla (1999) and Thapliyal et al. (2001): During the 1960s and after the year 1999, Himalayan snow has no longer been used as a predictor of the Indian monsoon by the Indian Meteorological Department.

Our Hypothesis

A temporally filtered response to snow anomalies over high mountains may be preserved in the land surface temperature anomaly

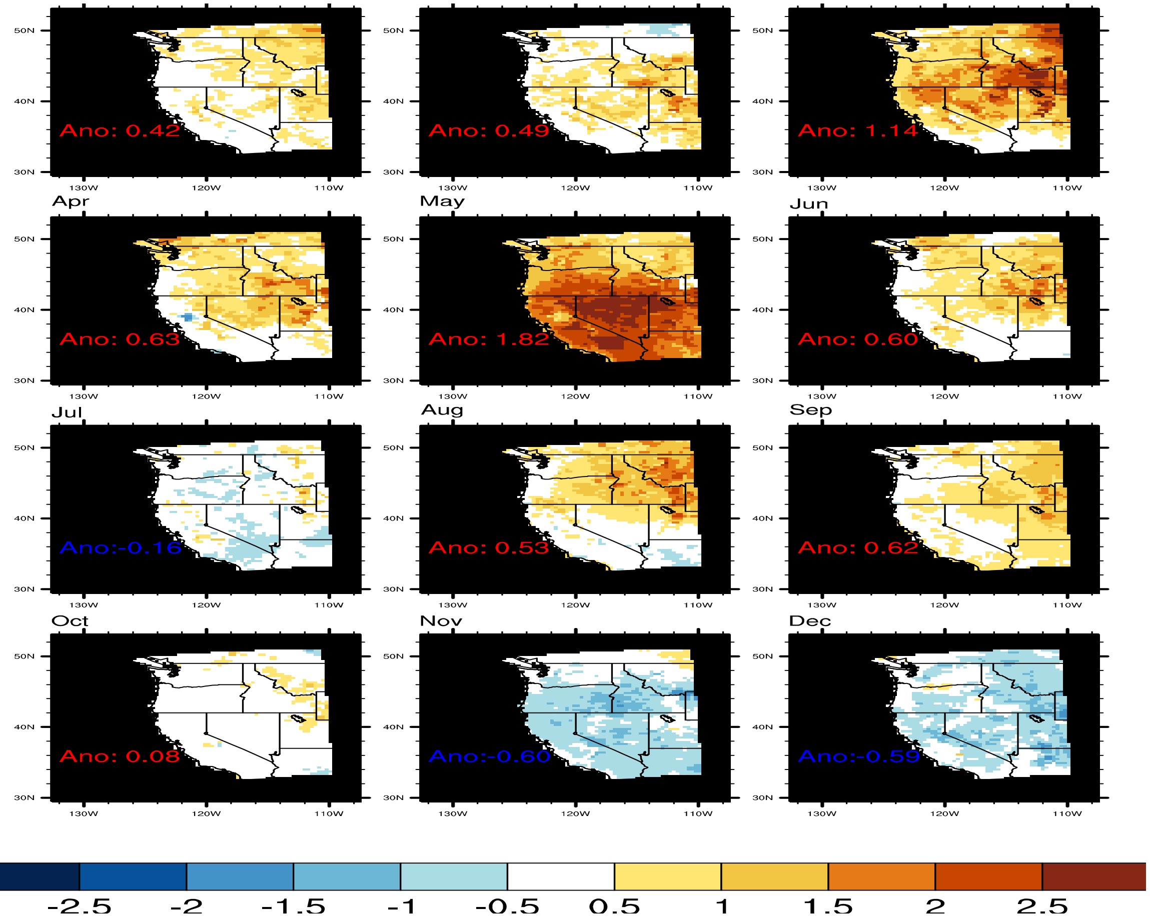
2). Background of Idea Development



Early study pursue to find land memory based on observed phenomena (Xue et al., 2012, JGR)

Land surface temperature anomalies could last for several months

CMA 2-m Temperature Difference between warm years and cold yeas °C

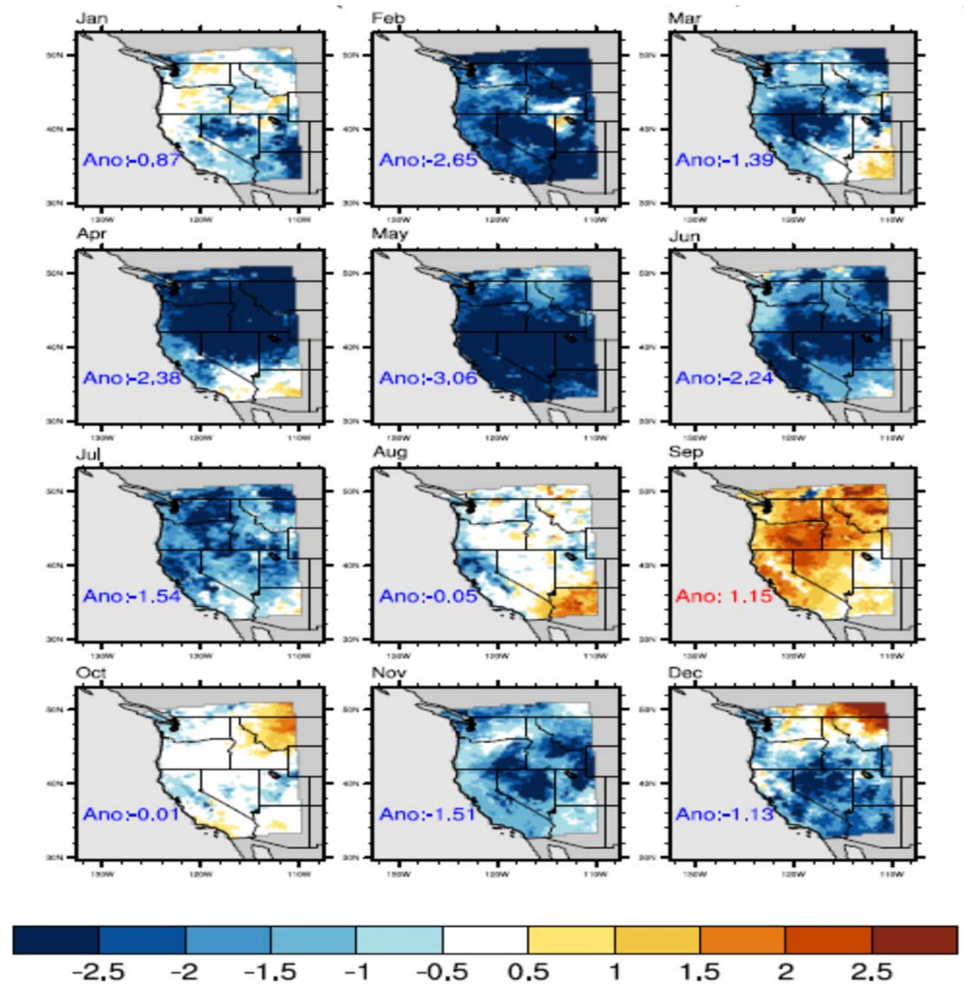


half std: 0.68 ^{o}C

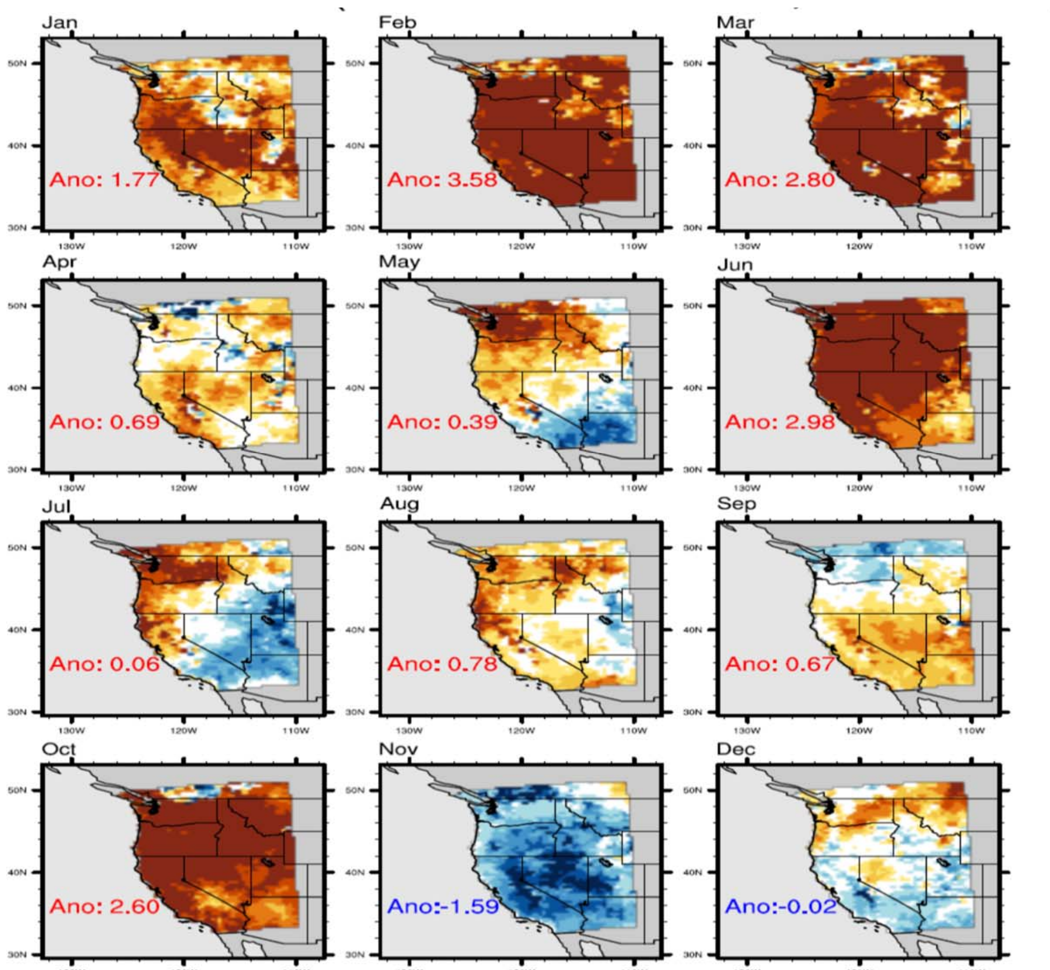
Warm years: 1982,1983,1990,1991,1992,1993,1994,1997,2000,2001,2006,2009

Cold years: 1985,1987,1995,1996,1998,1999,2002,2008,2010,2011

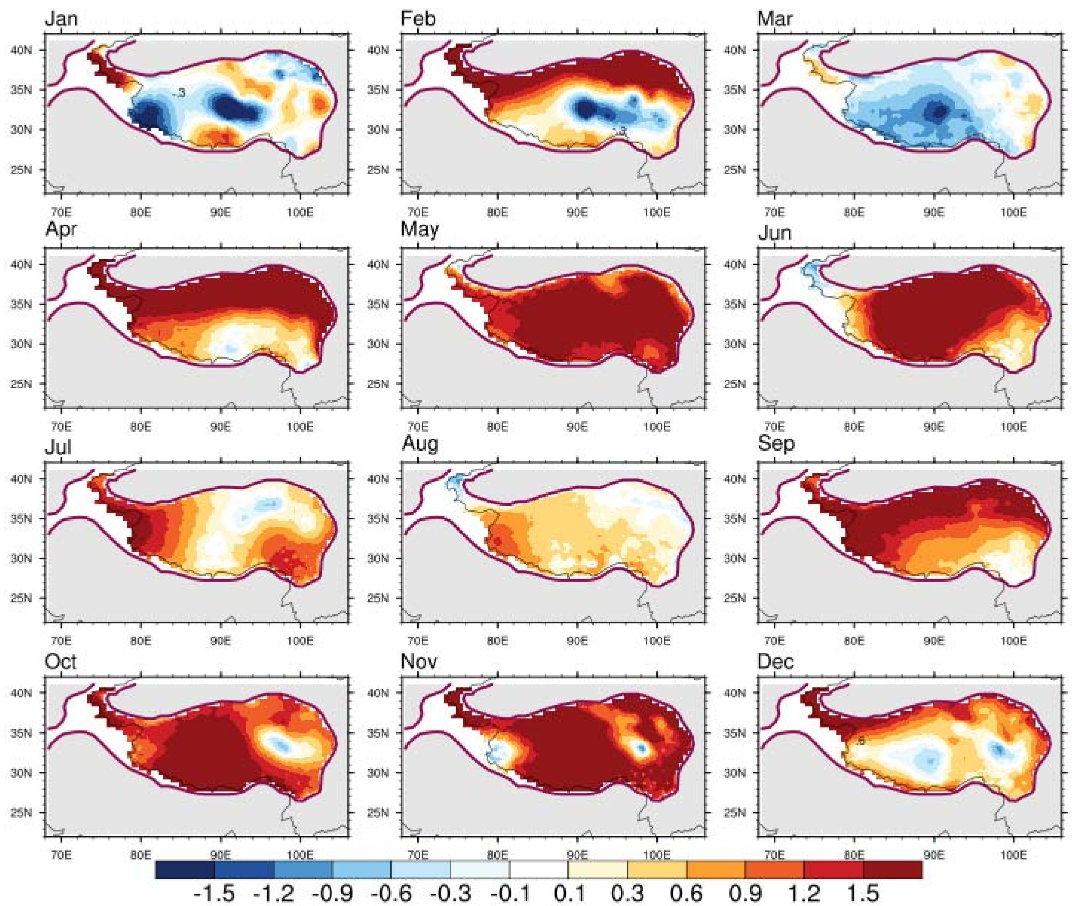
2011 Monthly mean T-2m anomaly



2015 Monthly mean T-2m anomaly

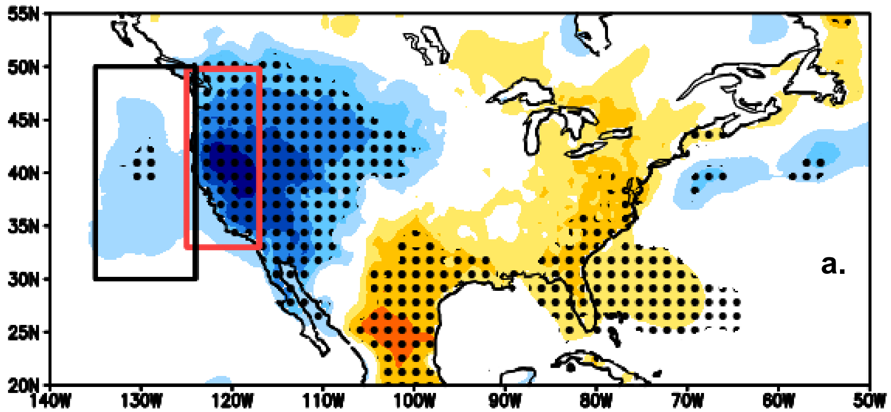


1998 Monthly mean T-2m anomaly

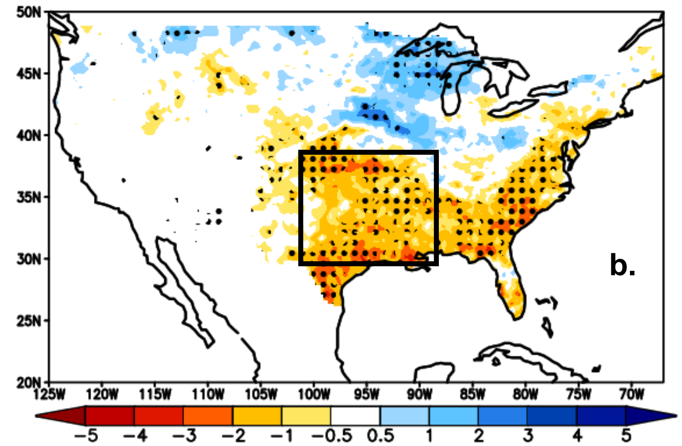


Observed differences between 9 coldest years and 9 warmest years (based on N.W. U.S. & S. E. Canada LST)

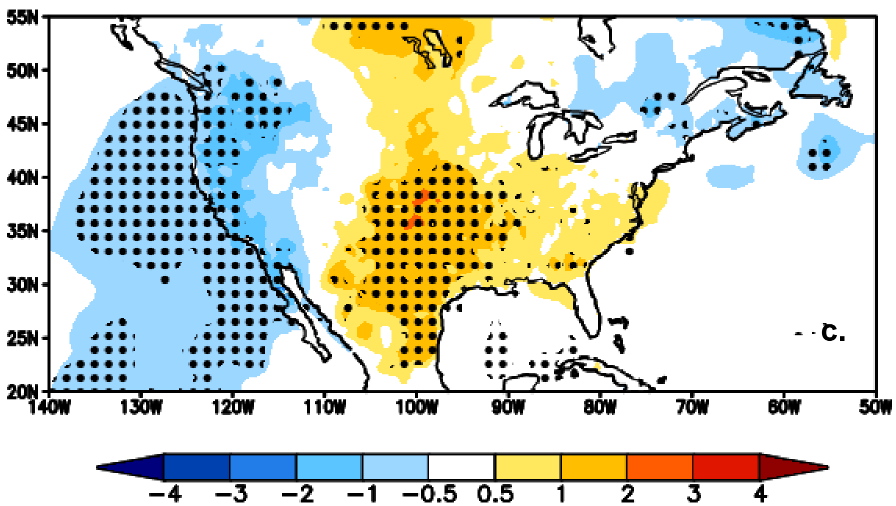
May Observed **LST** and **SST**



June Observed Precipitation



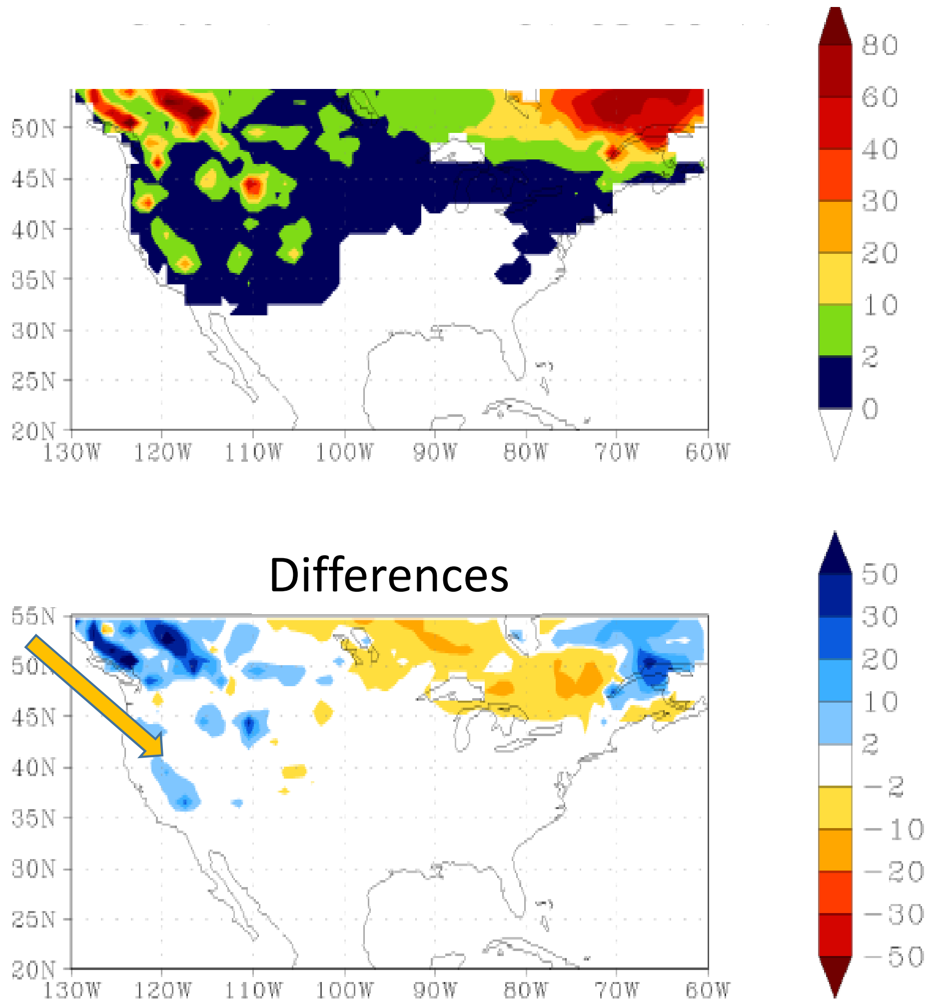
June Observed LST and SST

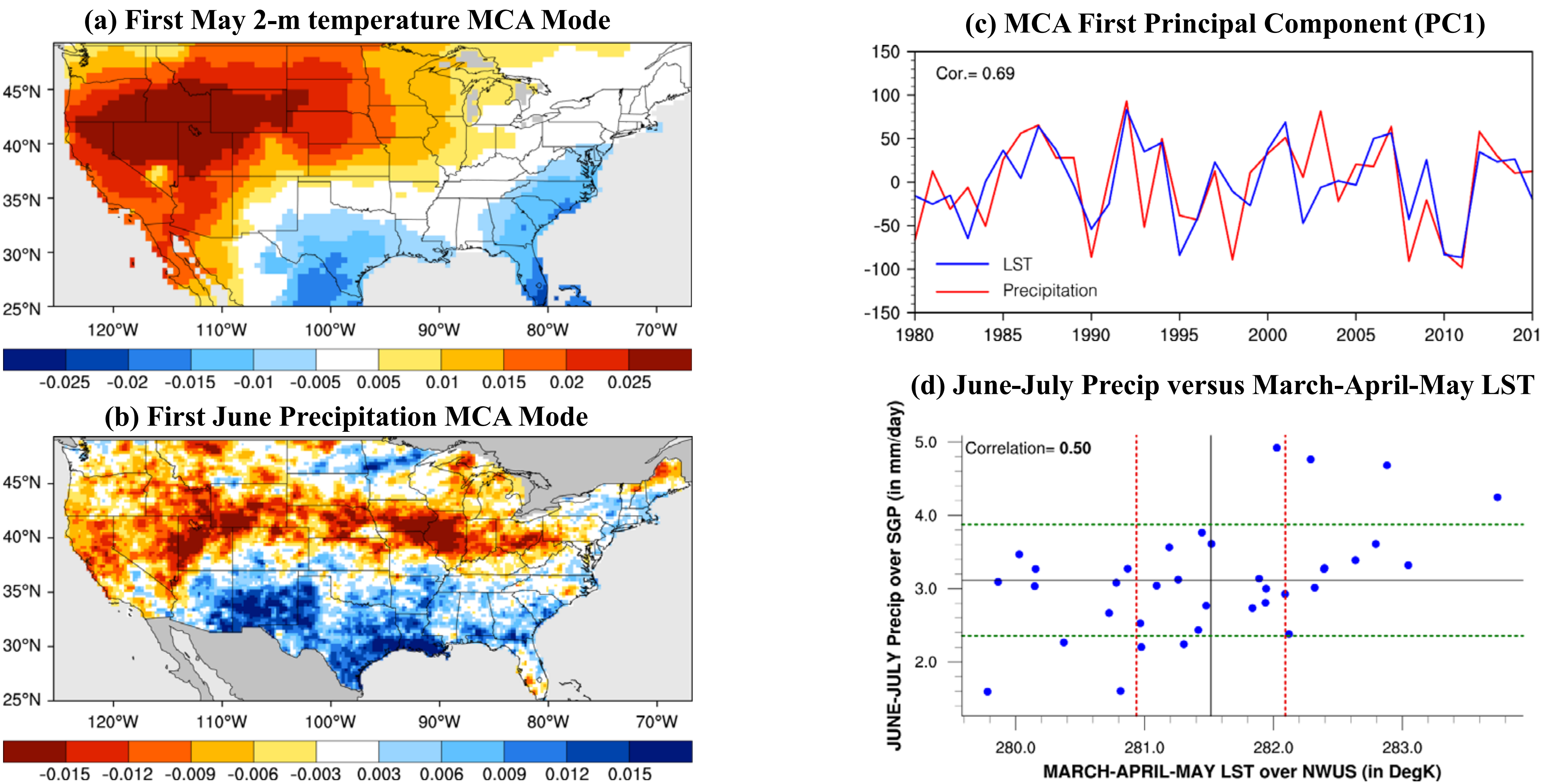


1) LST: land surface temperature

2) The dotted areas denote statistical significance less than α=0.1 level of t-test values. (Xue et al., 2016, ERL)

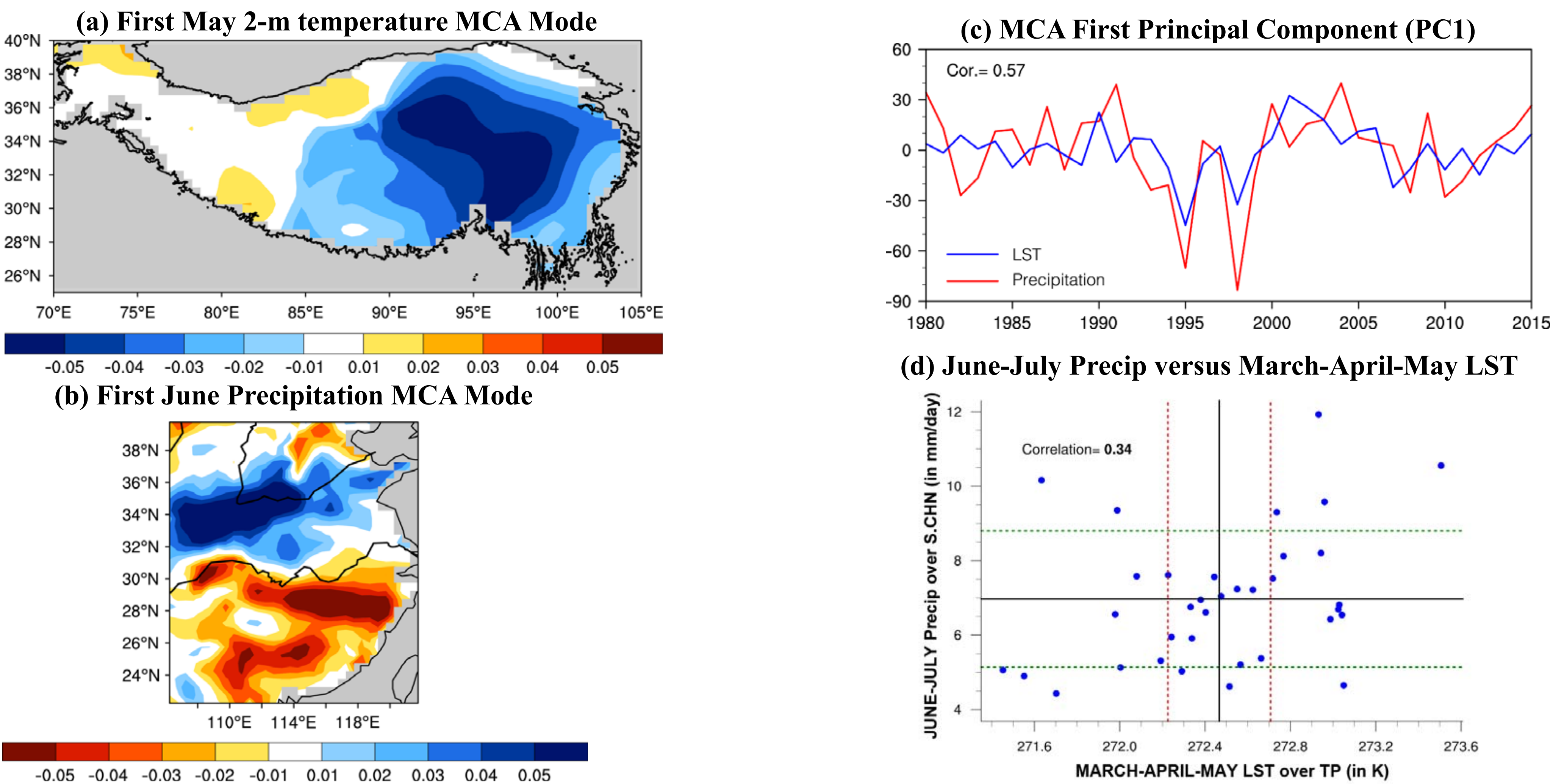
Observed April snow water equivalent and its difference between **Coldest** and **Warmest** Years over West U.S.





First MCA Mode (May 2-m Temperature vis June Precipitation)

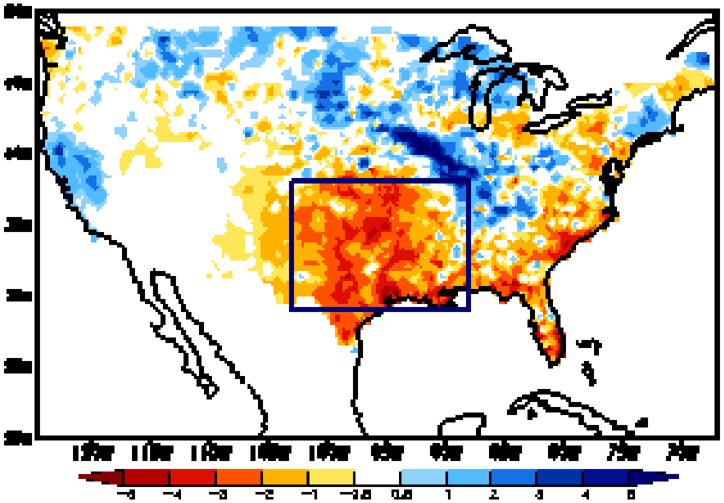
MCA: Maximum Covariance Analysis. Xue et al., 2018 JGR



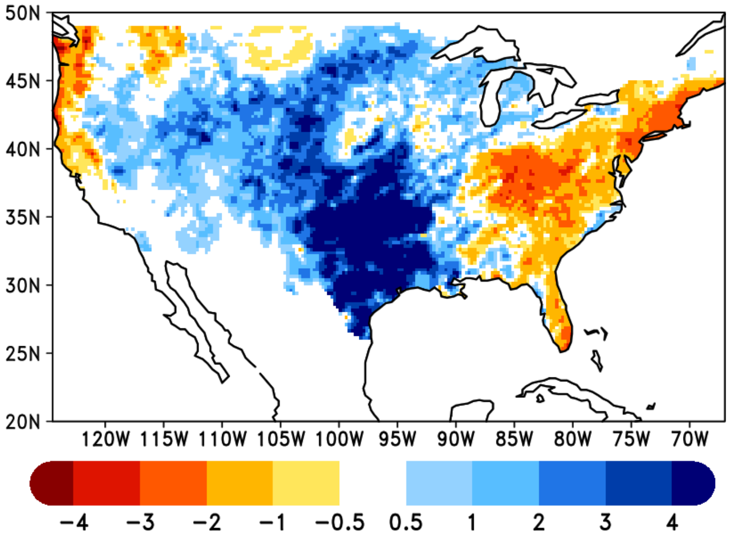
First MCA Mode (May 2-m Temperature vis June Precipitation)

2011 Texas Drought

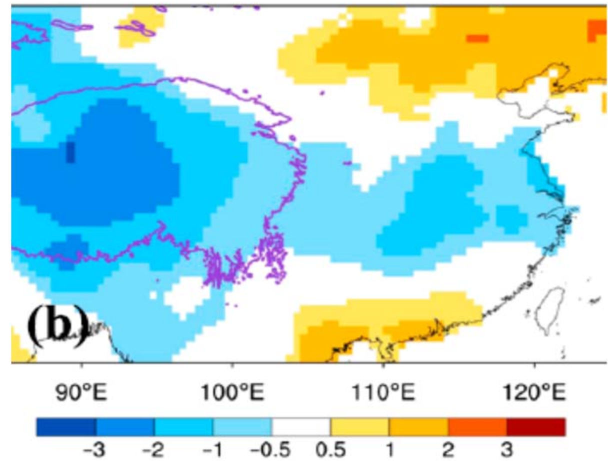
June 2011 precipitation Anomaly

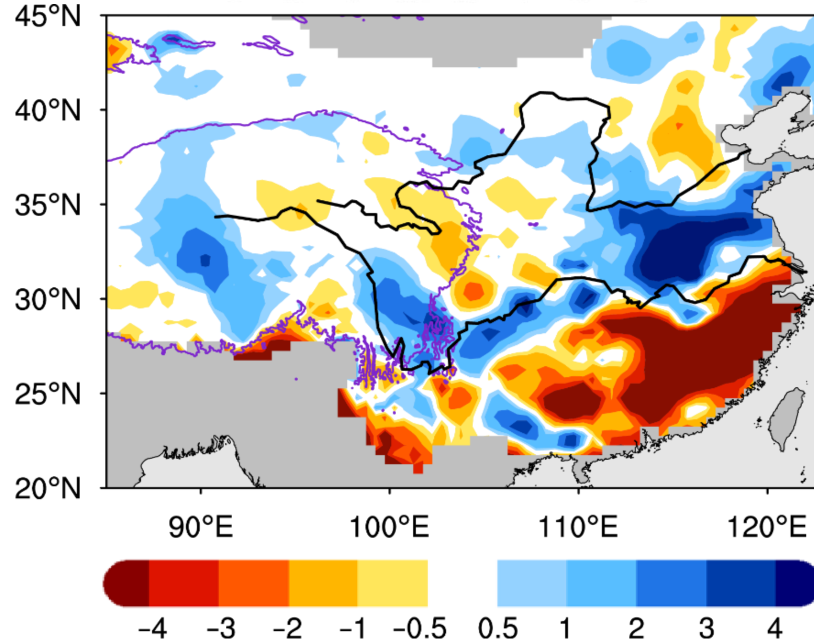


May 2015 precipitation Anomaly



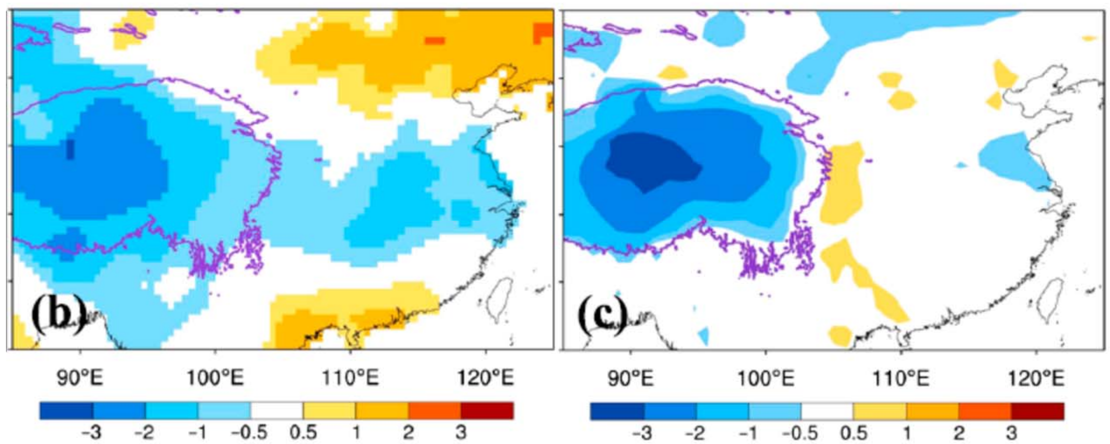
2003 East Asian Flood/droughts

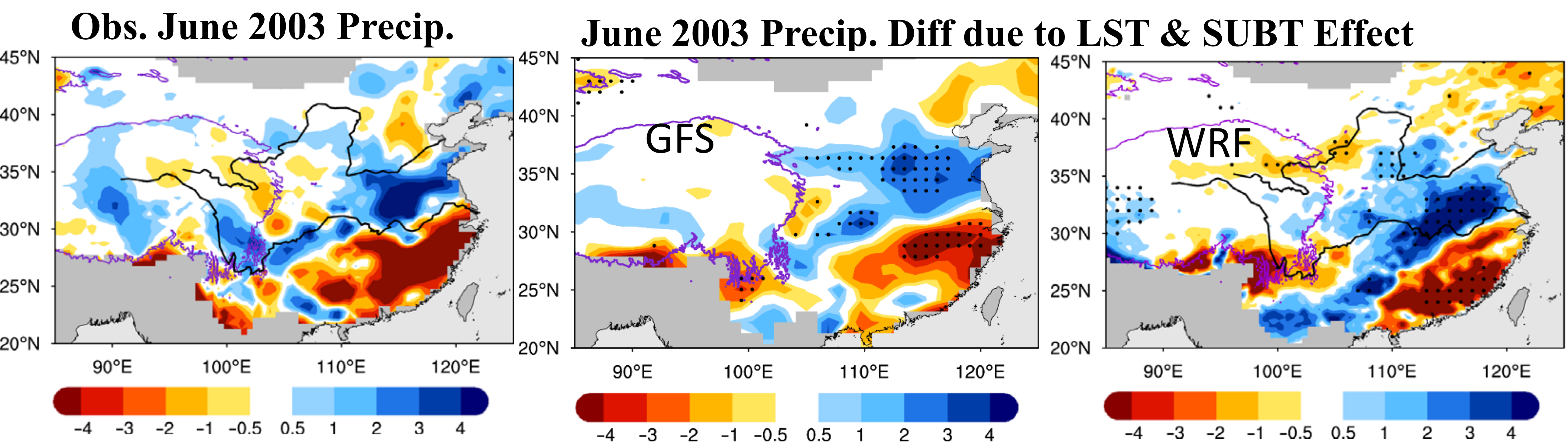




Using Specified land surface temperature and sub-surface temperature anomaly as initial condition

Observed May T2m Anomaly **Simulated May T2m Anomaly**

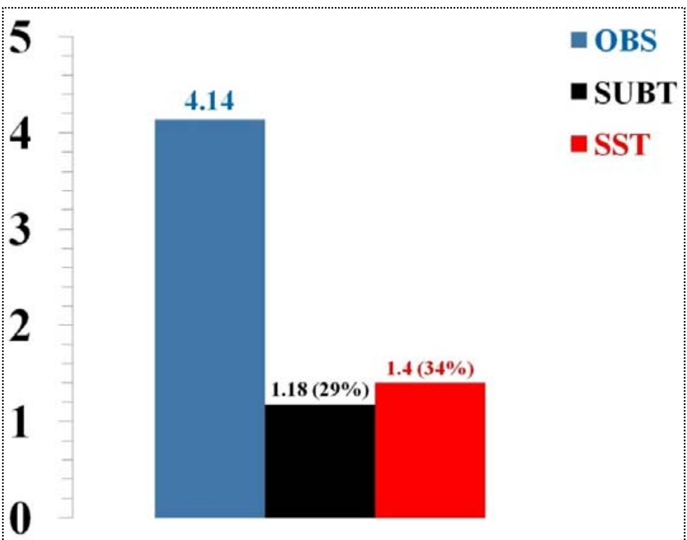




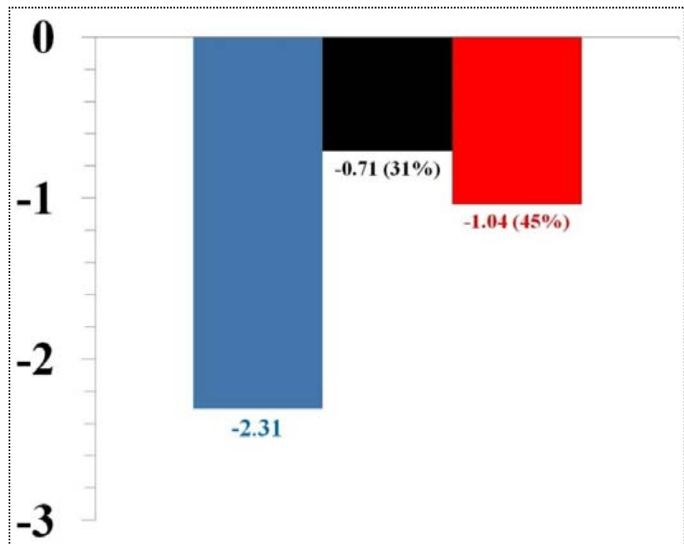
Observed and Simulated June 2003 Precipitation Anomalies over East Asia. (**a**) Observed June precipitation difference between 2003 and the benchmark years; (**b**) GFS-simulated precipitation difference due to LST effect; (**c**) same as (**b**) but for WRF; (Units: mm day^{-1}. The stippled areas denote statistical significance at the α <0.1 level of t-test values. The gray shaded areas indicate no observational data. Xue et al., 2018 JGR

Area-Averaged Obs. and WRF Simulated Precipitation anomalies for Diff. Years

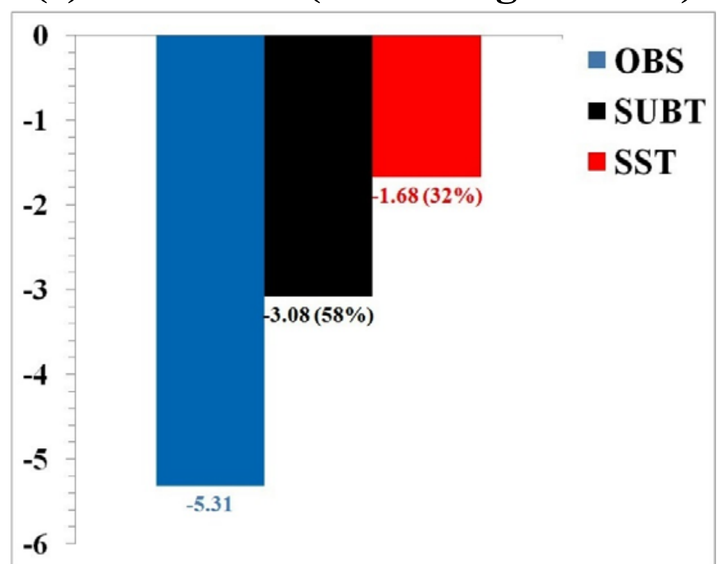
(a) May 2015 (SGP)



(b) June 2011 (SGP)



(c) June 2003 (S. of Yangze River)



Xue et al., 2018 JGR

3. Joint Efforts of GEWEX/GASS Initiative

Impact of initialized land temperature and snowpack on subseasonal to seasonal prediction (ILTSS2S) (First Phase)

Co-Chairs: Yongkang Xue (yxue@geog.ucla.edu), Tandong Yao (tdyao@itpcas.ac.cn); Aaron Boone (aaron.boone@cnrm.meteo.fr)

The Third Pole Experiment (TPE) Earth System Model (ESM) Intercomparison Project (TPEMIP)

Project Goals

- What is the impact of the initialization of large scale land surface temperature (LST)/subsurface temperature (SUBT) and snow pack, including the aerosol in snow, in climate models on the S2S prediction over different regions?
- What is the relative role and uncertainties in these land processes versus in SST in S2S prediction? How do they synergistically enhance the S2S predictability?

This LS4P project aims to pursue a new approach – complementing SST, snow, soil moisture, vegetation anomalies – in understanding and potentially predicting drought/flood events in the regions.

Note: 2-m temperature has global, reliable, and long-term observation

2018 work plan: forming the initiative, preliminary tests from the volunteer groups and a kick-off Workshop in 2018 AGU (Saturday and Sunday)

Participants – ESMs; Total 24; 8 have started preliminary test.

INSTITUTIONS	Contact Person	MODEL
BOM, Australia	Maggie Zhao et al.	Ukmet_au
CMA/NCC, China	Weiping Li	NCC GCM
CMA/NMC, China	Hongliang Zhang	NMC PRISM
CPTEC, Brazil	Paulo Nobre	BESM
DOE/LLNL, USA	Qi Tang et al.	DOE E3SM
ECMWF (TBC)	Gianpaolo Balsamo et al.	ERAS
Environment Canada	Hai Lin, R. Muncaster	ECCC-GEPS
ETHZ, Swaziland (TBC)	Sonia Seneviratne	ETHZ GCM
GFDL/NOAA, USA	Sarah B. Kapnick	GFDL FV3
Hokkaido University, Japan	Tetsu Nakamura	AFES v4.1
IITM, India	Subodh Saha	CFS (Indian Version)
KIAPS/KMA, Korea	Myung-Seo Koo, S.-Y. Hong et al.	KIM
KIT/IMK, Germany (TBC)	Anika Rohde	ICON

INSTITUTIONS	Contact Person	MODEL
Meteo France	Constantin Ardilouze et al.	CNRM-CM6
MPImet, Germany (TBC)	Daniel Klocke et al.	
MRI, Japan	Yuhei Takaya	JMA/MRI-CPS2
NASA/GSFC, USA	Hailan Wang, Kyu-myong Kim	NASA GEOD-5
NCEP, USA	Weizong Zheng, Jack Kain	FV3GFS
Tsinghua University, China	Yanluan Lin et al;.	CIESM
LASG/IAP/CAS, China	Qin Bao, Jing Yang	LASG GCM. BNU
IAP/CAS, China	Zhaohui Lin	CAS-ESM
UCLA, USA	Yongkang Xue et al.	CFS/SSiB
UK Meto office (TBC)	Adam Scafie	Ukmeto ESM
UMD, USA	William K.-M. Lau	NASA GEOS-5
Univ. Arizaona, USA	Xubin Zeng, Mike Brunke	NCAR ESM
San Diego State Univ, USA	Sam Shen	Statistic Model

Participants – RCMs, Data and Coordinators

RCM

INSTITUTIONS	Contact Person	MODEL
CSU, USA; CUIT, China,	Lixin Lu, Xiaofei Wu	RMS
CMA/NCC, China	Ying Shi	RegCM4
JAMSTEC, Japan	Shiori Sugumoto	NHRCM -> WRF, SCALE
Hokkaido University, Japan	Tomonori Sato	
Tokyo Metropolitan University, Japan	Hiroshi Takahashi	
IAP/CAS, China	Xuejie Gao	IAP RegCM
IAP/CAS, China	Jimin Feng	TEA RCM
NOAA, USA	Stan Benjamin	ESRL RCM
PNNL/DOE, USA	Samson Hagos et al.	WRF
Nanjing University, China	Weidong Guo	WRF/SSiB
Nanjing University, China	Shuyu Wang, et al.	RegCM4
NUIST, China	Yu Miao	RegCM4-CLM-CNDV
Sun Yat-Sen University, China	Zhenming Ji	RegCM
Univ. Connecticut, USA	Guiling Wang	RegCM
UMD, USA	Xinzhong Liang	CWRF

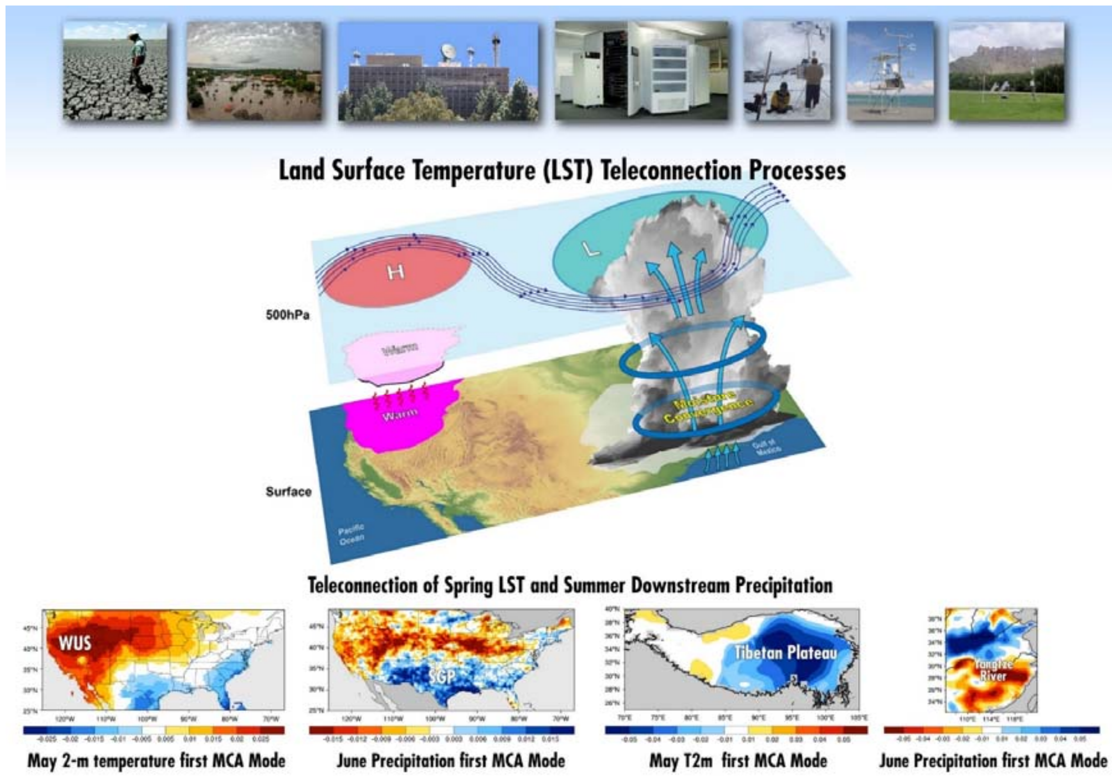
Data

INSTITUTIONS	Contact Person	DATA
CMA/CAMS, China	Ping Zhao	Tibetan Field Data (TIPEX III)
ITP/CAS, China	Xin Li, Yingying Chen et al.	TPE data, Database
NIEER, CAS, China	Shichang Kang	TPE Aerosol data
NMIC, CMA, China	Chunxiang Shi	China data
NUIST, China	Yongming Xu	Tibetan Satellite Data

Coordinator

INSTITUTIONS	Contact Person
ITP/CAS, China	Alikun
UCLA, USA	Ismaila Diallo
ITP/CAS, China	Weicai Wang

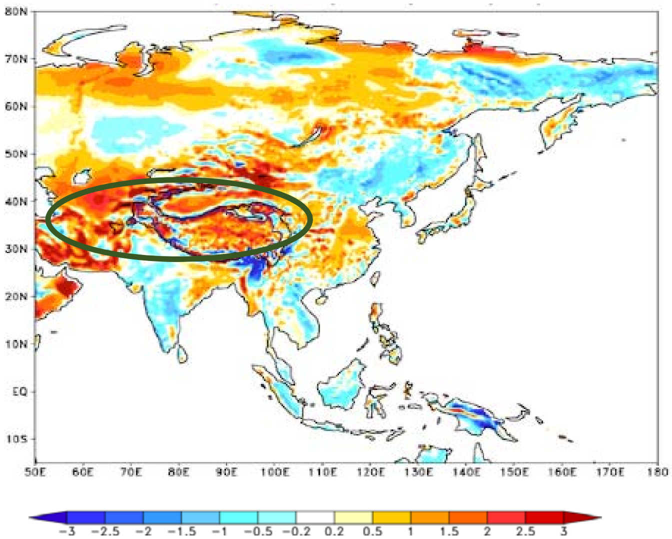
https://LS4P.geog.ucla.edu/



4). Early Testing from ESMs and Preliminary Results

INSTITUTIONS	Contact Person	MODEL
BOM, Australia	Maggie Zhao et al.	Ukmet_au
CMA/NMC, China	Hongliang Zhang	NMC PRISM
Environment Canada	Hai Lin, R. Muncaster	ECCC-GEPS
IITM, India	Subodh Saha	CFS (Indian Version)
KIAPS/KMA, Korea	Myung-Seo Koo, S.-Y. Hong et al.	KIM
MRI, Japan	Yuhei Takaya	JMA/MRI-CPS2
IAP/CAS, China	Zhaohui Lin	CAS-ESM
UCLA, USA	Yongkang Xue et al.	GFS/SSiB

May T-2m ensemble mean Bias

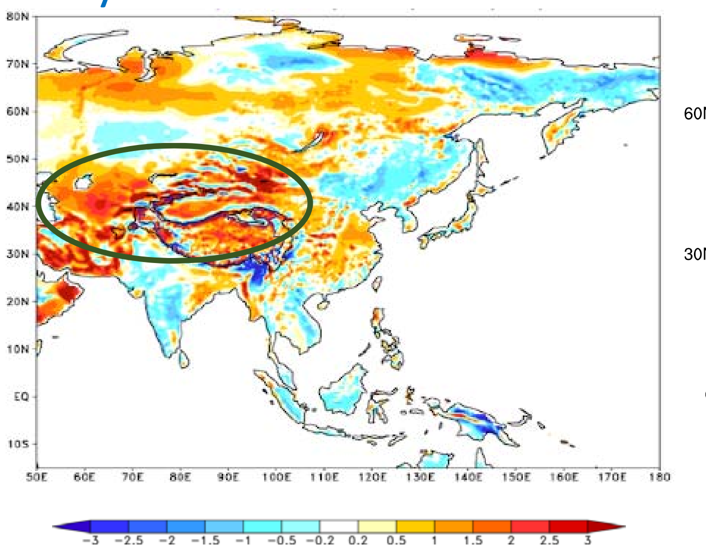


Based on each Model group's control run from about May 1 to June 30 with multiple members.

The ensemble mean has the largest bias on Third Pole area.

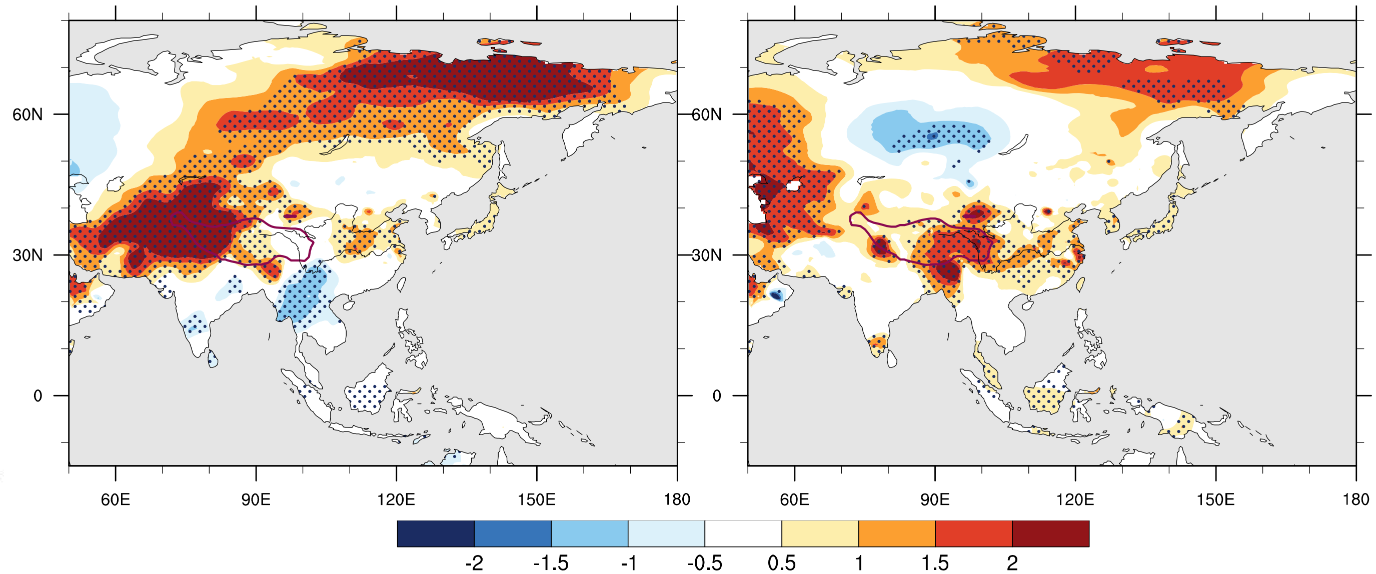
Observed May T-2m Diff. between Warmest and Coldest Years

May T-2m ensemble mean Bias



Central and Eastern TP

Western TP



The ensemble mean has the largest bias on Third Pole area. In other parts, the bias pattern and observed T-2m anomaly do not agree in general.

West TP(half std: 0.632°C)

Warm: 1981, 1990, 1999, 2000, 2001, 2006, 2007, 2008, 2011, 2015

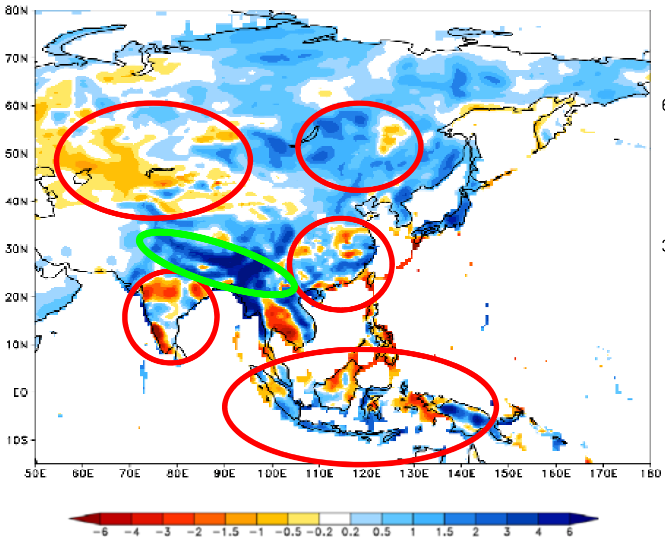
Cold: 1982,1983, 1985, 1986, 1987, 1989, 1991, 1992, 1996, 1997, 2003, 2005

Cent-East TP (half std: 0.359°C)

Warm: 1995,1998,2007,2008,2009,2010,2011,2012,2014

Cold: 1980,1981,1982,1984,1987,1988,1990,1992,2001,2002,2003

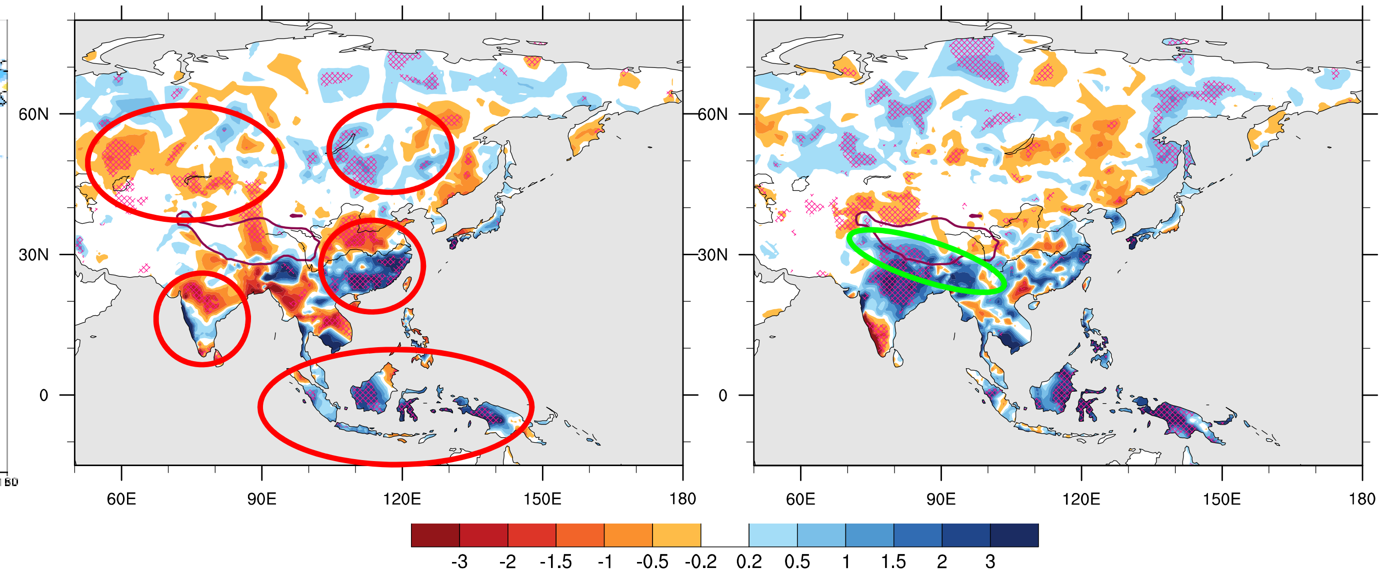
June Precip. ensemble mean Bias



Observed June Prec. Diff. between Warmest and Coldest Years

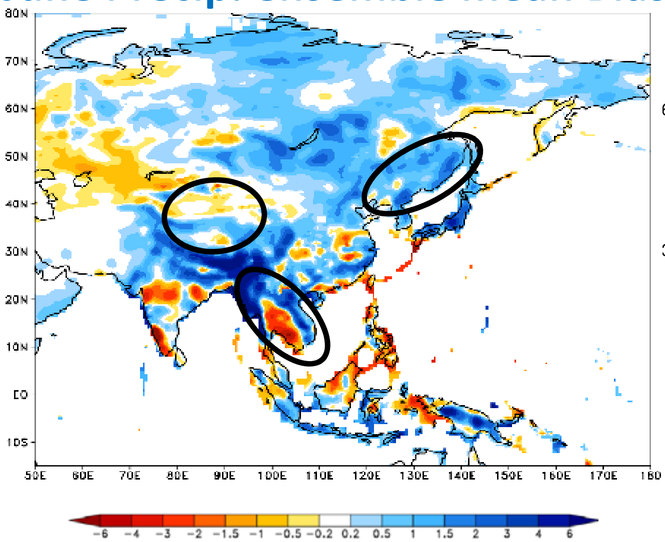
Central and Eastern TP

Western TP



June ensemble mean precipitation biases in some areas are in general agreement with the June precipitation anomalies between eastern-central TP/western TP warm minus cold years

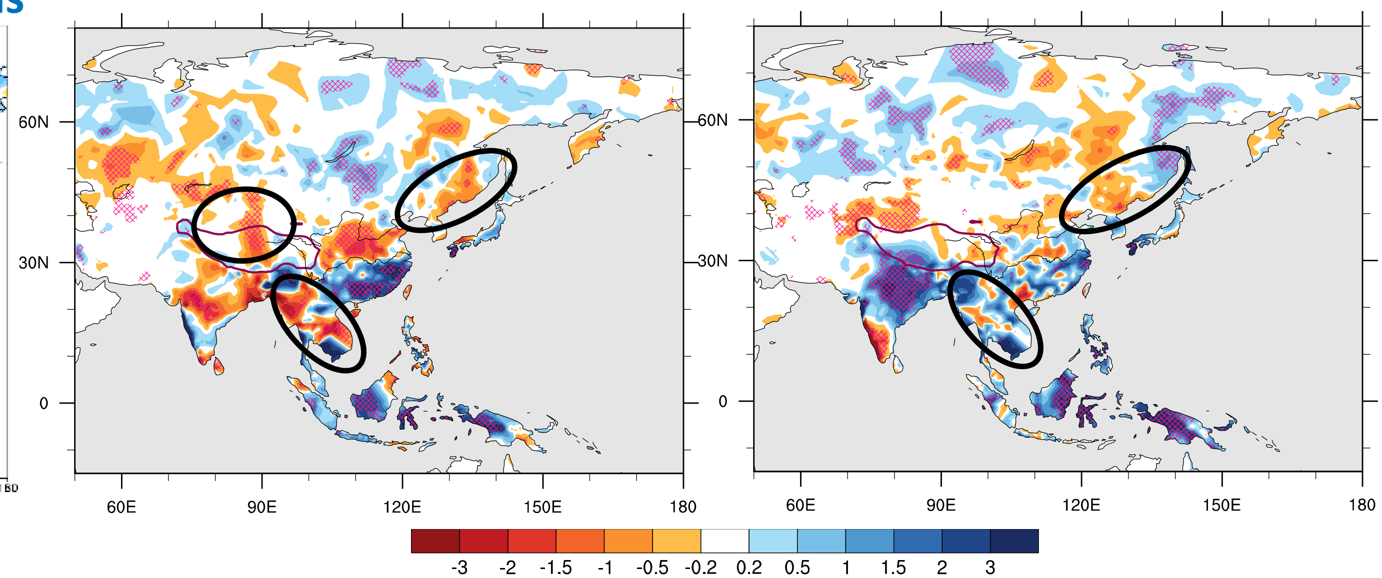
June Precip. ensemble mean Bias



Observed June Prec. Diff. between Warmest and Coldest Years

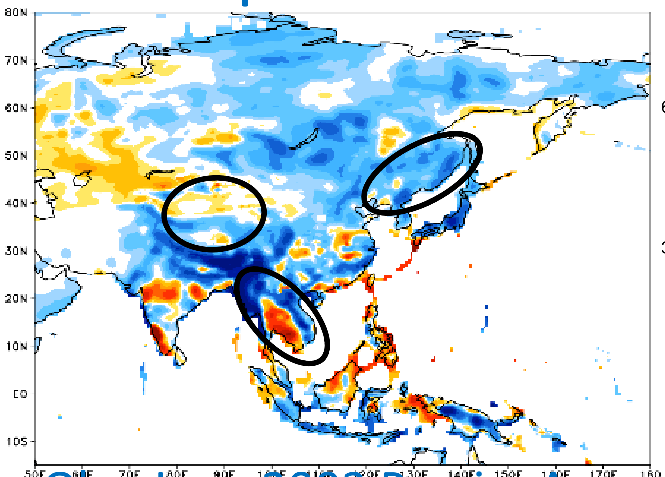
Central and Eastern TP

Western TP

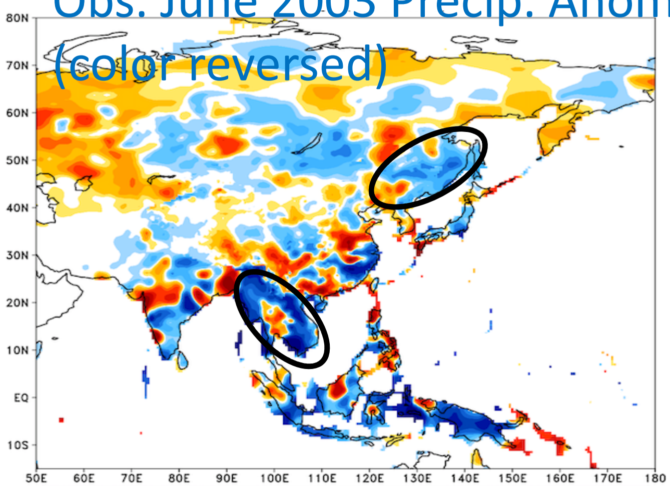


June ensemble mean precipitation biases in some areas NOT are in general agreement with the June precipitation anomalies between eastern-central TP/western TP warm years minus cold years

June Precip. ensemble mean Bias



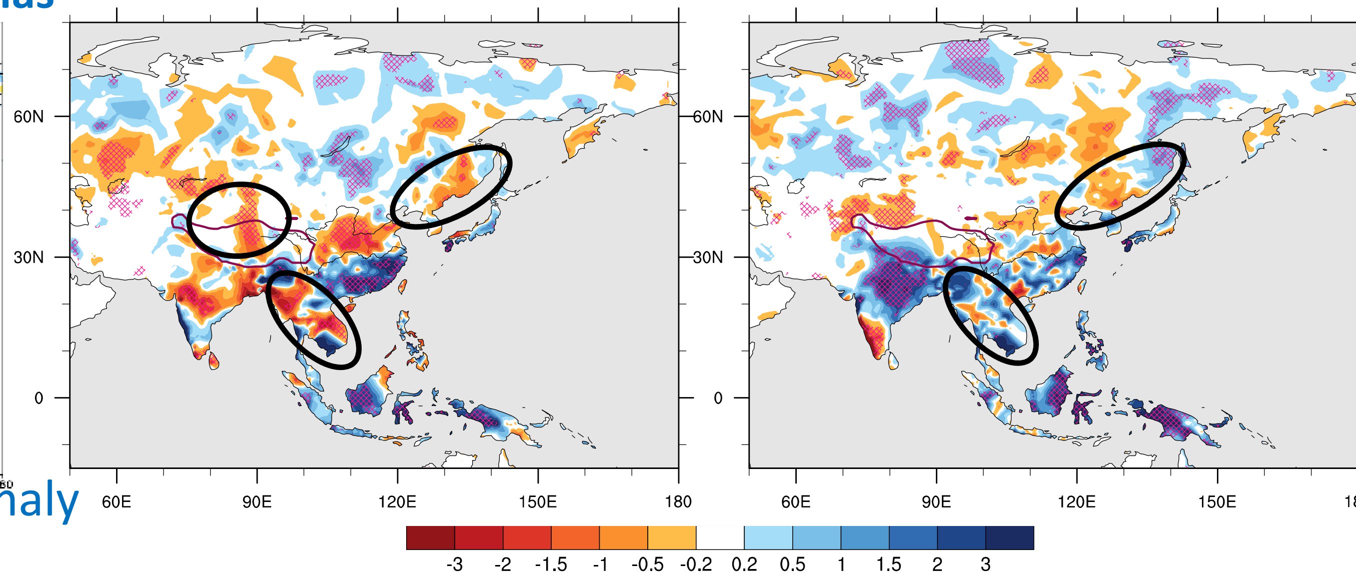
Obs. June 2003 Precip. Anomaly (color reversed)



Observed June Prec. Diff. between Warmest and Coldest Years

Central and Eastern TP

Western TP



But are consistent with year 2003

Summary

1). Observed T-2m anomaly persist for several months , especially in spring, with large interannual variability in West U.S. high elevation area and Third Pole region

2). Statistic analysis reveals the spring T-2m anomaly and June downstream region drought/floods have significant relationship. Preliminary modeling study support the spring land surface temperature (LST)/subsurface temperature anomaly cause the summer downstream drought/flood, and the effects are compatible with the SST effect.

3). The preliminary results from LS4P early tests show the relationships between the May T-2m bias and June precipitation bias in Asia in participating ESMs are consistent with the relationship between observed TPE T-2m May anomaly and precipitation June anomaly, which provides evidence for further study.