From Understanding to Prediction of extreme events :
A Physics-based Empirical Model (PEM) approach

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And co-authors

PNU, May 17 2018

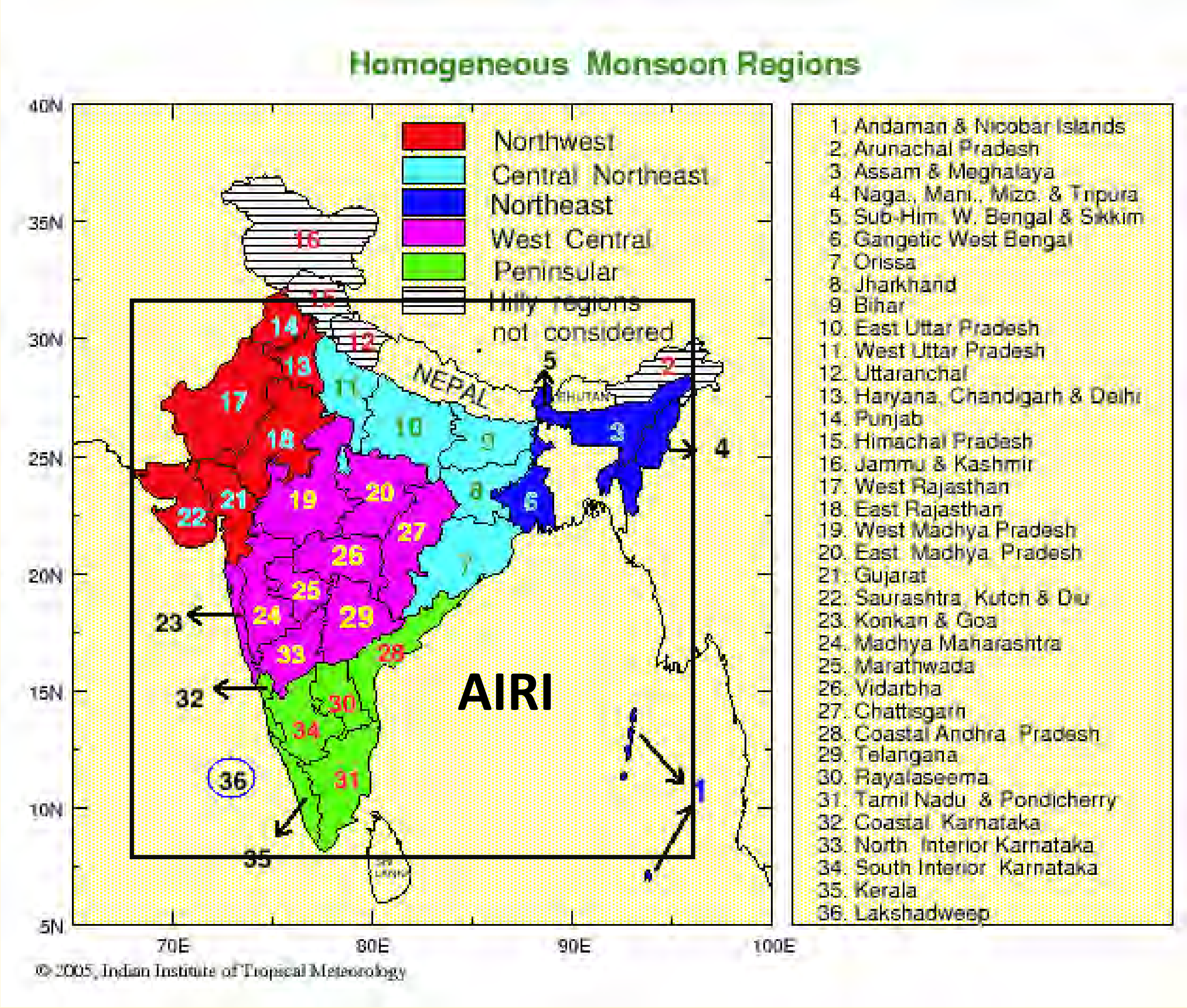
Climate prediction of rainfall is a Long-standing Challenge

"Unfortunately, our abilities to predict (monsoon) variability have not changed substantially over the last few decades."

"Combination of modeling problems and empirical non-stationarity has plagued monsoon prediction on interannual time scales. Empirical forecasts have to contend with the specter of statistical non-stationarity …."

Webster, P.J., 2006: "The coupled monsoon system",
Chapter 2 in "The Asian Monsoon".

Prediction of AIRI (All Indian rainfall index)



Predictand:

The **AIRI** is the total amount of summer (June-to-September, JJAS) rainfall averaged over the entire Indian subcontinent.

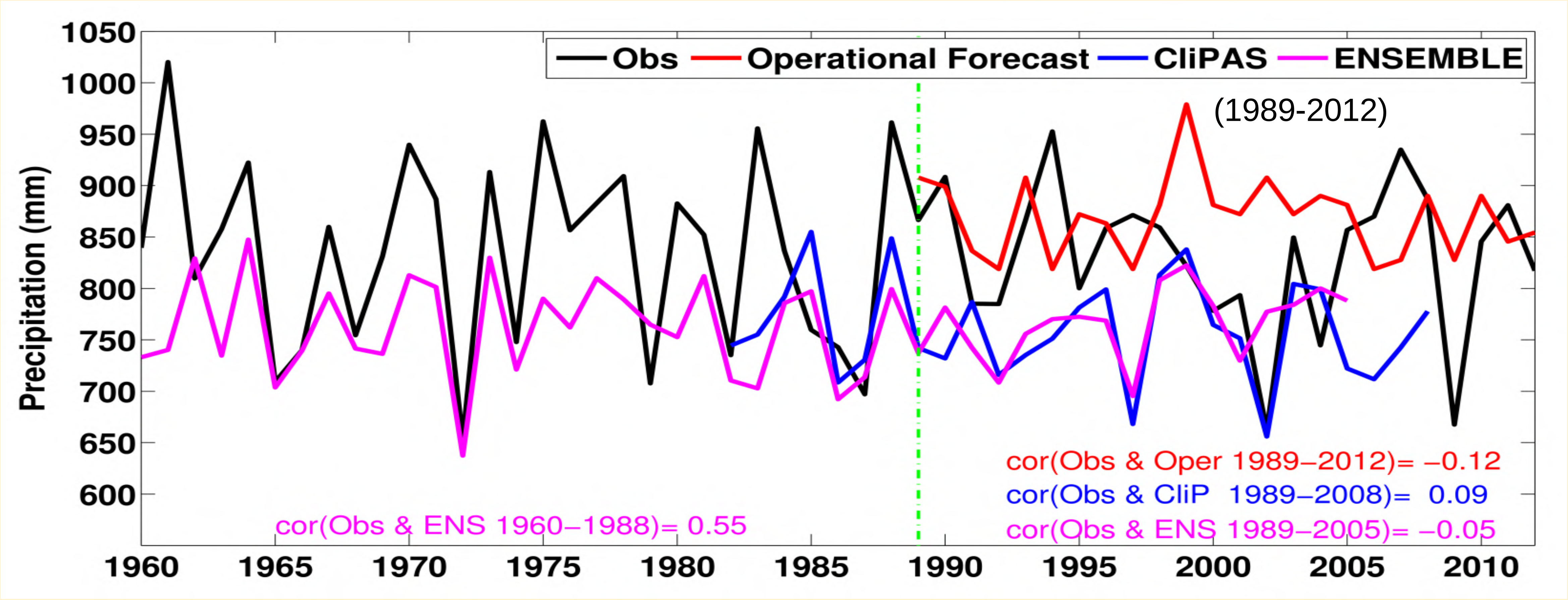
Data

- **Rainfall** data：
  AIRI data : IITM (1871-2016); IMD (2017)

- **SST** data :
  ERSST monthly data (1871-2018.3)

- **SLP, 2 meter temperature** data**:**
  The twentieth century (**20C**) reanalysis monthly data (1871–2012)
  NCEP2 reanalysis monthly data (2013-2018.3)

IMD official operational forecasts and dynamic model's MMEs hindcast show no skills since 1989



The time series of observed (black line) and predicted AIRI The corresponding MSSE skills for operational, ENSEMBLE and CliPAS are, respectively, -0.36 (1960-2012), 0.09 (1989-2008).

Wang et al. 2015

Current dynamical models are

- **of little skill in seasonal prediction of mean rainfall anomalies over land;**
- **unable resolve extreme vents due to coarse resolution,**
- **premature for estimation of the potential predictability**

New Approaches are demanded

to study predictability and prediction

Physics-based empirical models (PEMs)

Rethinking Indian monsoon rainfall prediction in the context of the recent global warming

Bin Wang, Baoqiang Xiang, Juan Li, Peter. J. Webster, M. Rajeevan, Jian Liu, and Kyung-Ja Ha

May 2015
Nature Communication

Four steps to establish PEMs

- Identify major modes of variability (Often EOF modes or focus on Index)
- Detect and Interpret sources of variability based on physical understanding of the lead-lag relationships between the predictors and predictand (often numerical experiments involved).
- Construct PEMs using only physically meaningful predictors
- Estimate predictability using predictable mode analysis method. (Wang 2007)

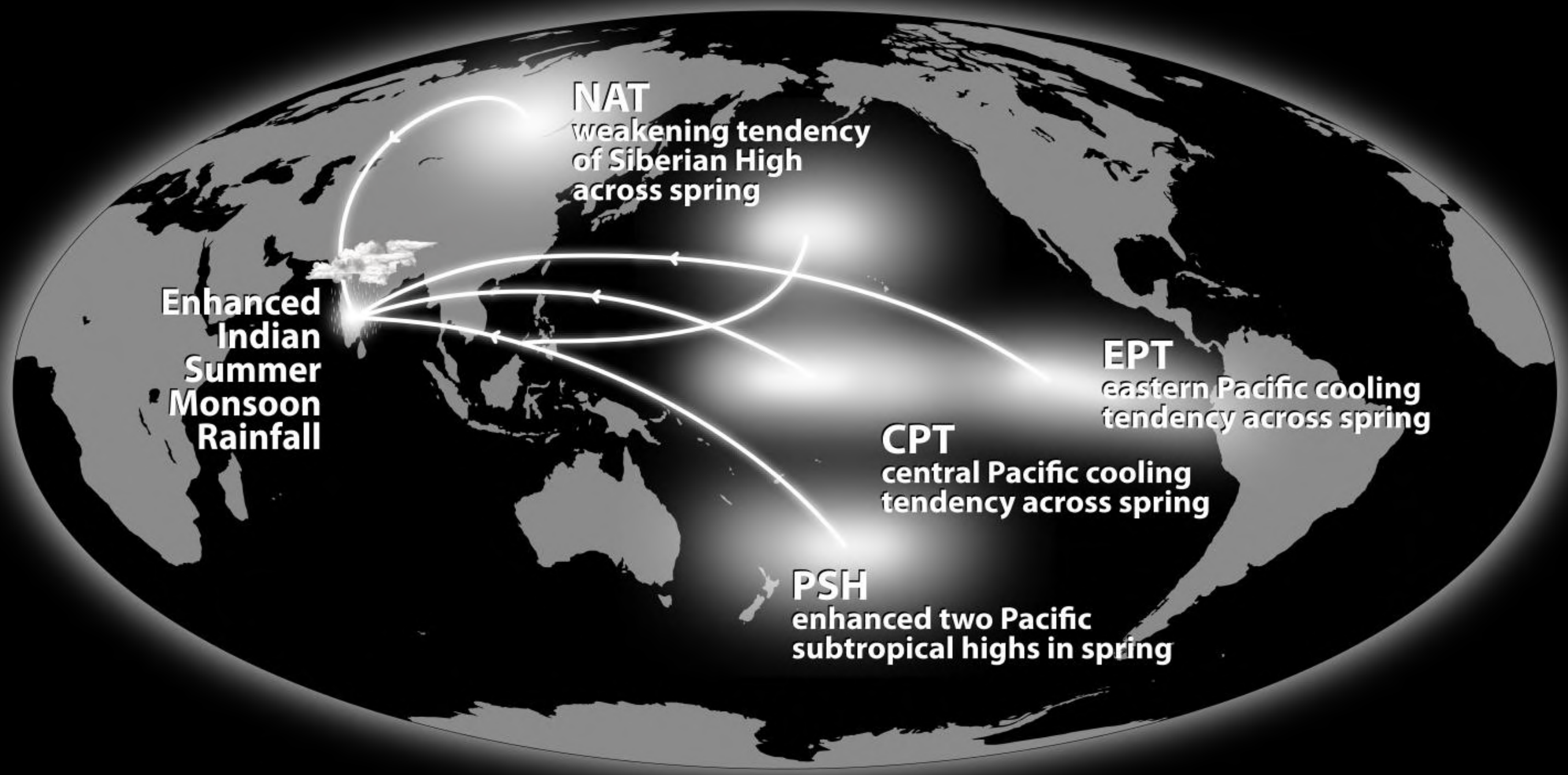
How to search for predictors

- Only two predictor fields: SST/2m air temperature over land and SLP anomalies——Reflecting ocean and land surface anomalous conditions
- Only two types of signals in the lower boundary anomalies:

a) ***persistent*** signals in the pre-forecast season. Reflect local positive feedback processes which may help maintain the lower boundary anomalies.

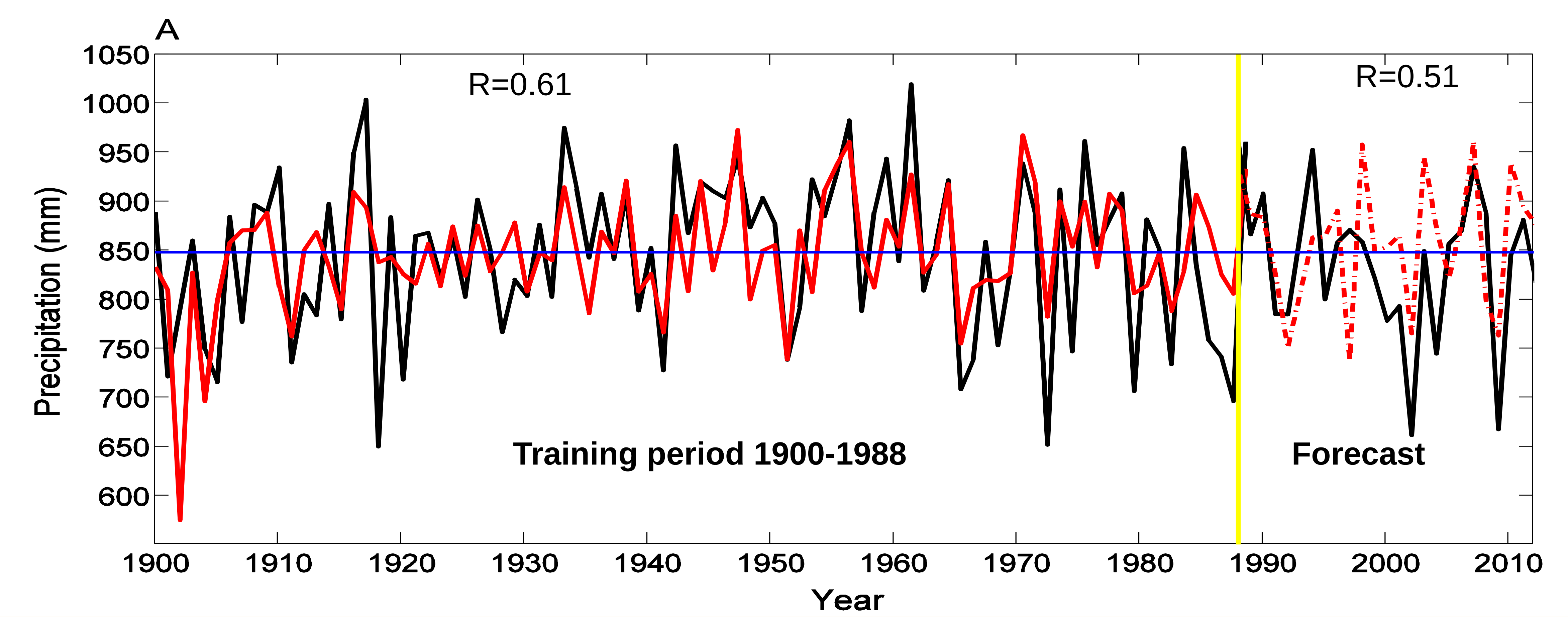
b) ***tendency*** signals from the previous seasons to the pre-forecast season : denote changes before the pre-forecast season that often tip off the direction of subsequent evolution.

Four physically consequential predictors for AIRI foreshadow EP-ENSO, Mega-ENSO, CP-ENSO and anomalous Asian Low



CP-ENSO and anomalous Asian Low predictors represent new predictability sources emerging during the recent global warming. Operational forecast and dynamical models do not capture these changes so failed seasonal prediction in the last 2-3 decades. The Physical based empirical model with the four predictors can produce a 92-y (1921-2012) retrospective independent forecast

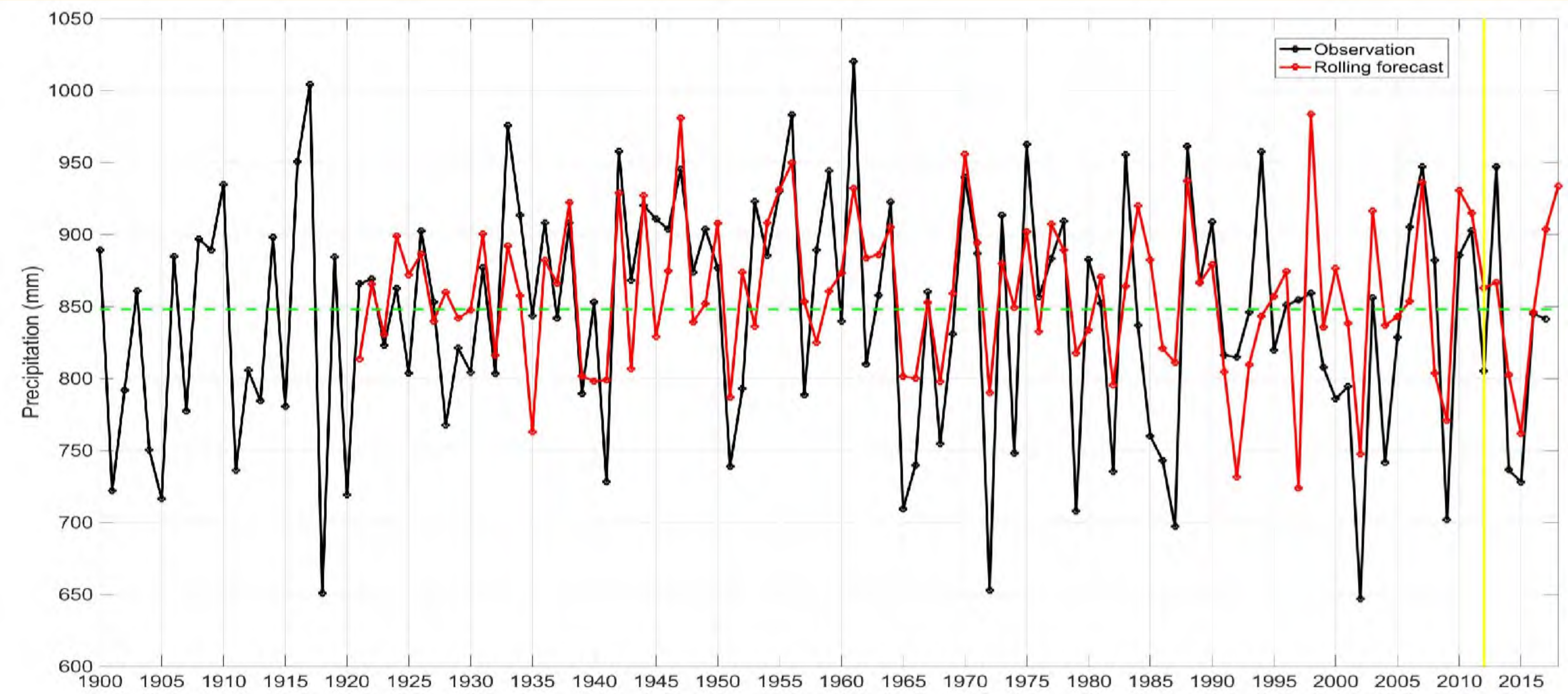
24-y **independent forecast** validation (1989-2012)



Practical predictability estimate

Verification (2013-2018)

98 years rolling hindcast (the prediction equation is derived using only 50-y training data and the AIRI is predicted for the ensuing 10 years.)



CC (Predicted AIRI and Observed AIRI) =0.63 (1921-2017)

=0.54 (1989-2017)

This talk covers

Seasonal prediction of Heavy rainfall, cold surges, and heat waves in China

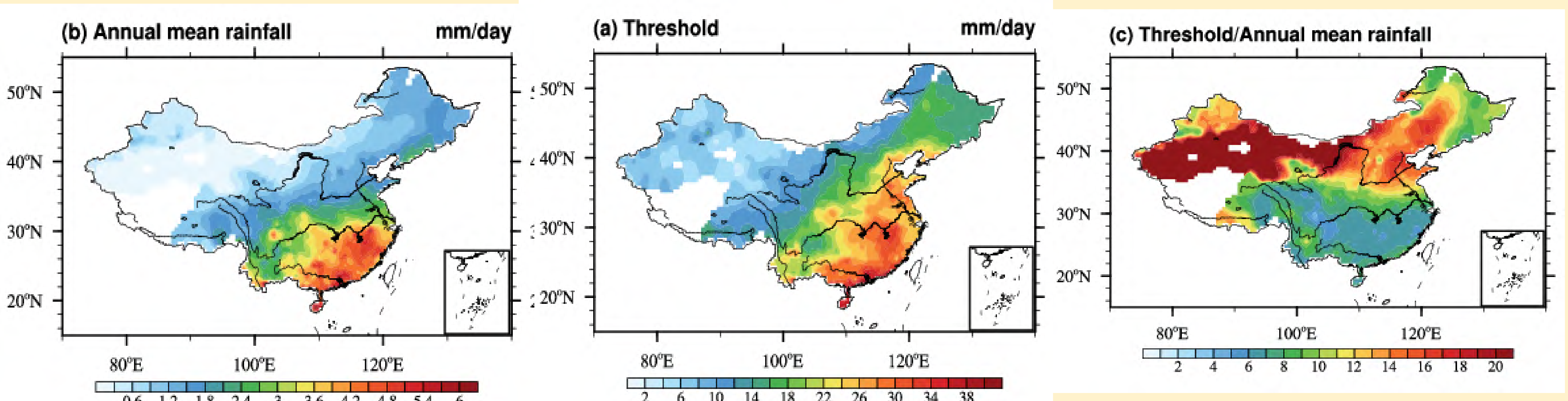
- Li , Juan and Bin Wang, 2017: Predictability of summer extreme precipitation days over eastern China. *Climate Dyn*. DOI 10.1007/s00382-017-3848-x
- Luo, Xiao and Bin Wang, 2017: Predictability and prediction of the total number of winter extremely cold days over China. *Climate Dyn.*, DOI 10.1007/s00382-017-3720-z
- Gao, Miani, Bin Wang, and Jing Yang, 2017: Are sultry heat wave days over central eastern China predictable? *J. Climate, 31, 2185-2196.*

I. Predictability of the total number of extreme precipitation days (EPDs) over eastern China

Li , Juan and Bin Wang, 2017: Predictability of summer extreme precipitation days over eastern China. *Climate Dyn*. DOI 10.1007/s00382-017-3848-x

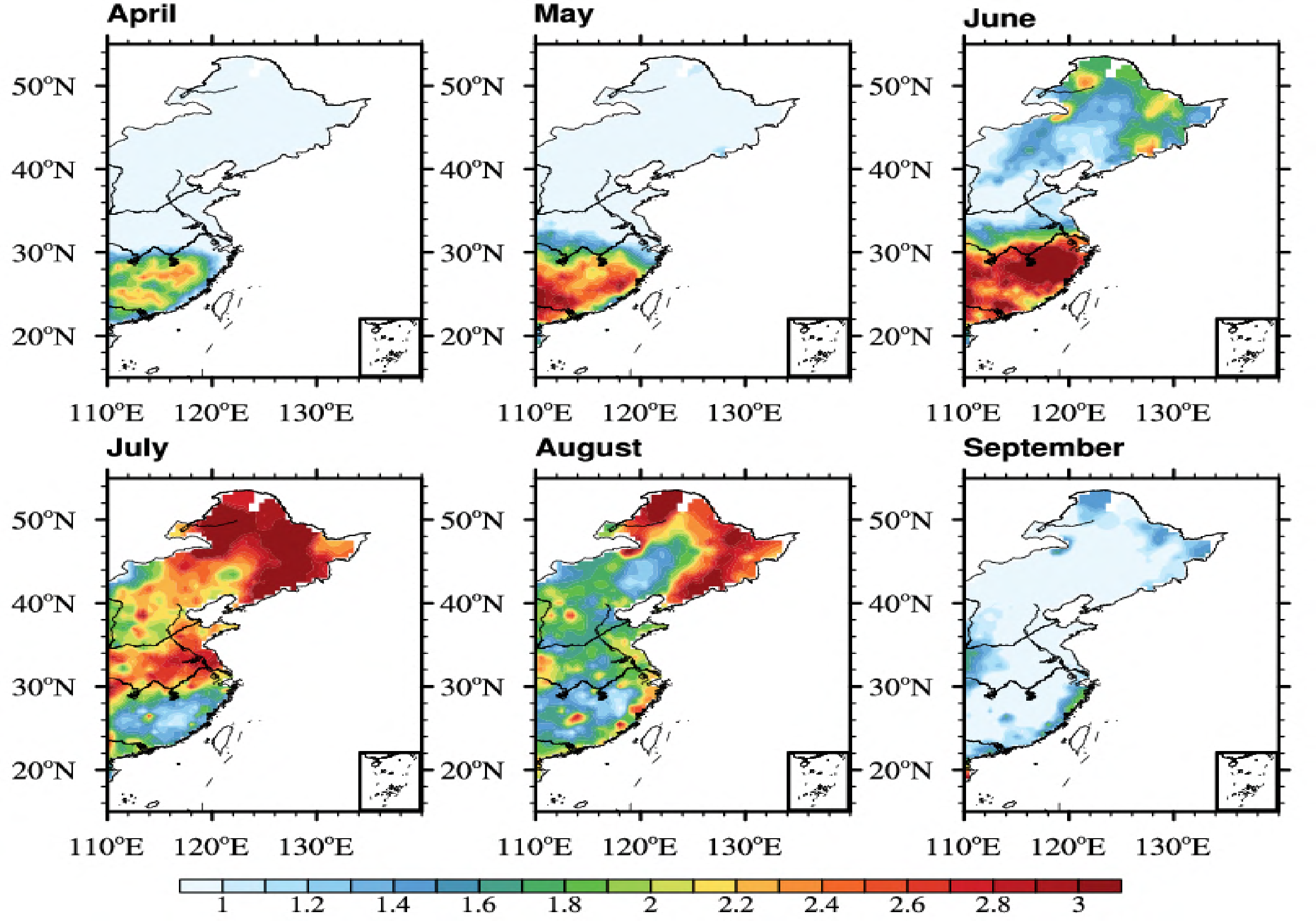
Definition of EPDs

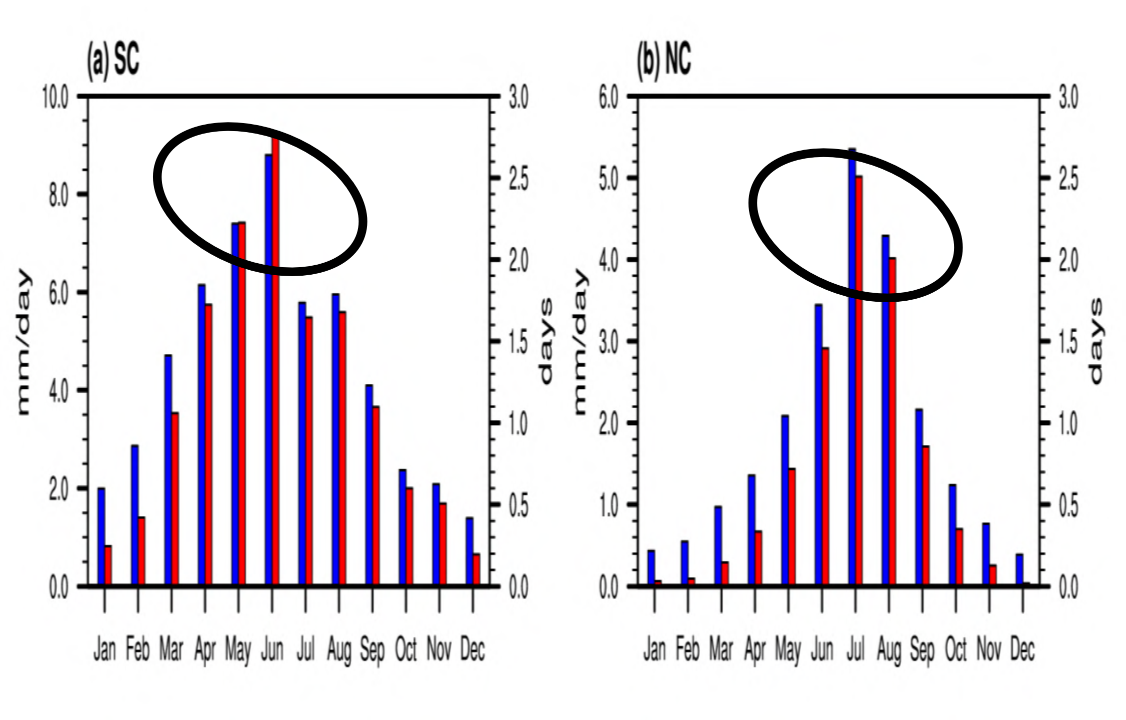
- EPD: Daily precipitation is beyond the 90th percentile threshold of all rainy records (daily rainfall >0.1mm) for the whole 35 years (1979–2013).
- Each station defines its own threshold in the same manner.
- NEPD: The number of days when the daily precipitation exceeds the corresponding threshold is regarded as EPDs.



Regional EPDs indices: SC (MJ) and NC(JA)

Seasonal march of climatological monthly mean EPDs from April to September

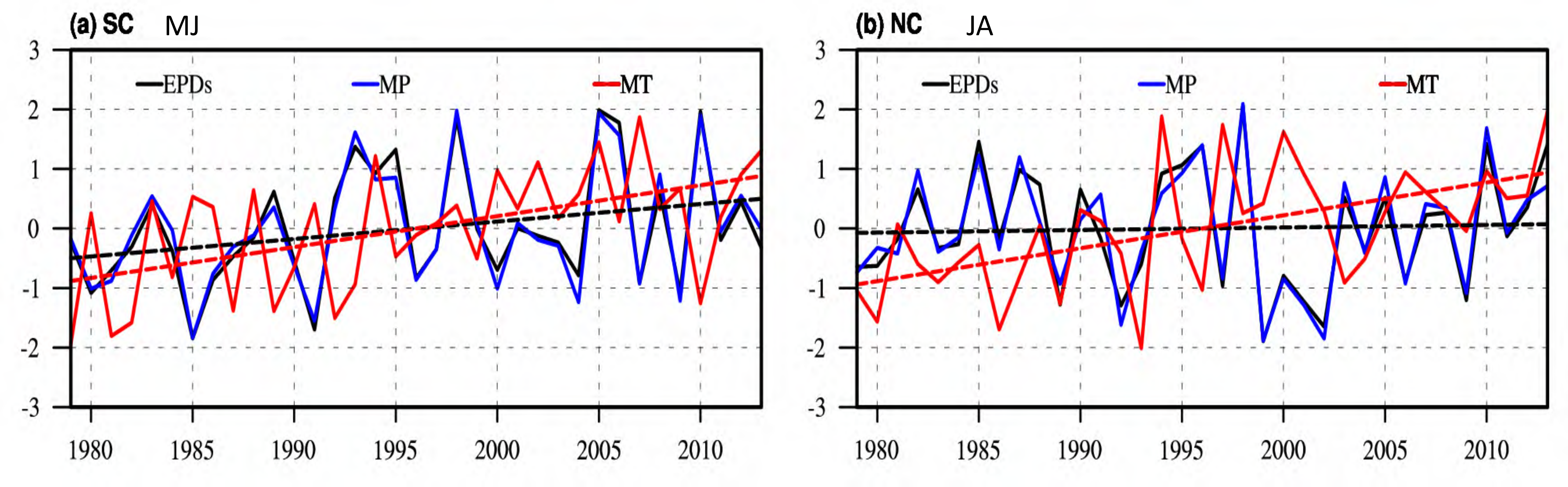




Maximum center of EPDs:
South China (SC, south of 30°N) in May-June (MJ),
North China (NC, north of 30°N) in July-August (JA).
All stations over the eastern China are divided into two domains: SC and NC.

Climatological annual cycle of EPDs (red bar), mean precipitation (blue bar) averaged over SC and NC

Prediction of EPDs ~= Prediction of Mean precipitation



Normalized time series

CC(EPD&MP)=0.98

EPDs trend:0.02 days/year
MT trend: 0.031 ^{o}C/year

Shift in 1993

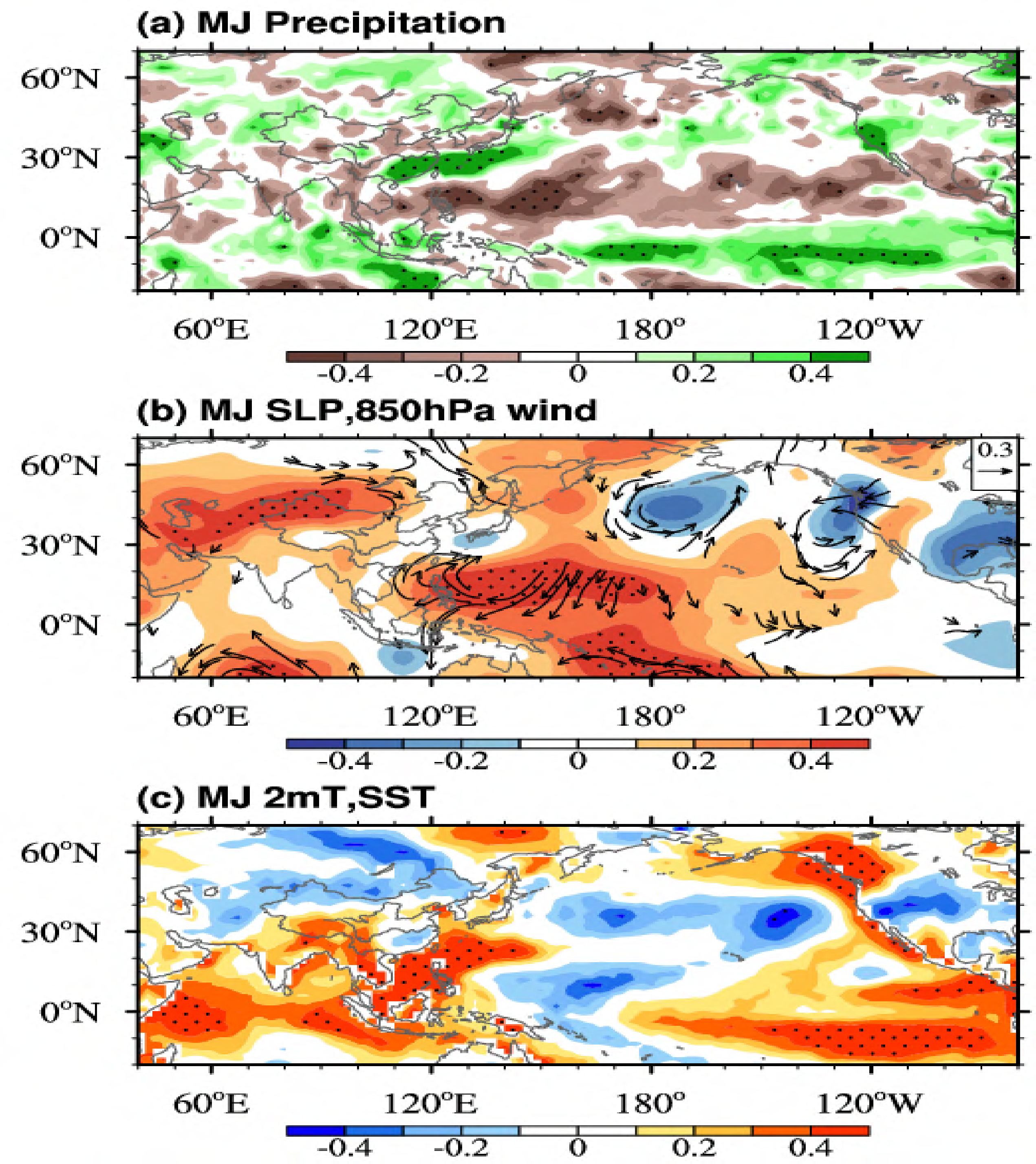
CC(EPD&MP)=0.96

EPDs trend:0.004 days/year
MT trend: 0.032 ^{o}C/year

1999-2002 Drought

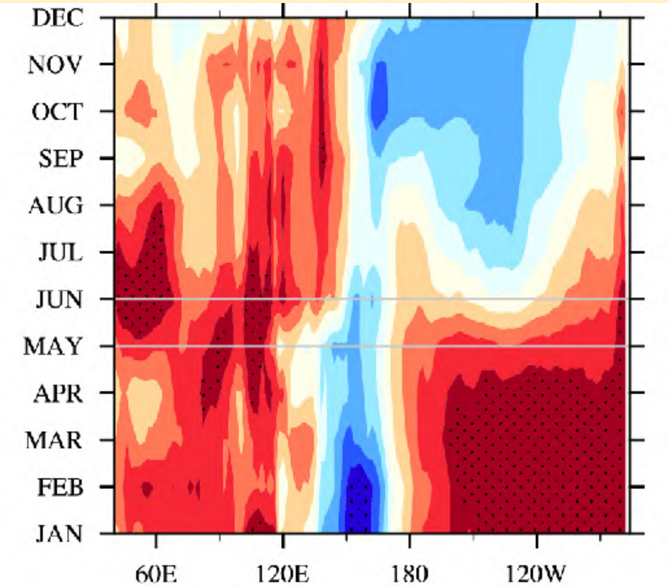
EPD trends?

Global scale anomalies associated with EPDs over SC (MJ)?

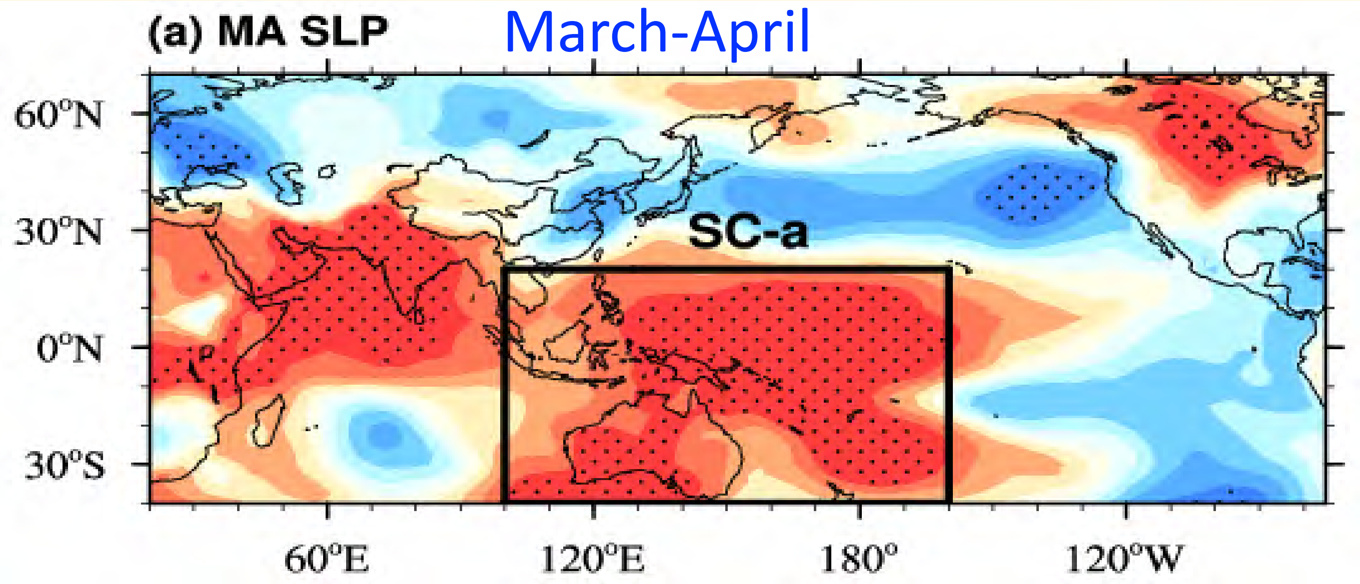


Simultaneous (MJ) correlation fields associated with EPDs-SC

The lead–lag correlation coefficients between equatorial Indian-Pacific (40°E–80°W) SST anomalies averaged between 5°S and 5°N and EPDs-SC



One Predictors for EPDs-SC (MJ)



One predictor for EPDs-SC

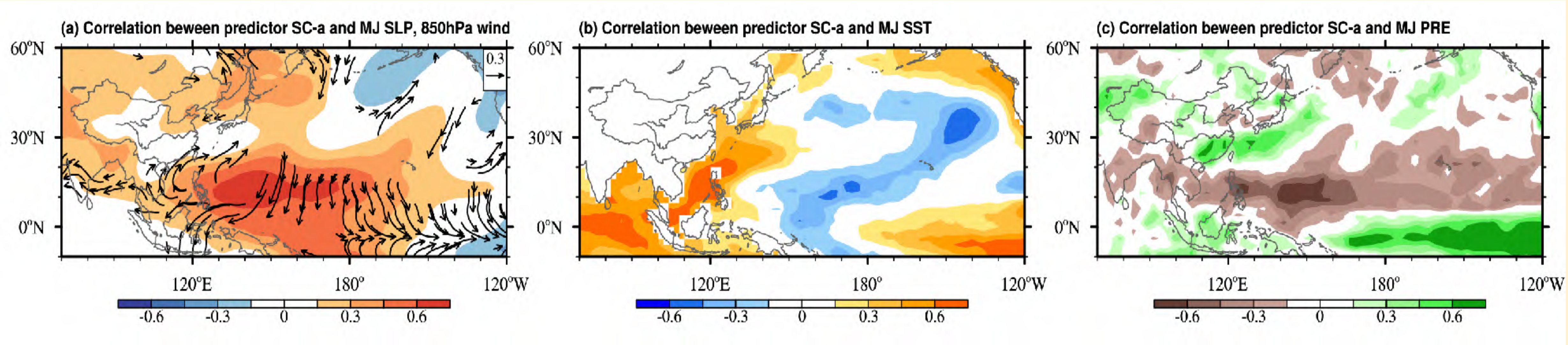
Predictor SC-a: SLP(40°S-20°N, 100°E-160°W) in March-April

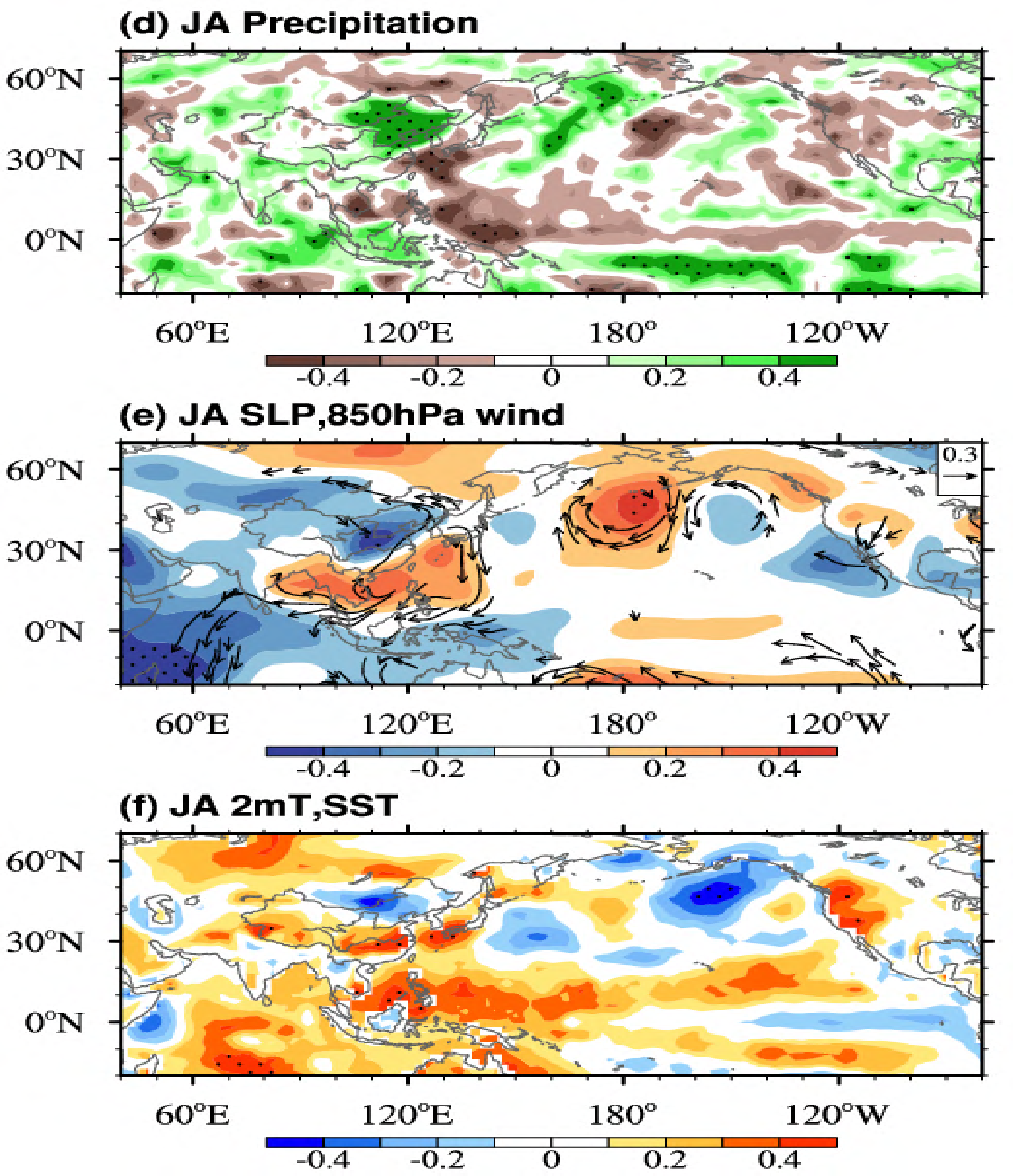
The lead-lag correlations between predictor SC-a and MJ fields

SLP&850hPa wind

SST

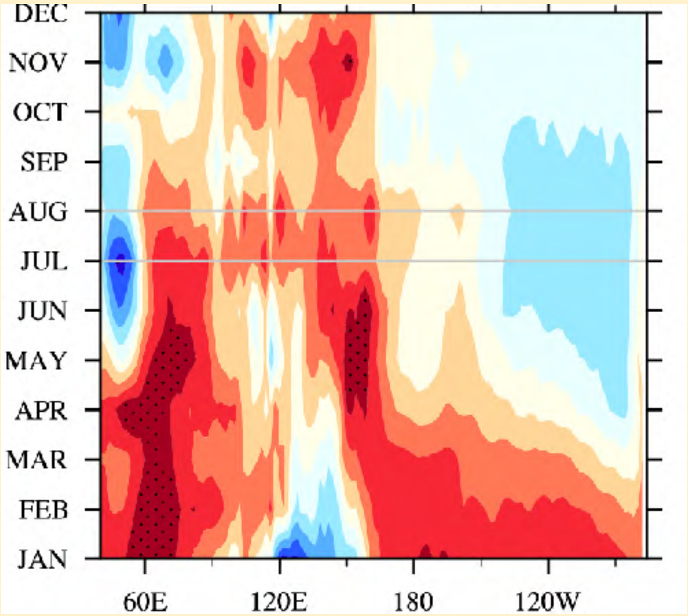
Precipitation



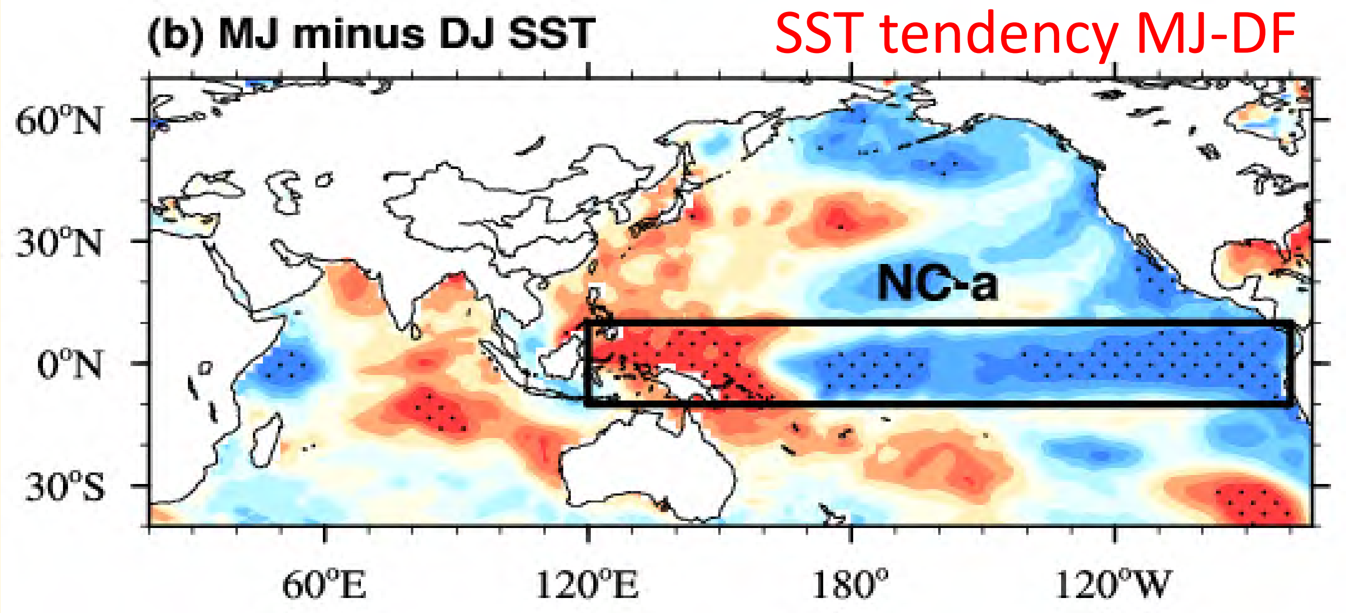


Global scale anomalies associated with EPDs over NC (JA)?

The lead–lag correlation coefficients between equatorial Indian-Pacific (40°E–80°W) SST anomalies averaged between 5°S and 5°N and EPDs-NC



First Predictors for EPDs-NC (JA)



First predictor for EPDs-NC

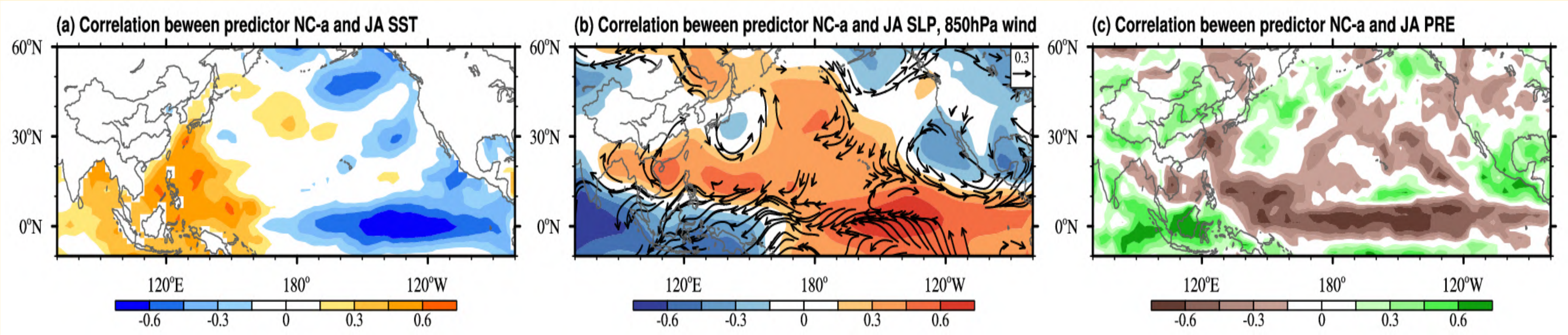
Predictor NC-a: SST(10°S-10°N, 120°E-80°W) from Dec.-Jan. to May-June

The lead-lag correlations between predictor NC-a and JA fields

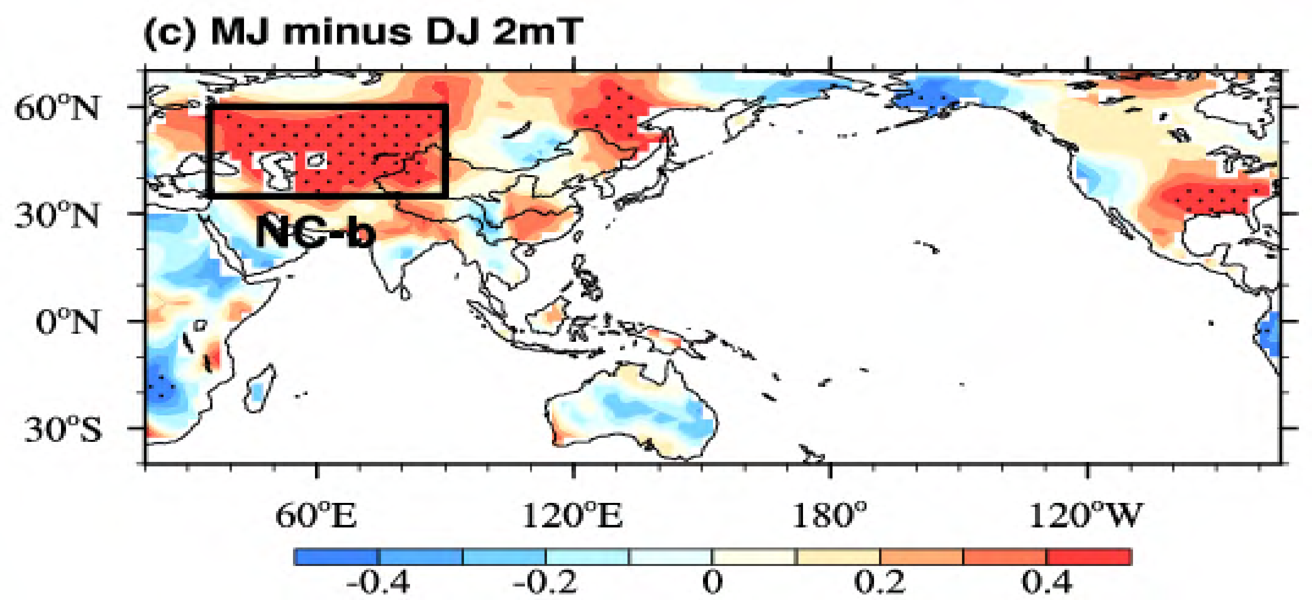
SST

SLP&850hPa wind

Precipitation



Second Predictors for EPDs-NC (JA)

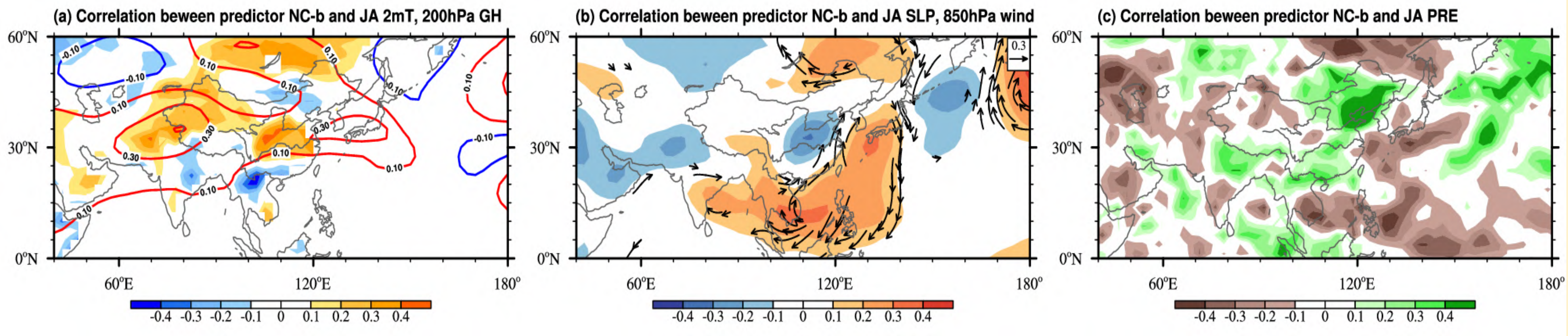


Second predictor for EPDs-NC

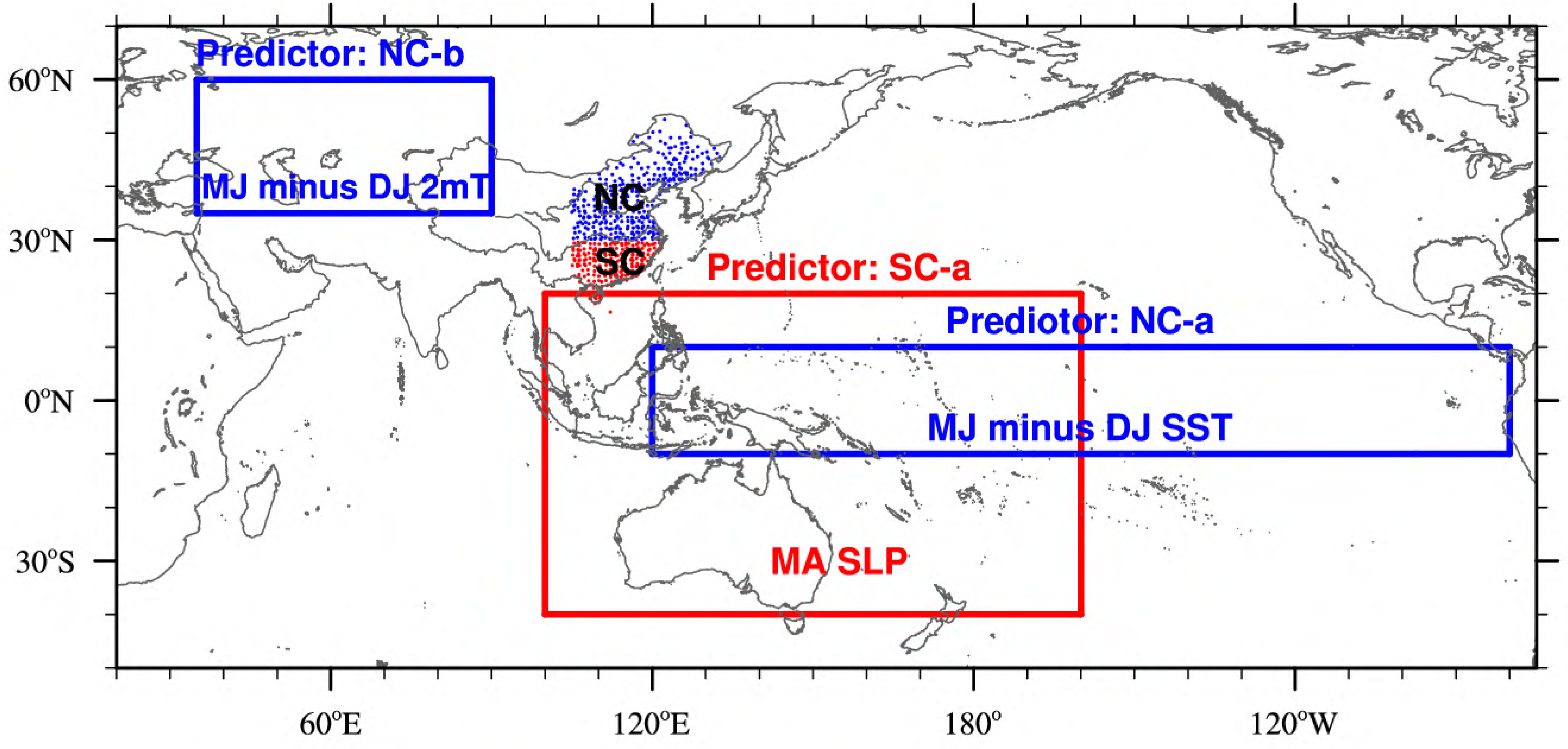
Predictor NC-b: 2mT (35°N-60°N, 35°E-90°E) from Dec.-Jan. to May-June

The lead-lag correlations between predictor NC-b and JA fields

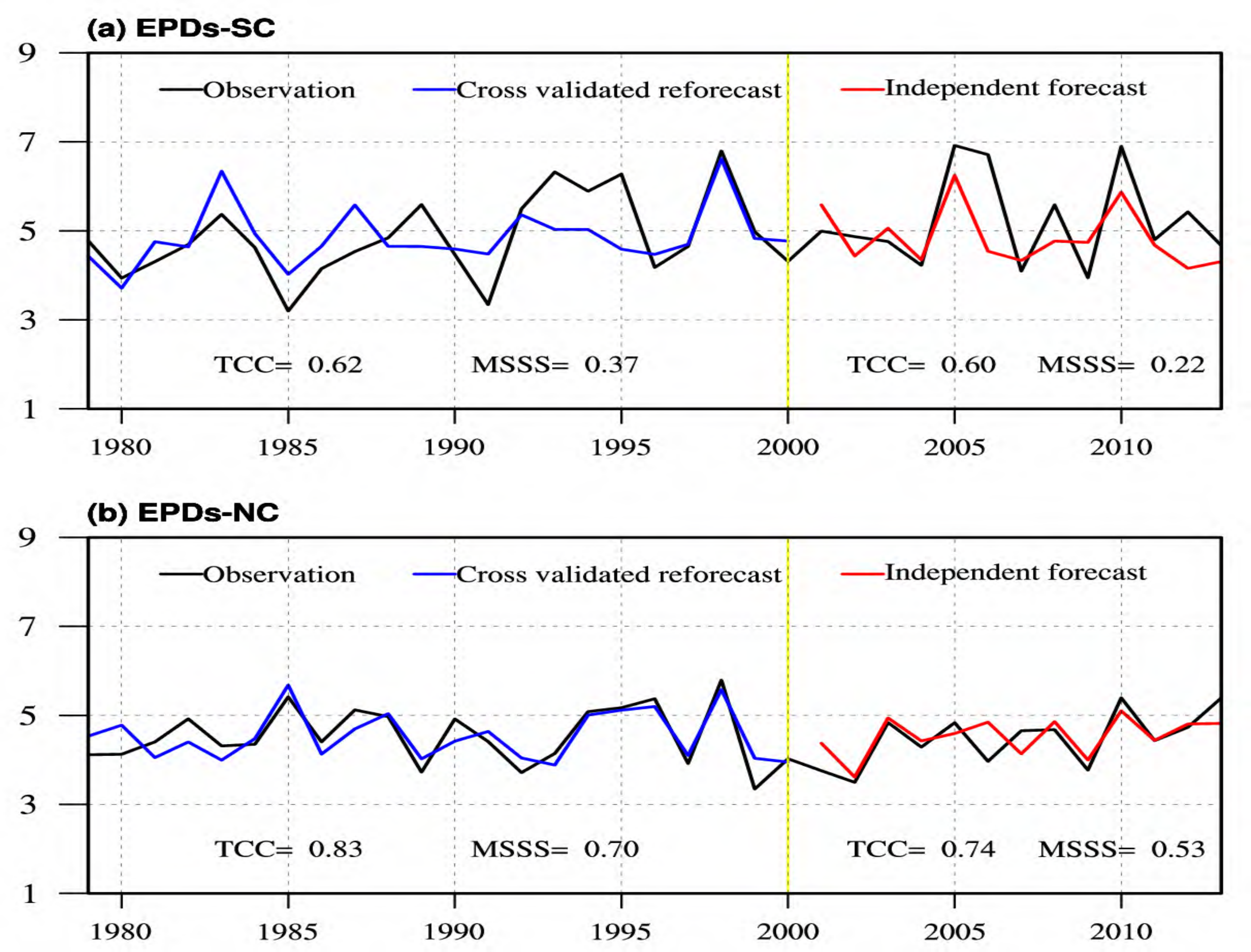
2mT(shading), 200hPa GH(contour) SLP&850hPa wind Precipitation



Summary of Predictors for EPD-SC (Red) and EPD-NC (Blue)



Two validation methods



(a) Cross-validated reforecast. Leave-three-out cross validation is used to validate the reforecast skill for 1979-2000.

(b) Independent forecast. The PEM is built with the training data for 1979–2000, and independent forecast for the 13-year period of 2001–2013. All predictors are selected from the period of 1979–2000.

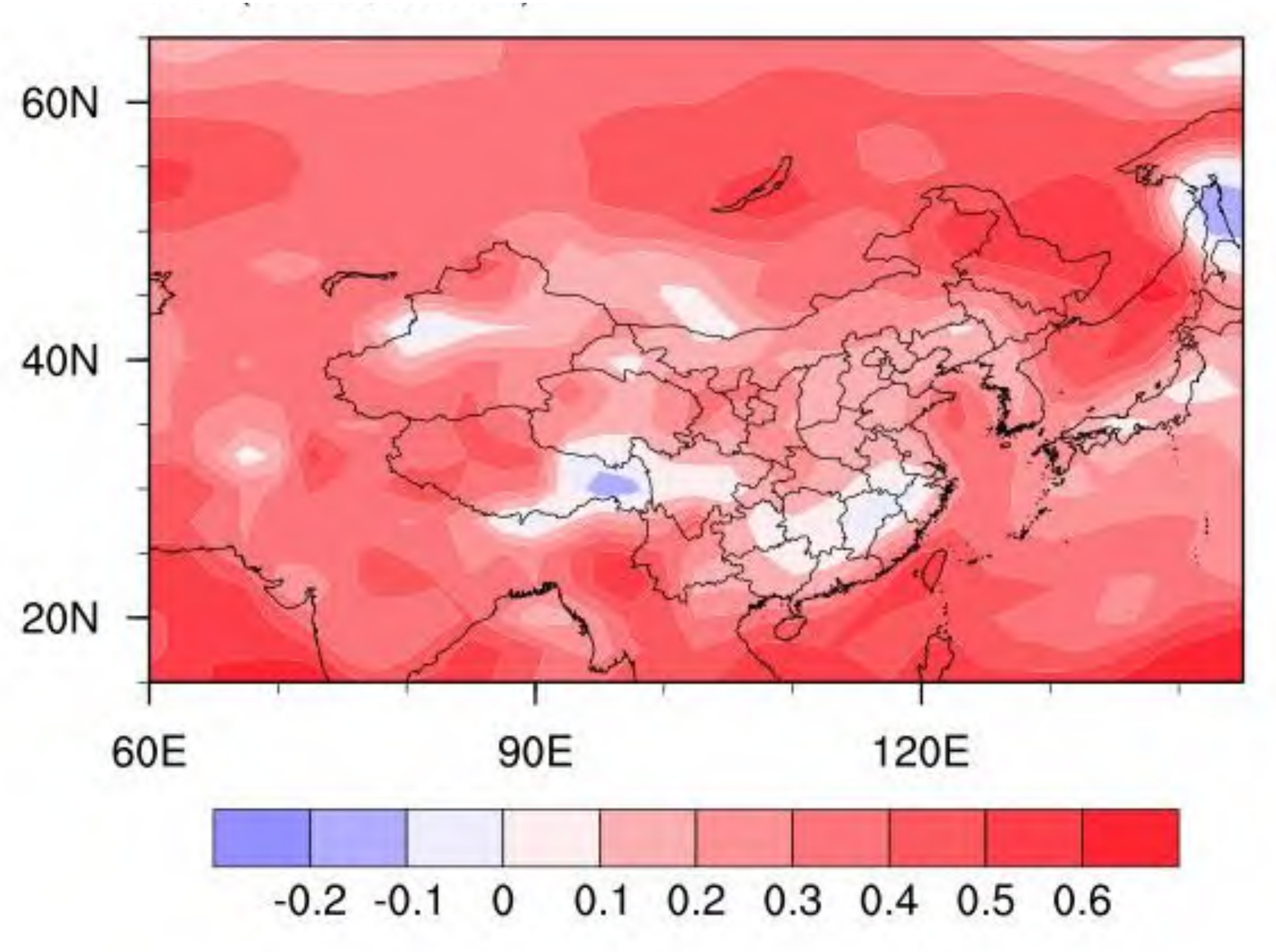
MSSS=1- $\frac{MSE}{MSE_c}$,

II. Predictability of the total number of winter extremely cold days over China

- Luo, Xiao and Bin Wang, 2017: Predictability and prediction of the total number of winter extremely cold days over China. *Climate Dynamics*, DOI 10.1007/s00382-017-3720-z

Even for winter temperature the current dynamical model also lacks prediction skill over China

Temporal correlation skill at each grid point



ENSEMBLE MME hindcast (1960-2005)

China domain averaged temporal correlation skill is limited : **0.23**

dynamical prediction (limited skill)

Luo and Wang 2017

Definition of Extremely Cold Day

- **ECD:** Daily mean temperature lower the 10th percentile values of each month during DJF.
- **NECD:** total number of ECD at each 2.5 by 2.5 grid.

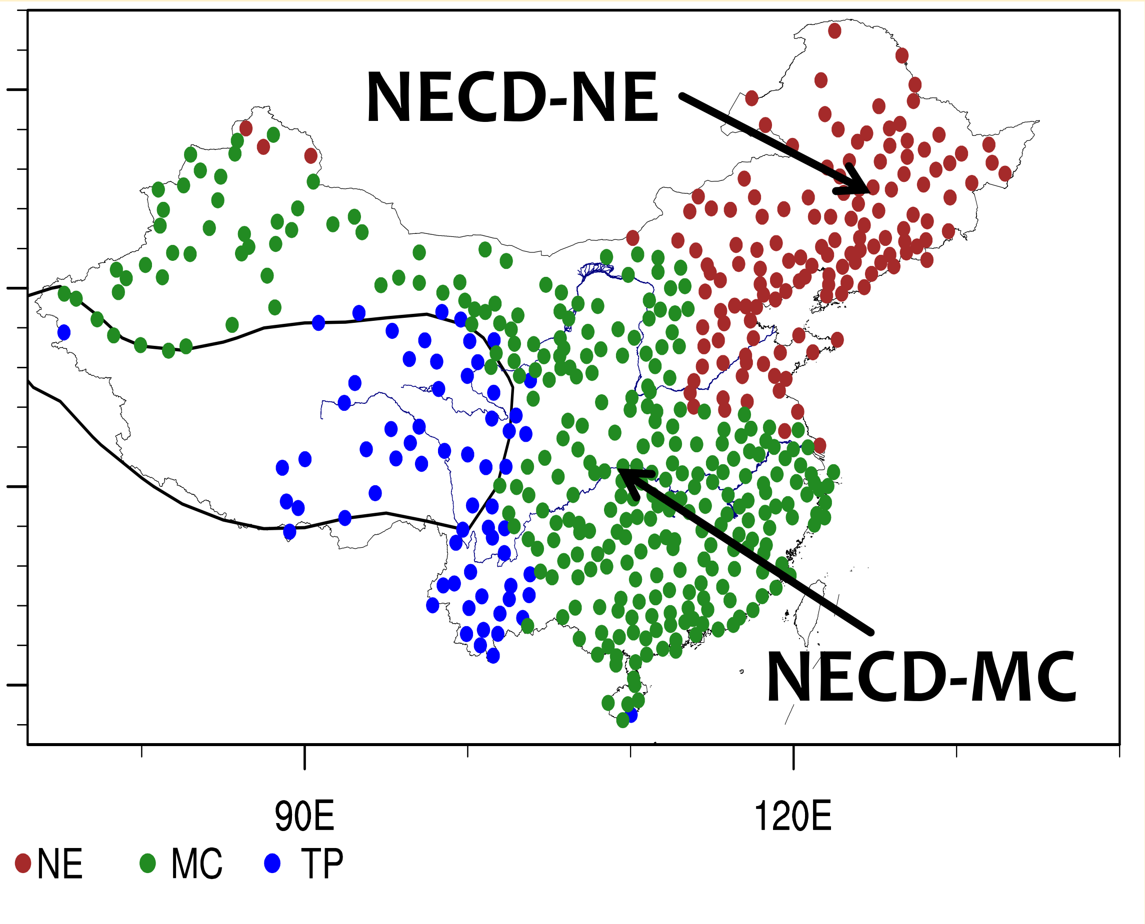
Time series of NECD for 1973-2013 (41 years)

Questions:

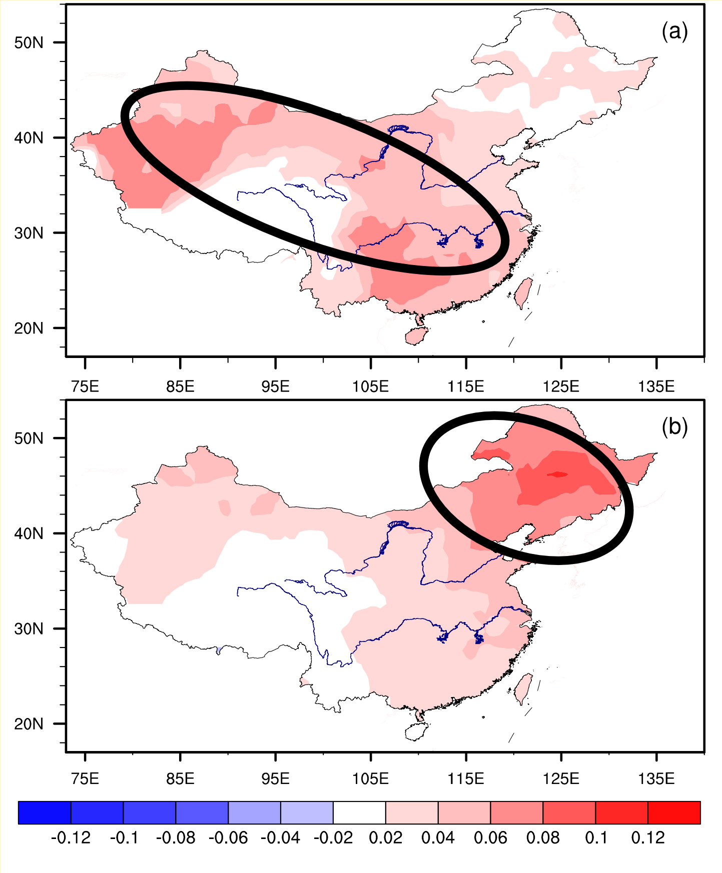
- **What are the major regional modes of NECD in China?**
- **What are the physically consequential precursors for predicting NECD over China?**
- **What is the predictability of winter NECD over China?**

What are the major regional modes of NECD in China?

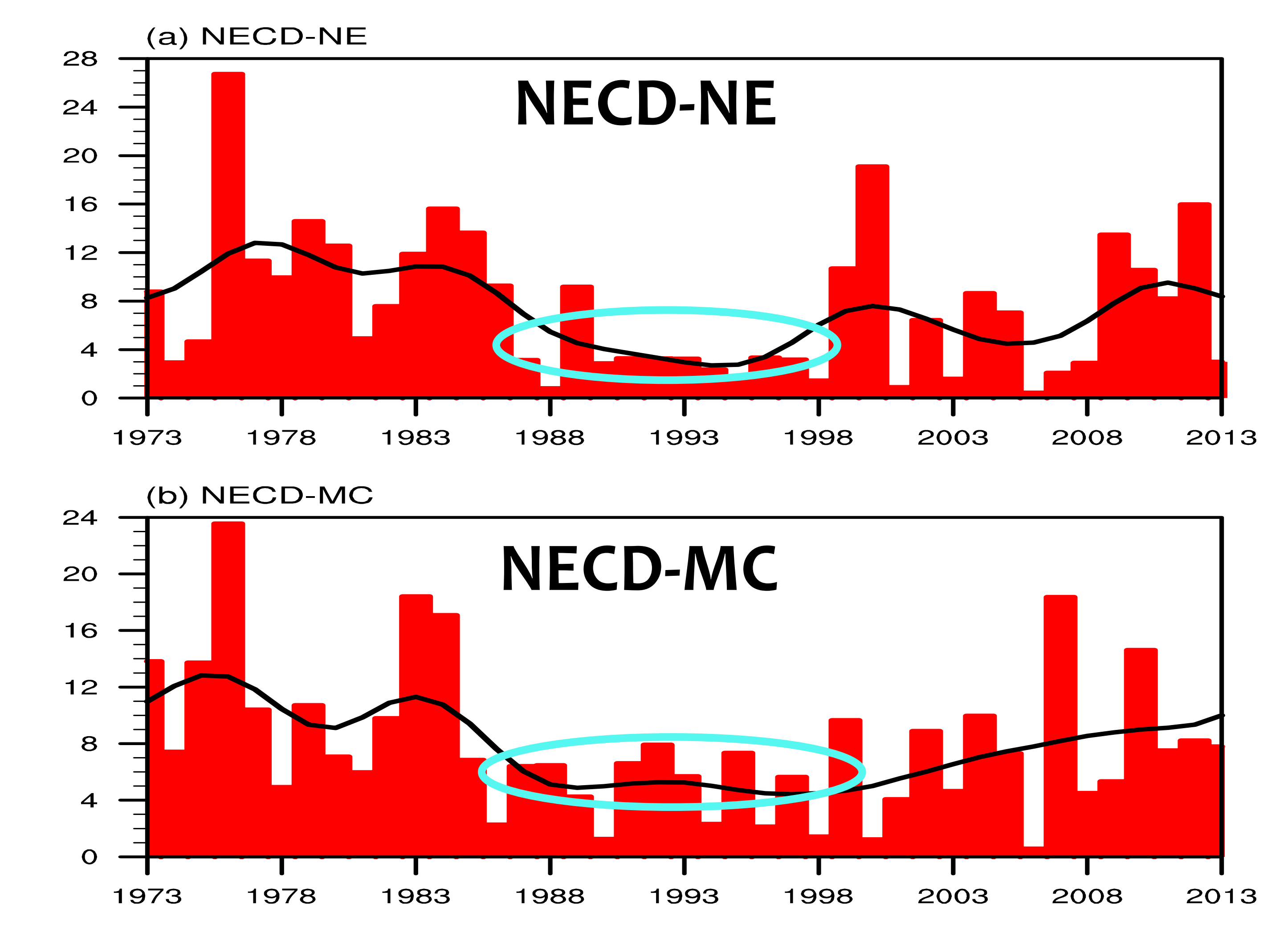
Detected by k-means cluster analysis
3 clusters



Detected by REOF analysis
Spatial patterns of the first two modes



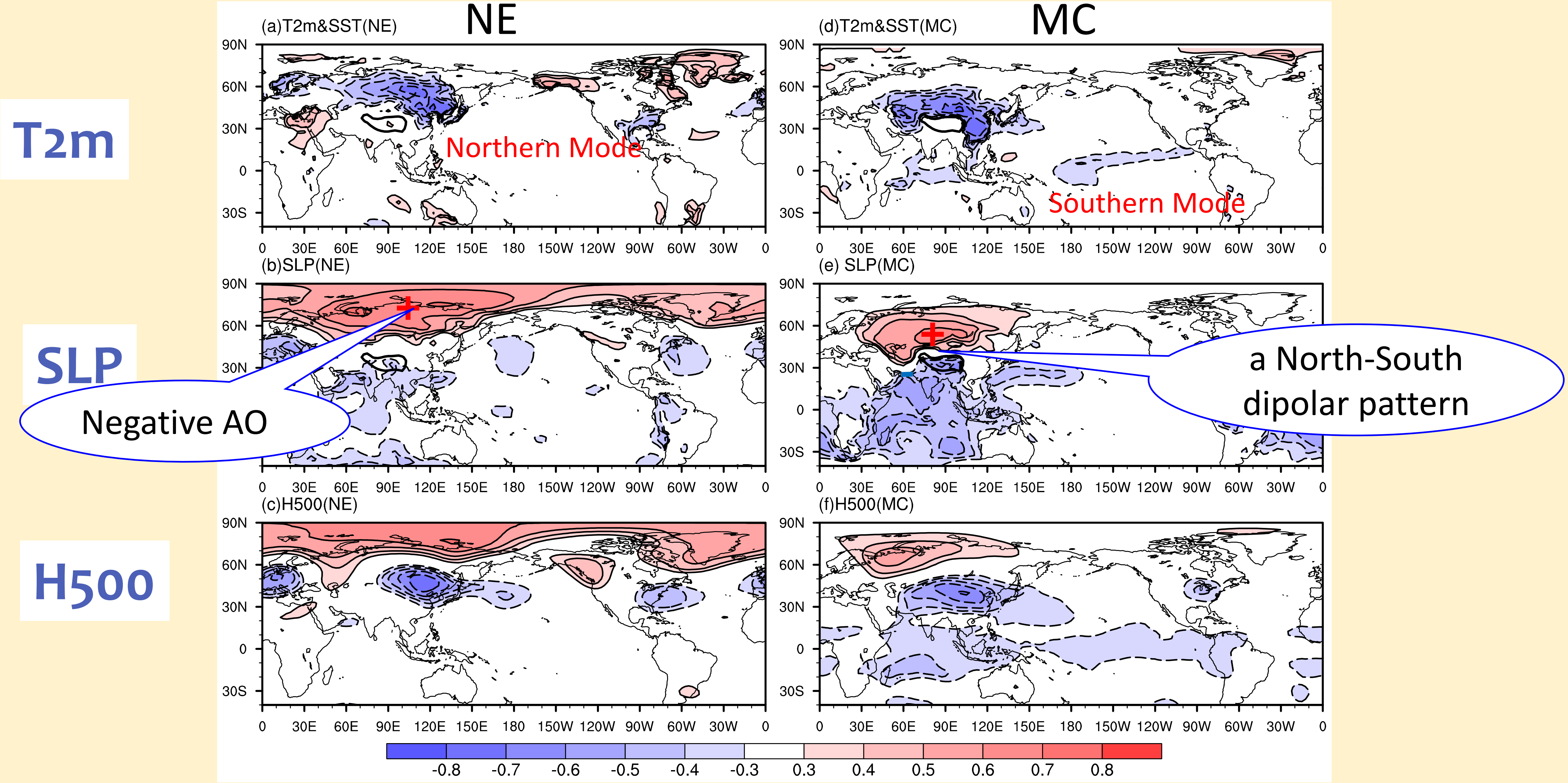
Predictands: NECD-NE and NECD-MC (1973-2013)



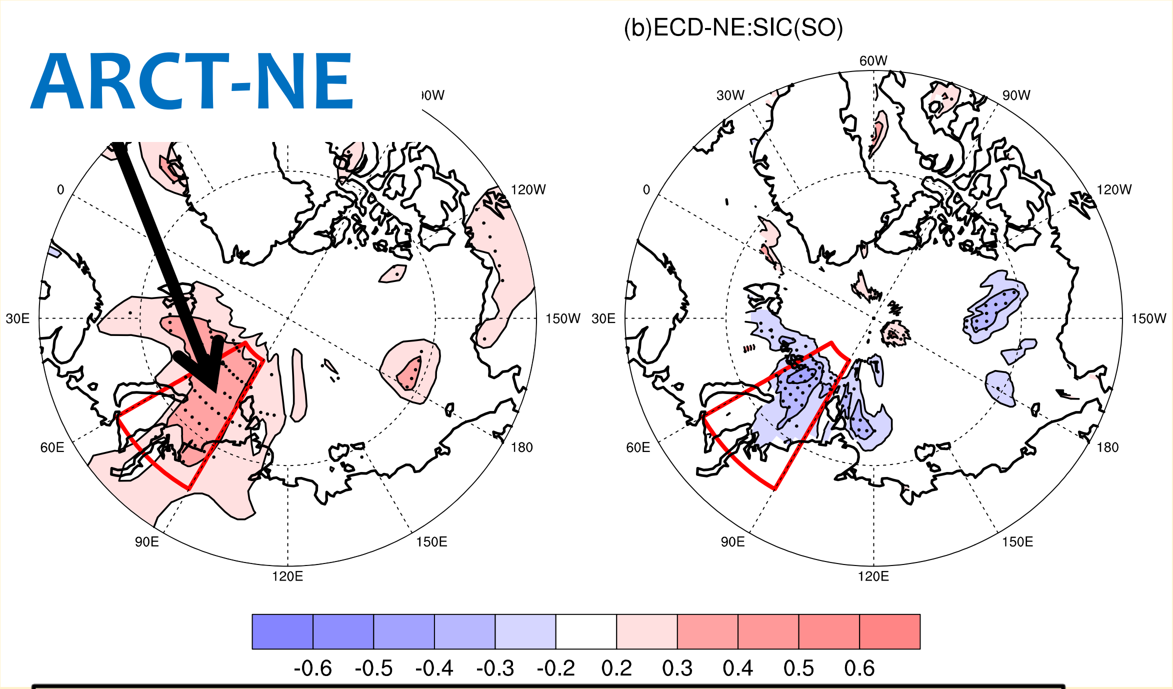
Decreasing trends?

Time series of (a) NECD-NE and (b) NECD-MC indices CC:0.48

What DJF Circulation anomalies are associated with high NECD?



How ARC-SST affect NECD over NE

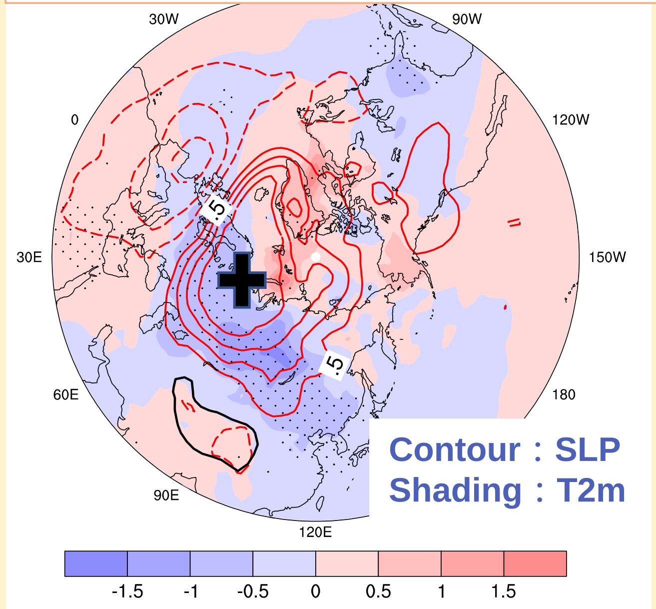


Mechanism:
Arctic warming in SO persists into the next winter

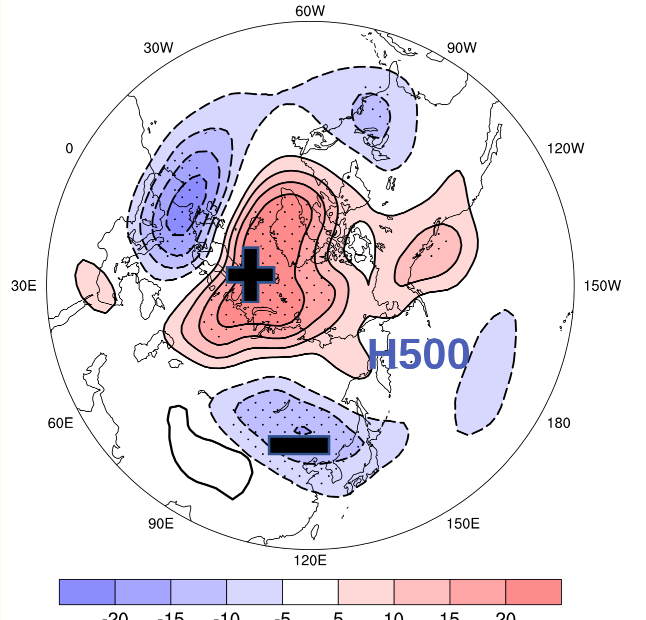
induce an anticyclonic anomaly extending from polar region to Ural Mountain (Kug et al. 2015)

Rossby wave propagation lead to downstream low pressure anomalies that deepen and shift westward East Asian trough (Kug et al. 2015)

Winter circulation anomalies regressed to precursor

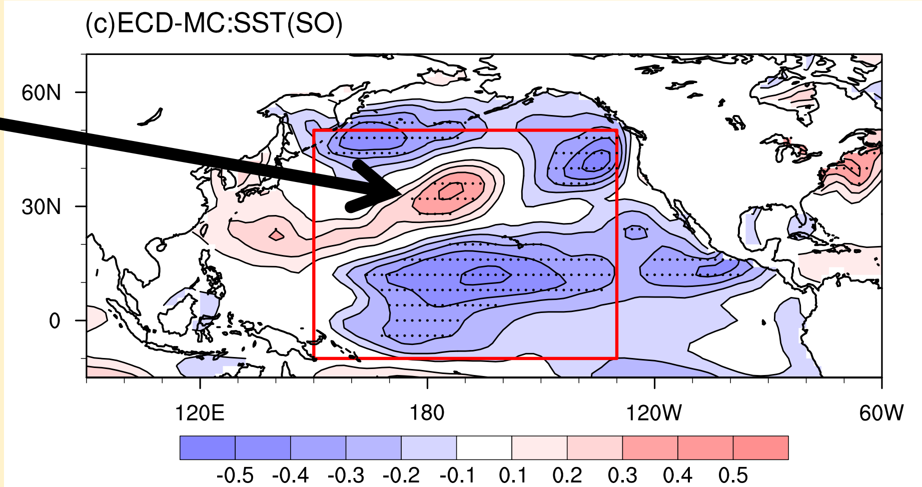


H500 regressed to ARCT-NE

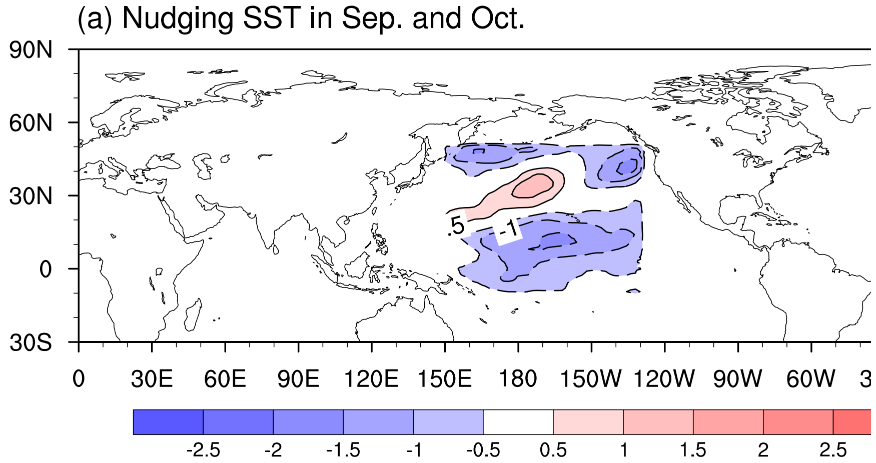


How developing La Nina enhances NECD over MC

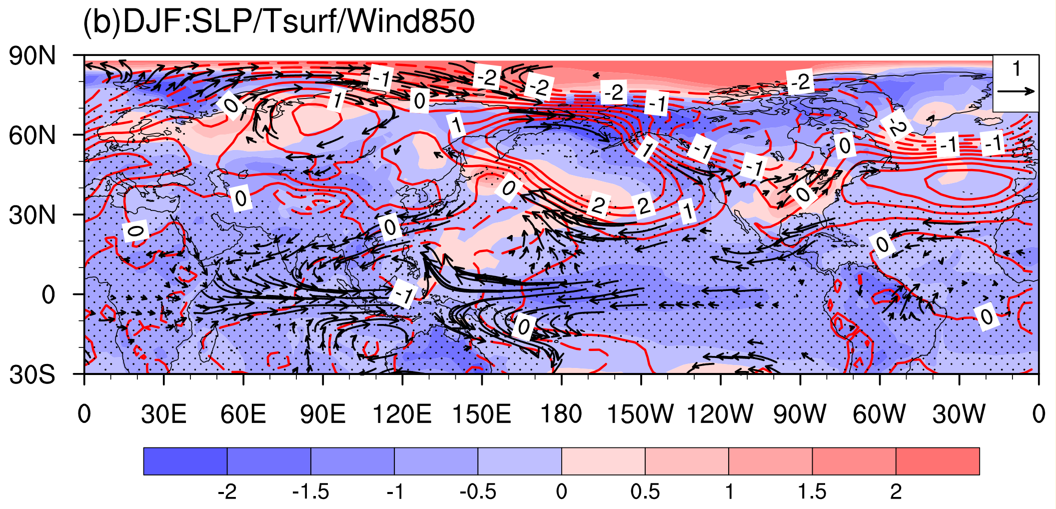
TNPSST-MC



Model simulated DJF anomaly associated with TNPSST-MC

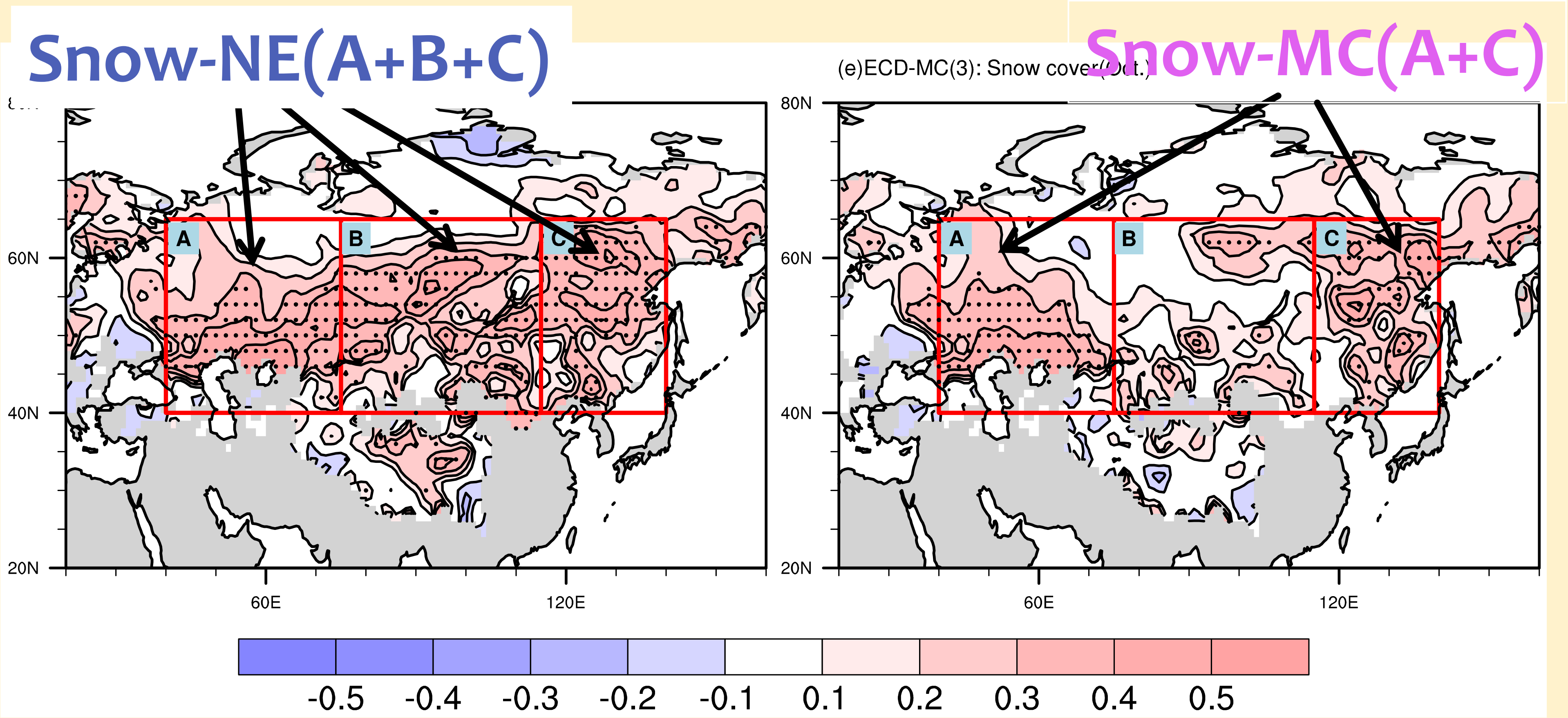


TNPSST-MC related nudged SO SST field in for (+) SST experiment



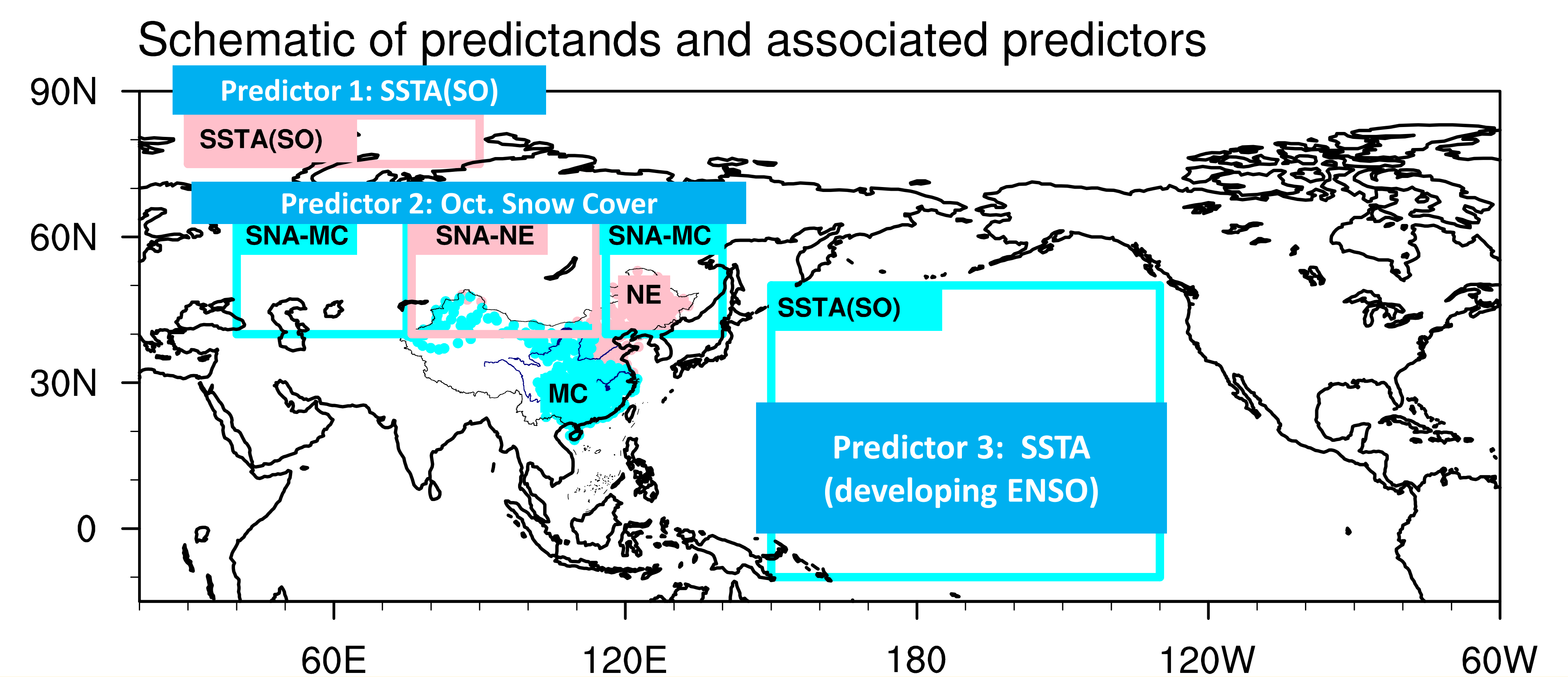
Differences in the ensemble mean DJF surface between (+) SST and (-) SST experiment

How fall Snow anomalies affect NECD



LCC map of Snow cover and (left) NECD-NE (right) NECD-MC

Autumn predictors for NECD over NE (Pink) and MC(Green)

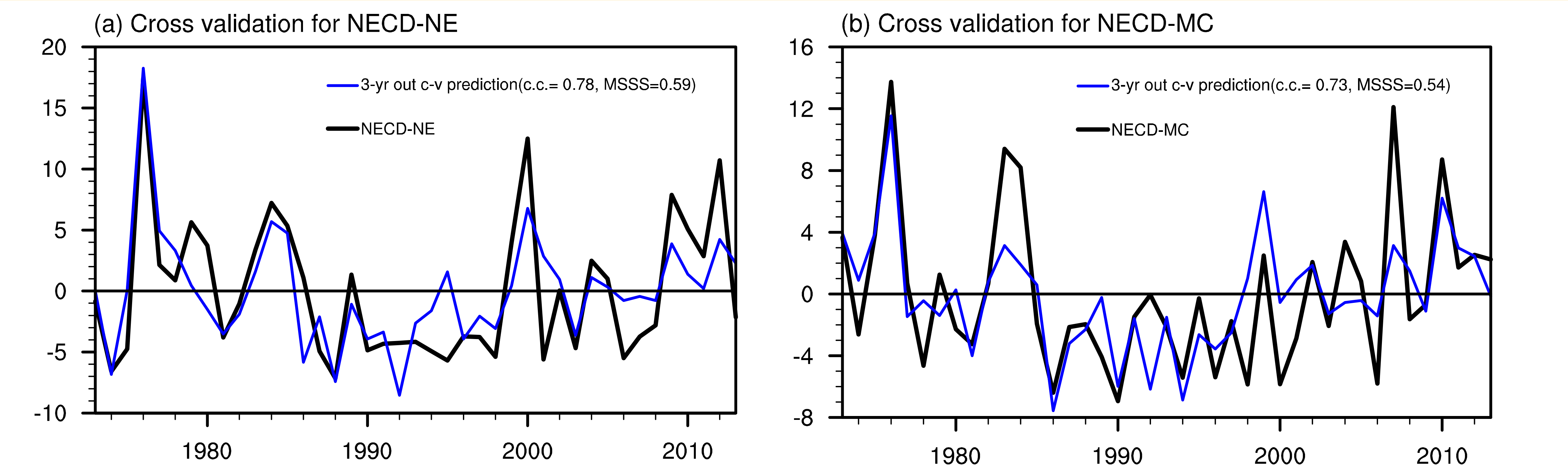


Normalized Simulation equation:

NECD-NE= 3.67*SNOW-NE+2.16*ARCT-NE

NECD-MC= 2.08*SNOW-MC+2.37*TNPSST-MC

Cross-validated Prediction skills of the PEM



NECD-NE:

R=0.78, MSSS=0.59

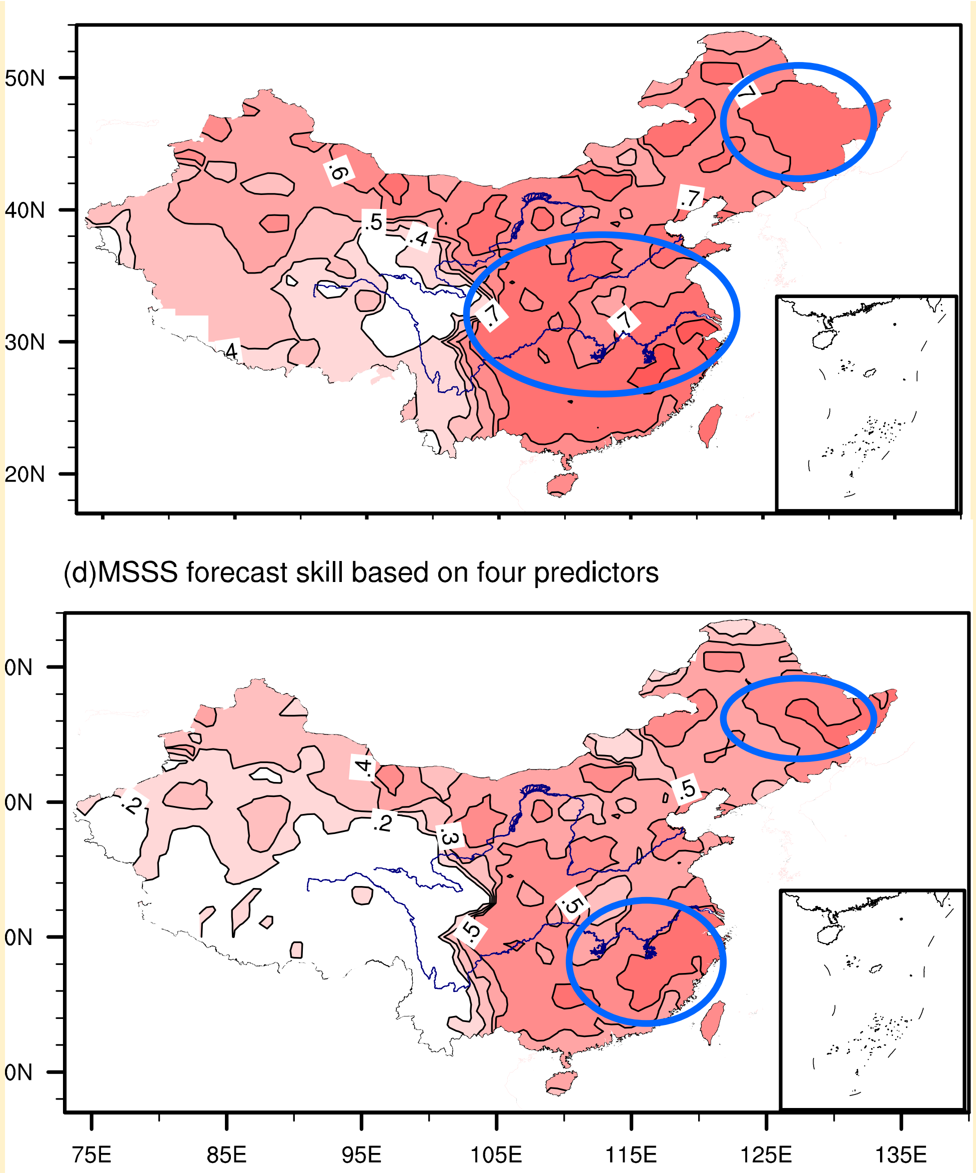
NECD-MC:

R=0.73, MSSS=0.54

Hindcast Prediction skills of the PEM for each station

TCC Skill:
~0.7

MSSS Skill:
~0.5



Spatial distribution of prediction skill of NECD based on multiple regression using the four identified predictors

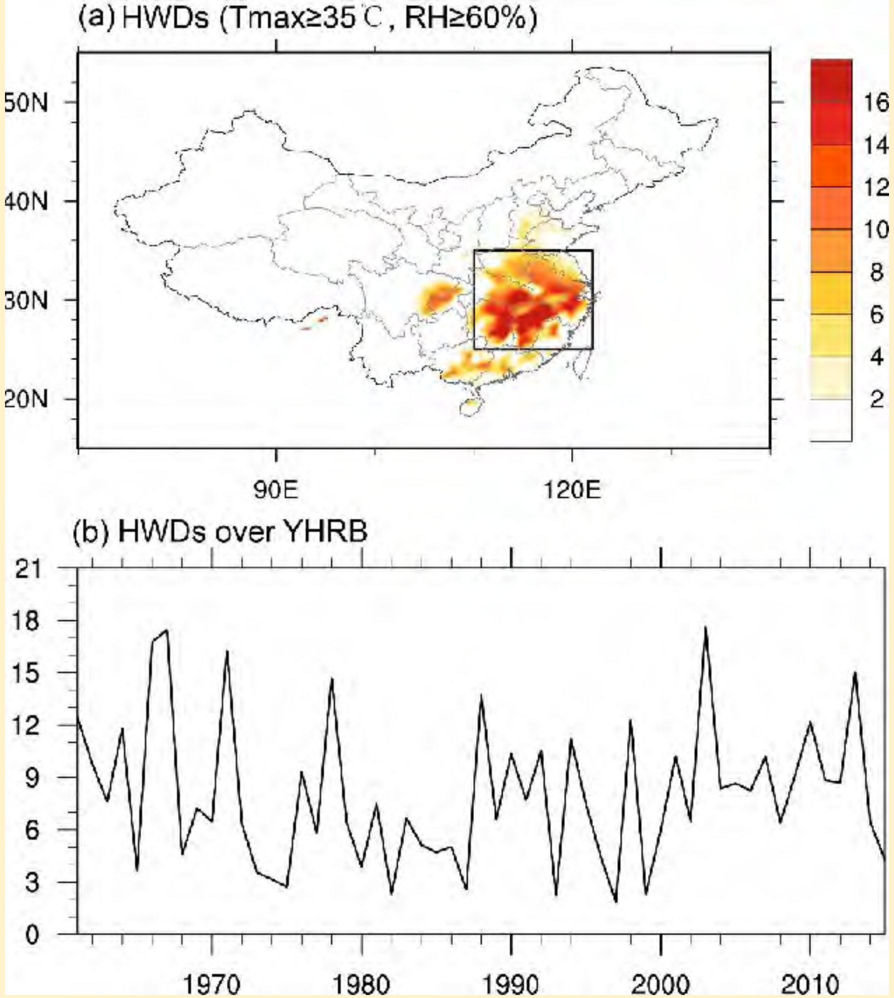
Conclusions

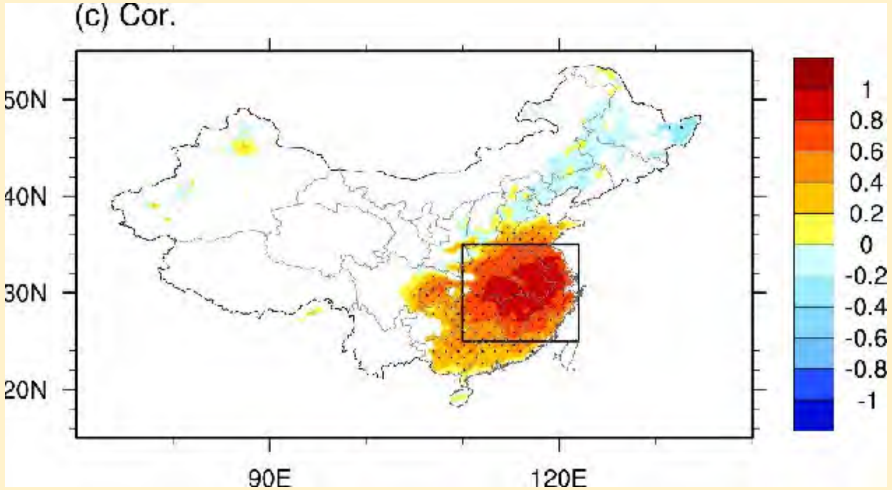
- China can be classified into 3 homogeneous regions with with coherent variations of the NECD , i.e., NE, MC and the TP
- Predictability of the NECD originates from SST and snow cover anomalies in the preceding September and October.
- For SST, The NE predictor is in the western Eurasian Arctic while the MC predictor is over the tropical-North Pacific.
- For snow cover, the NE predictor primarily resides in the central Eurasia while the MC predictor is over the western and eastern Eurasia.
- about 60% (55%) of the total variance of the NECD in Northeast (Main) China is likely predictable with one month lead time .

III. How predictable is the total number of sultry heat wave days in July-August over central eastern China?

- Gao, Miani, Bin Wang, Jing Yang, Wenjie Dong, and Zhangang Han, 2018: Are sultry heat wave days over central eastern China predictable? *J. Climate, 31, 2185-2196*.

Sultry HWDs Definition: Tmax ≥ 35℃ & RH ≥ 60%





- The integrated predictand is highly representative of the HWDs at each grid over YHRB

What happens during HW?

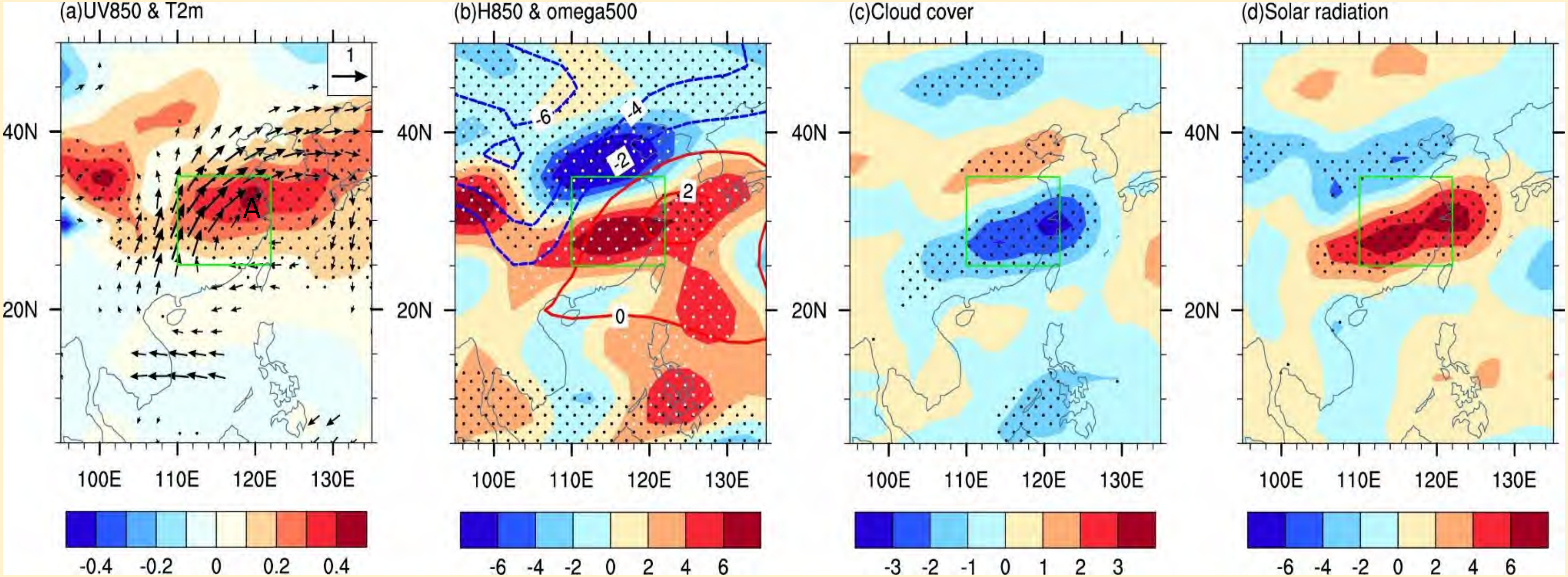
Local characteristics

Low-level anticyclone

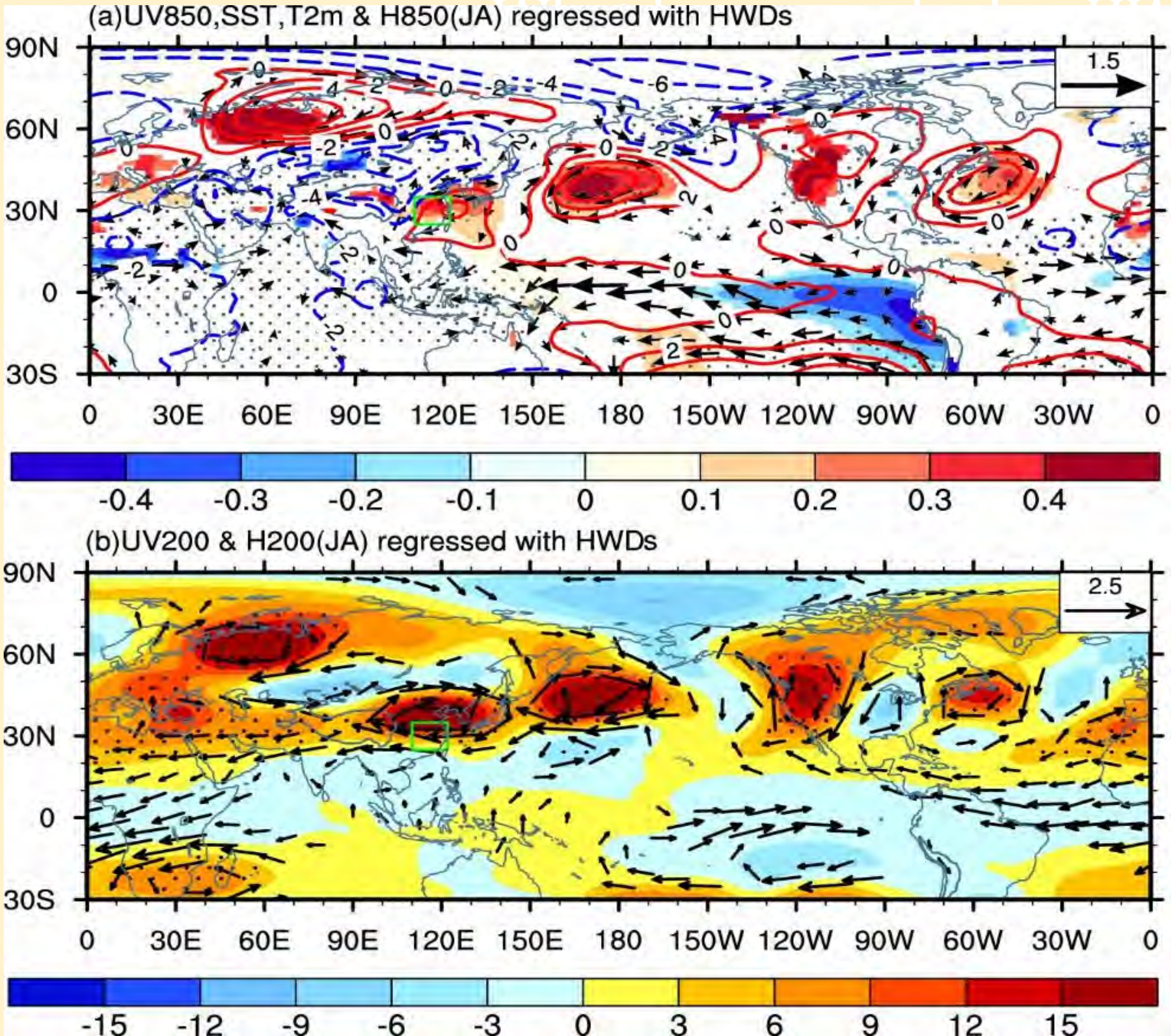
Descending motion
High pressure

Decreasing cloud cover

Increasing solar radiation



Global scale settings

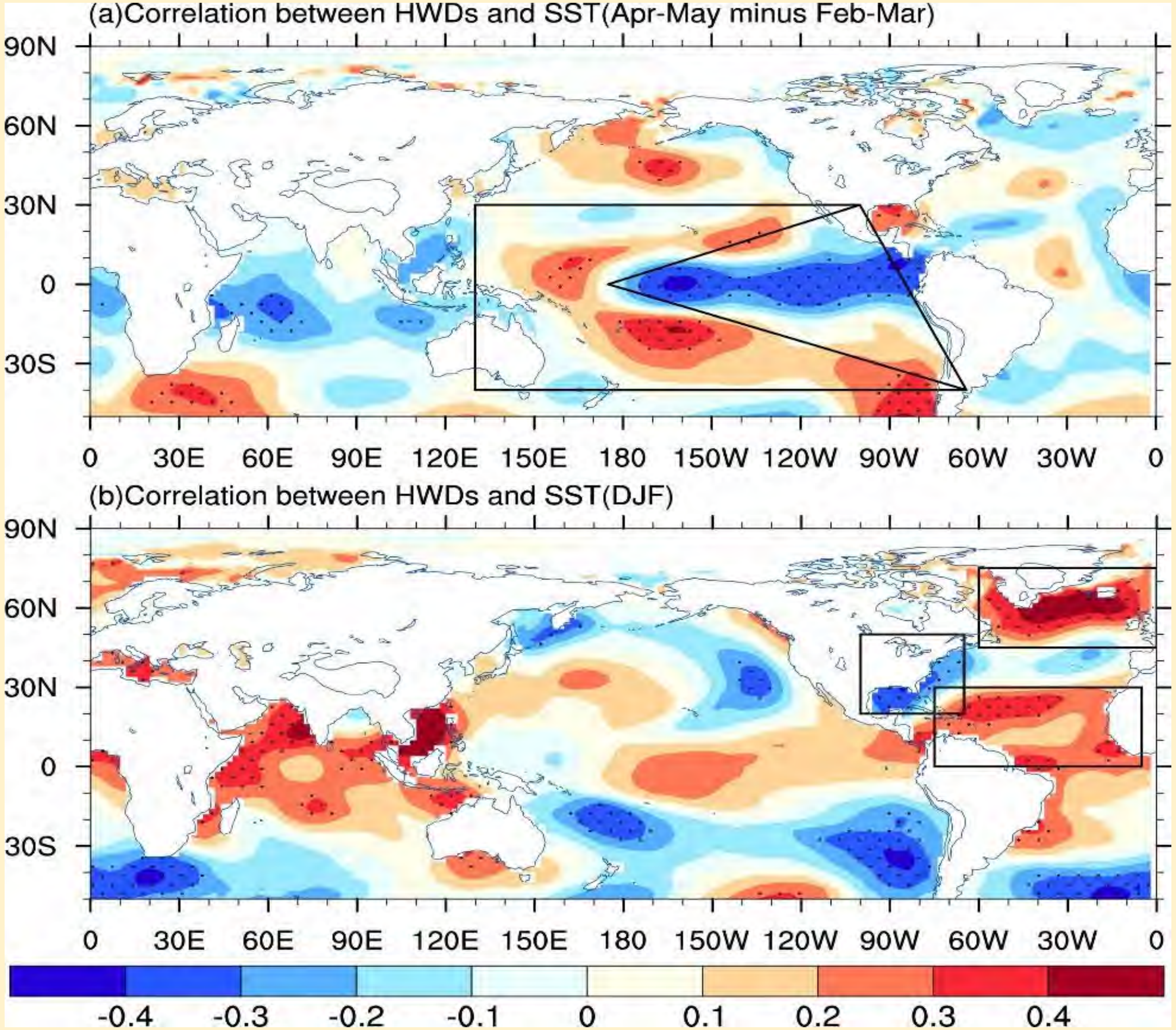


Developing EP-La Niña

Circum-global teleconnection (CGT)

2 SST Predictors

Searching for predictors



- Zonal dipole SST tendency in Pacific, EP-SST
- Meridional tripole SST over North Atlantic, NAO-SST

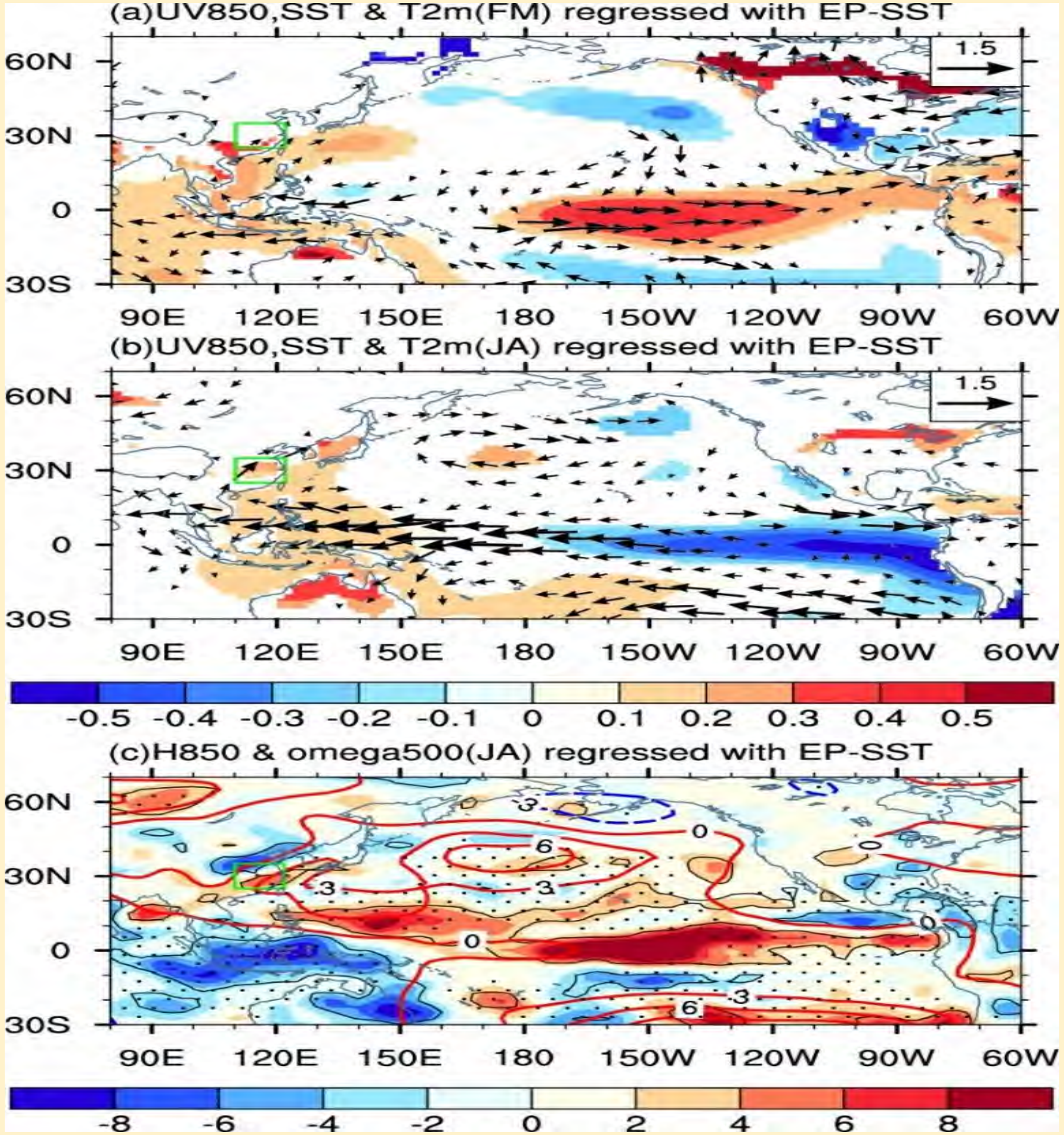
The correlation coefficients between predictand and predictors

Cor.	HWDs	EP-SST	NAO-SST
HWDs		**0.53**	**0.54**
EP-SST			**0.39**
NAO-SST			

The bold numbers denote statistically significant at 99% confidence level

EP-SST Predictor

Zonal dipole SST tendency in Pacific



Decaying CP-El Niño in early spring

Developing EP-La Niña in late summer

Modifies Walker circulation

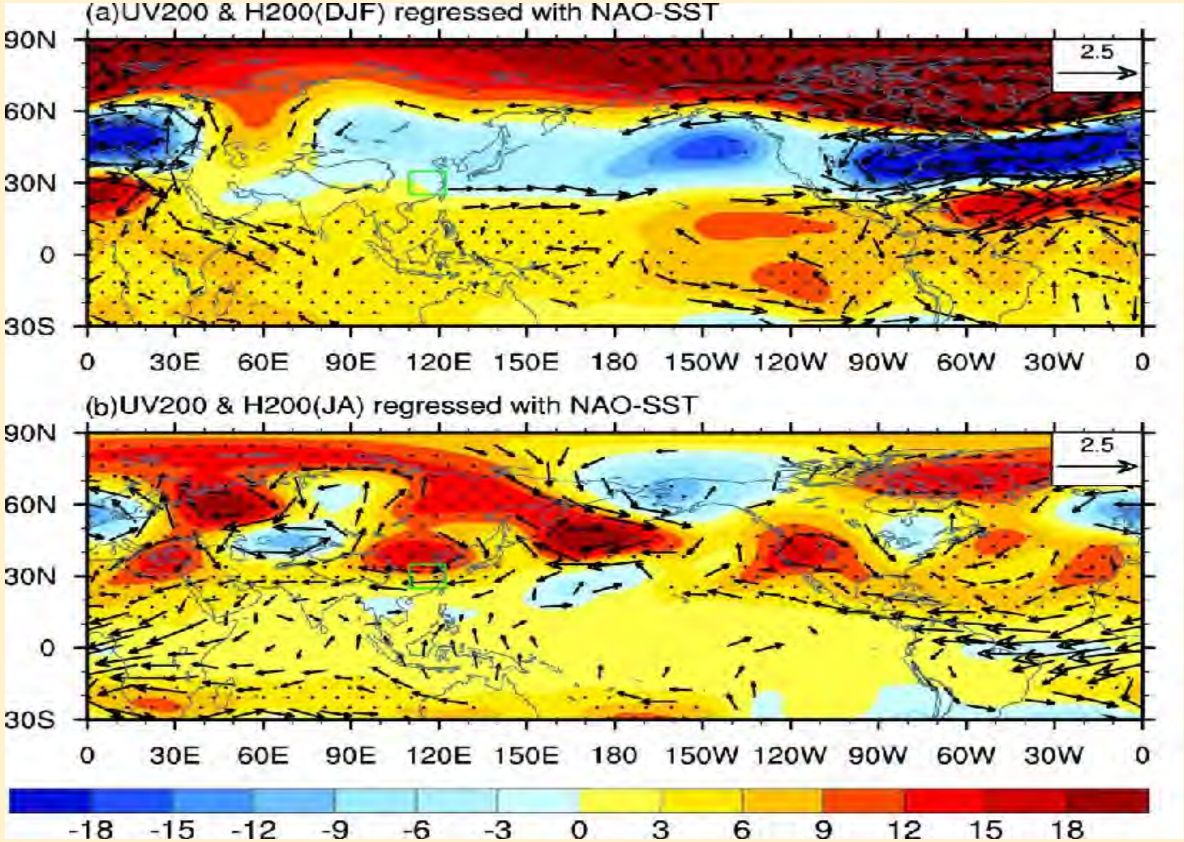
Enhances maritime continent convection, induces P-J teleconnection

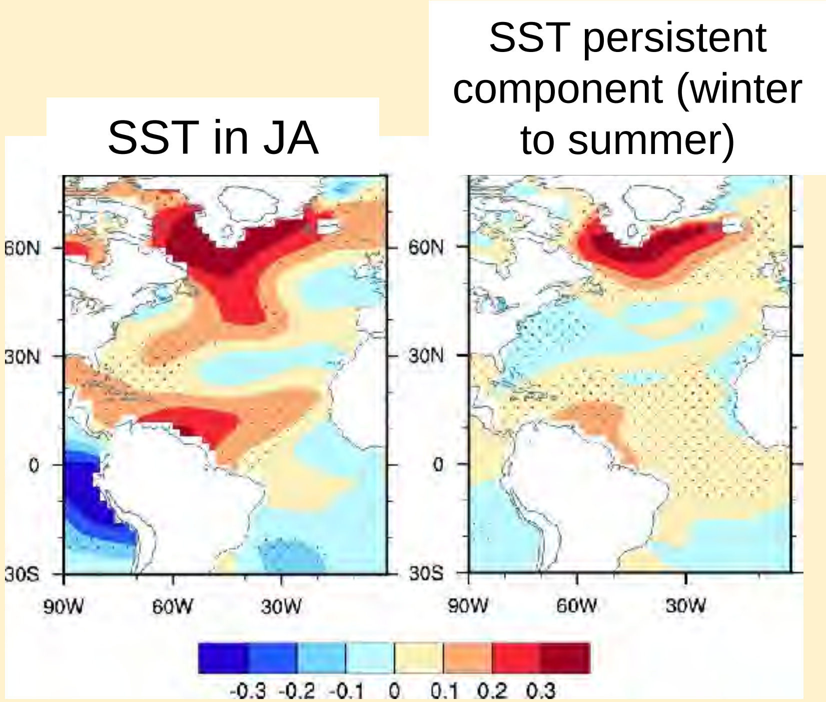
Reinforces equatorial CP convection, induces Rossby wave responses

(Nitta 1987; Wang et al. 2013)

NAO-SST Predictor

Meridional tripole SST over North Atlantic

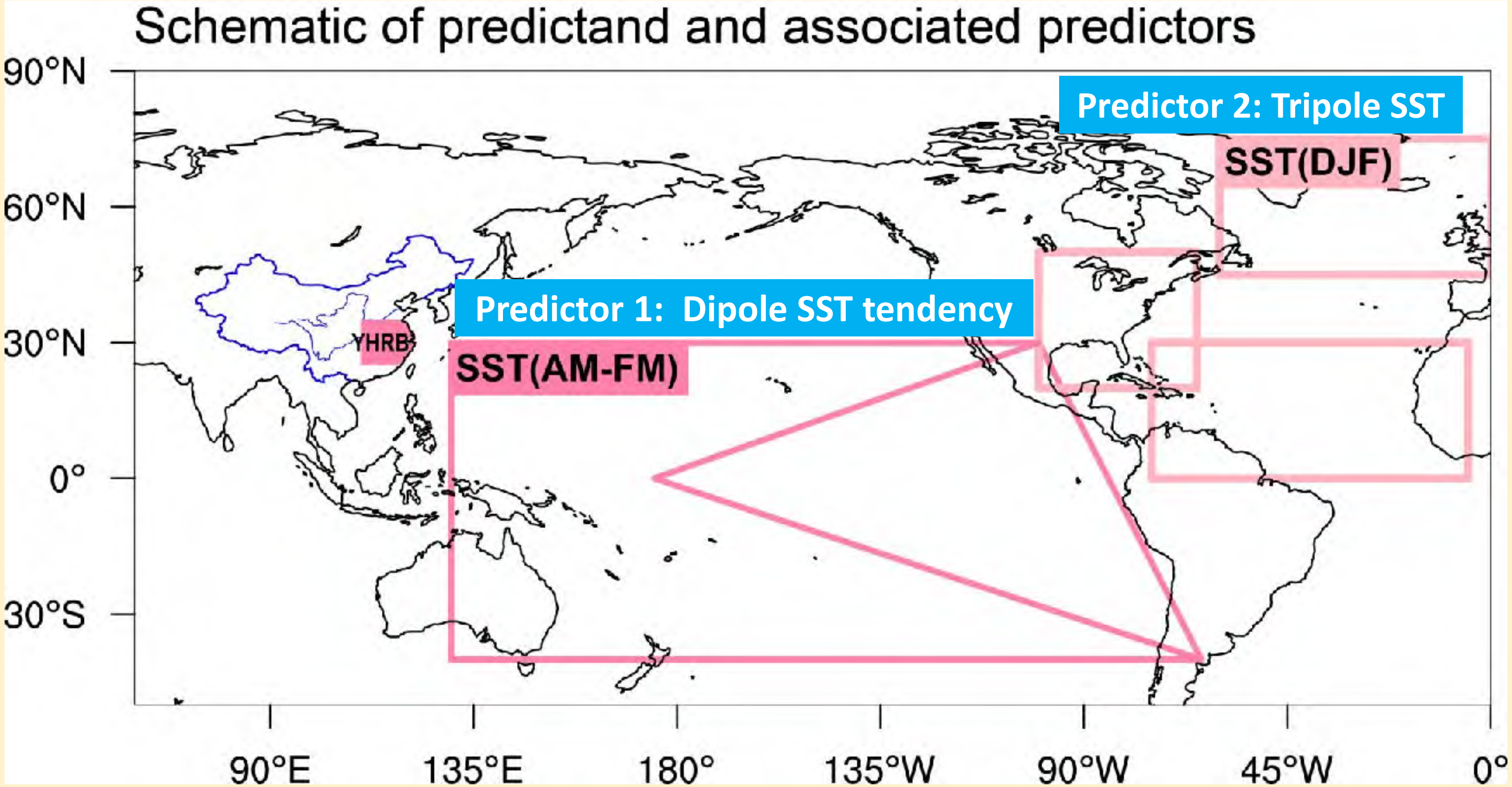




Tripole SST over North Atlantic in winter → Persists to the following summer through positive air-sea feedback and ocean memory effect → Excites CGT

(Ding and Wang 2005; Pan 2005; Wu et al. 2009; Ding et al. 2011)

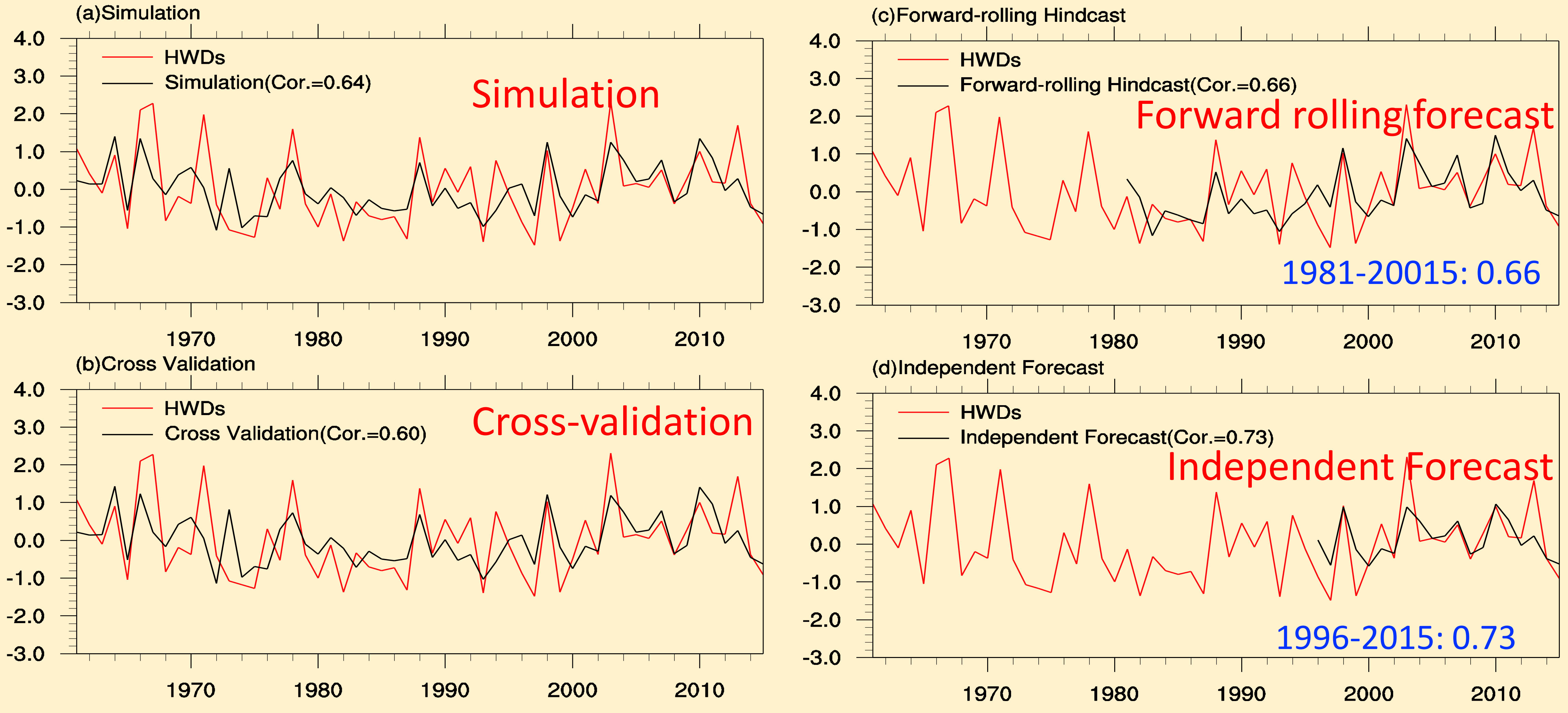
Predictors for HWDs over YHRB



Normalized Simulation equation:

$$\boxed{\text{HWDs} = 0.377\times\text{EP-SST} + 0.388\times\text{NA-SST}}$$

Forecast validation



Summary

Strong year-to-year variations of HWDs over YHRB

Low-level Anticyclone

WP high pressure anomaly

CP-La Niña

Modifies Walker circulation

Persists from winter to summer

Excites CGT

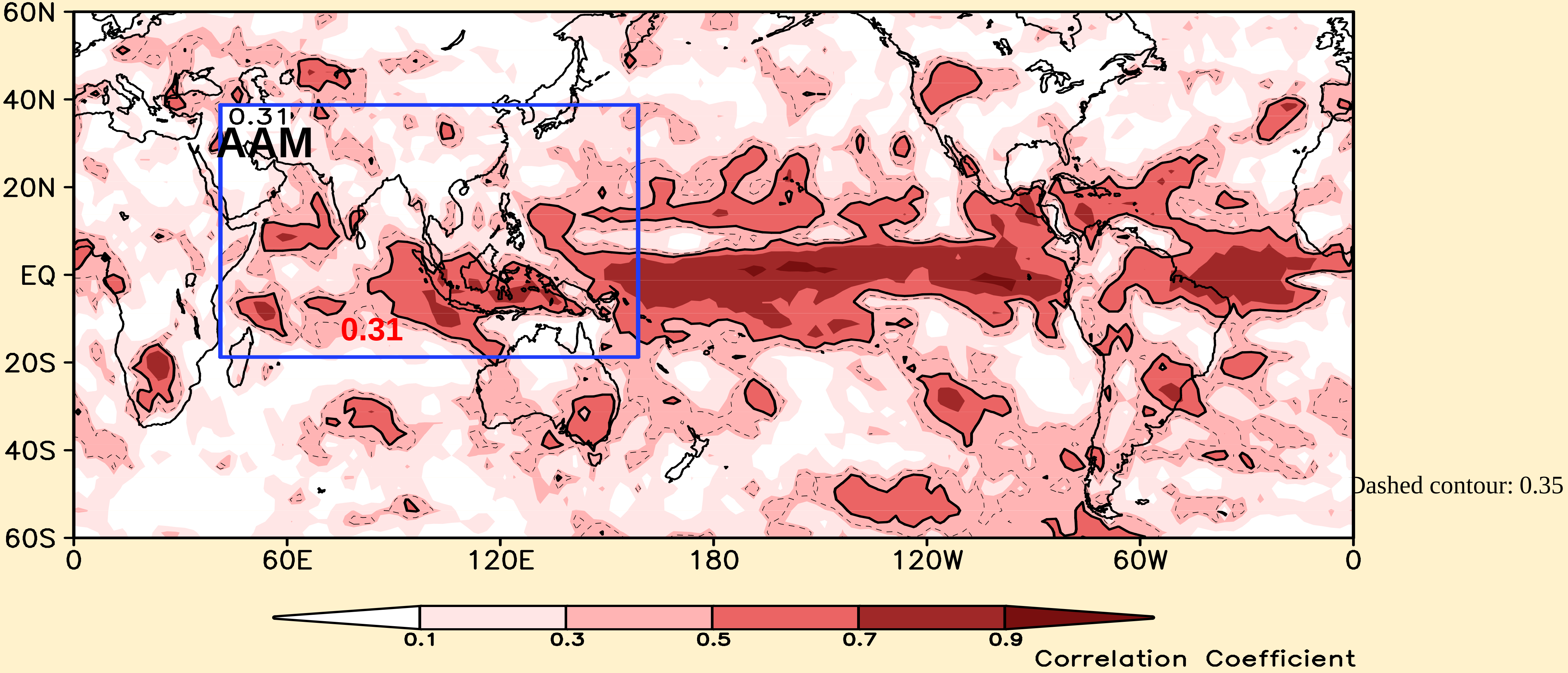
Mega-ENSO tendency pattern in Pacific

Winter Meridional tripole SST pattern over North Atlantic

About 55% of the total variance of HWDs over YHRB may be potentially predictable.


Mahalo!
Any
comment?

Dynamic Prediction of summer land monsoon rainfall



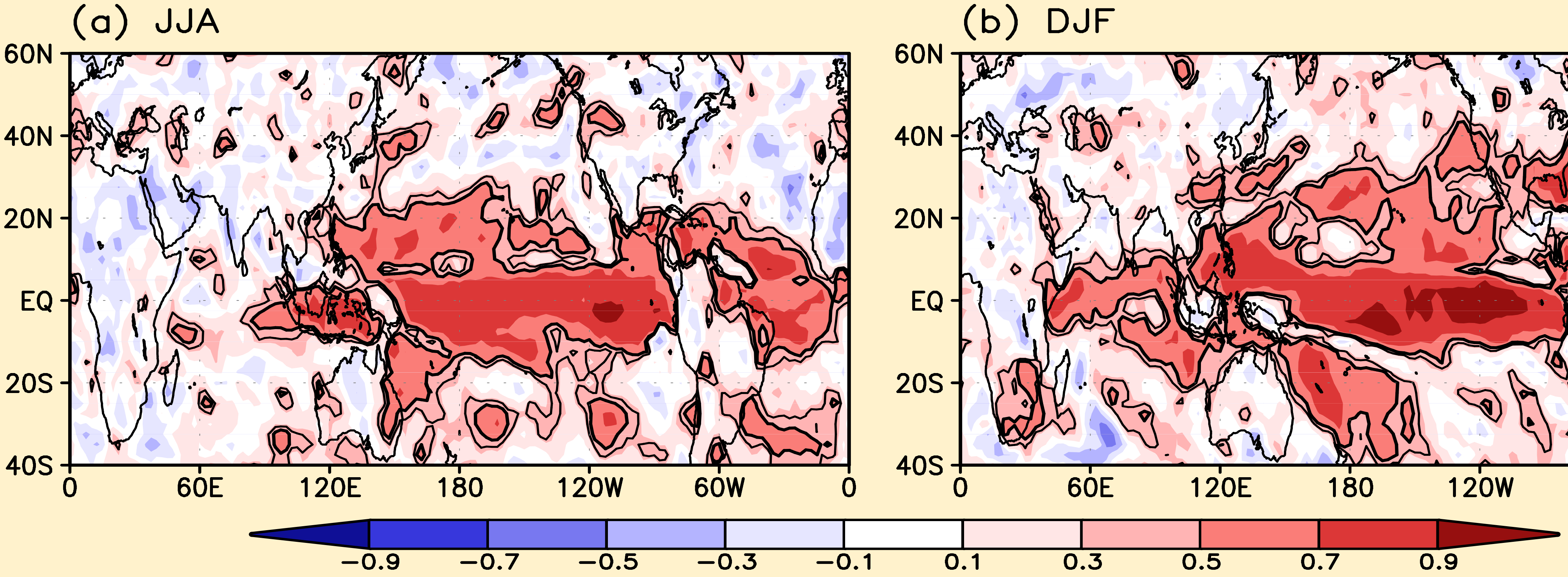
Four dynamical models' MME Temporal correlation skill for JJA rainfall (1979-2010)

NCEP CFS version 2 (Saha et al. 2011), ABOM POAMA version 2.4 (Hudson et al. 2011),
GFDL CM version 2.1 (Delworth et al. 2006), and FRCGC SINTEX-F model (Luo et al. 2005).

Wang et al. 2015b

Climate prediction of rainfall is most difficult compared to temperature and circulations

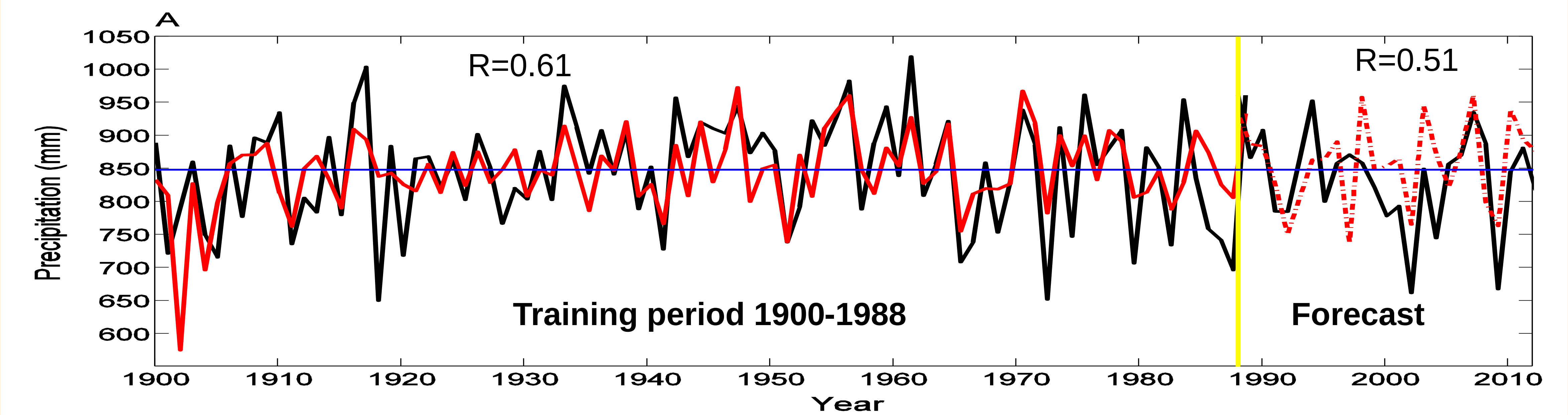
Precipitation



13 CGCM Multi-model ensemble seasonal prediction skill

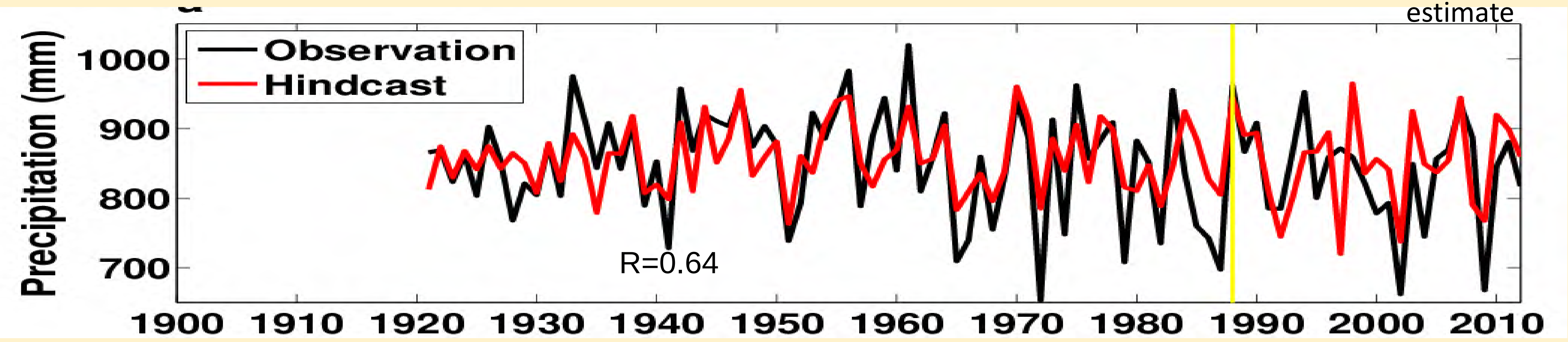
Wang et al.(2009)

24-y **independent forecast** validation



92-y (1921-2012) **forward rolling independent forecast**

Practical predictability estimate



Data

- **Daily rainfall** data：

Daily precipitation records of **746 stations over China** for the period of 1979–2013 were utilized. This dataset was obtained from the National Meteorological Information Center of China Meteorological Administration.

- **SST** data :

Monthly mean sea surface temperature (SST) data were derived from an arithmetic mean of two datasets: **HadISST** (Rayner et al. 2003) **and ERSST** version 4 (Huang et al. 2015) for 1979–2013.

- **SLP, 850 hPa wind, 2 m temperature and 200hPa geopotential height** data**:**

The monthly sea level pressure (SLP), 2-meter temperature, 200hPa geopotential height and 850 hPa winds were obtained from the **ERA-Interim Reanalysis** (Dee et al. 2011) during 1979–2013.

- **Global rainfall** data:

The global monthly mean precipitation data from **GPCP**(v2.3) datasets (Adler et al. 2003) were employed to analyze the global precipitation from 1979 to 2013.

Summary (EPDs)

- Based on the region- and season-dependent variability of EPDs, two domain-averaged EPDs indices during their local high EPDs seasons (May-June for SC and July-August for NC) are therefore defined.
- The increased EPDs over SC are controlled by Philippine Sea anticyclone anomalies in May-June duringa rapid decaying El Nino and controlled
- The increased EPDs over NC are accompanied by a developing La Nina and anomalous zonal sea level pressure contrast between the western North Pacific subtropical high and East Asian low in July-August.
- The causative relationships between the predictors and the corresponding EPDs over each region are discussed using lead-lag correlation analyses.
- Using these selected predictors, a set of PEMs is derived. The 13-year (2001–2013) independent forecast shows significant temporal correlation skills of 0.60 and 0.74 for the EPDs index of SC and NC, respectively, thus providing an estimation of the predictability for summer EPDs over eastern China.

Discussion

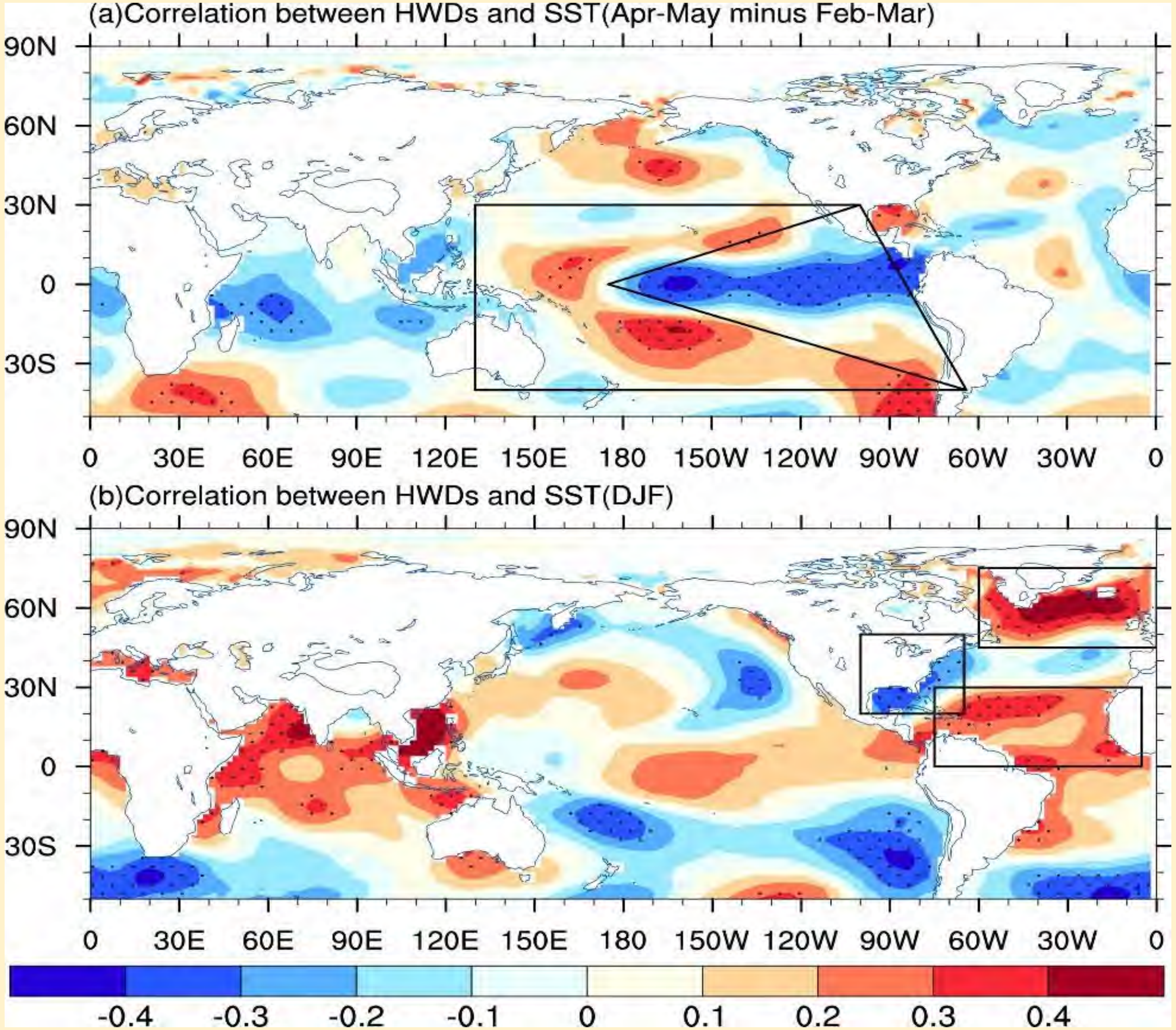
- Further well-designed numerical experiments are needed to test the speculations (physical meanings of the predictors) proposed in the present study.
- The predictors derived from the current 35 years of data may vary with time or experience secular changes.

Introduction

- Heat wave (HW) brings widespread impacts on human health, society, economy and ecosystems.
  - 2003 HW in Europe: 70000 deaths; Crop losses of around US$12.3 billion (Robine et al. 2003; Schär & Jandritzky, 2003)
  - 2010 HW in Russia: 54000 deaths; Economic damage of 1.4% GDP (Porfiriev, 2014)
  - 2013 HW in China: 5758 heat-related cases (Gu et al. 2016)
- HW in China increased in recent decades and will occur with a higher frequency and longer duration in the future (e.g., Ding and Ke 2015; Collins et al. 2013).
- Improving HW prediction skill is important

2 SST Predictors

Searching for predictors



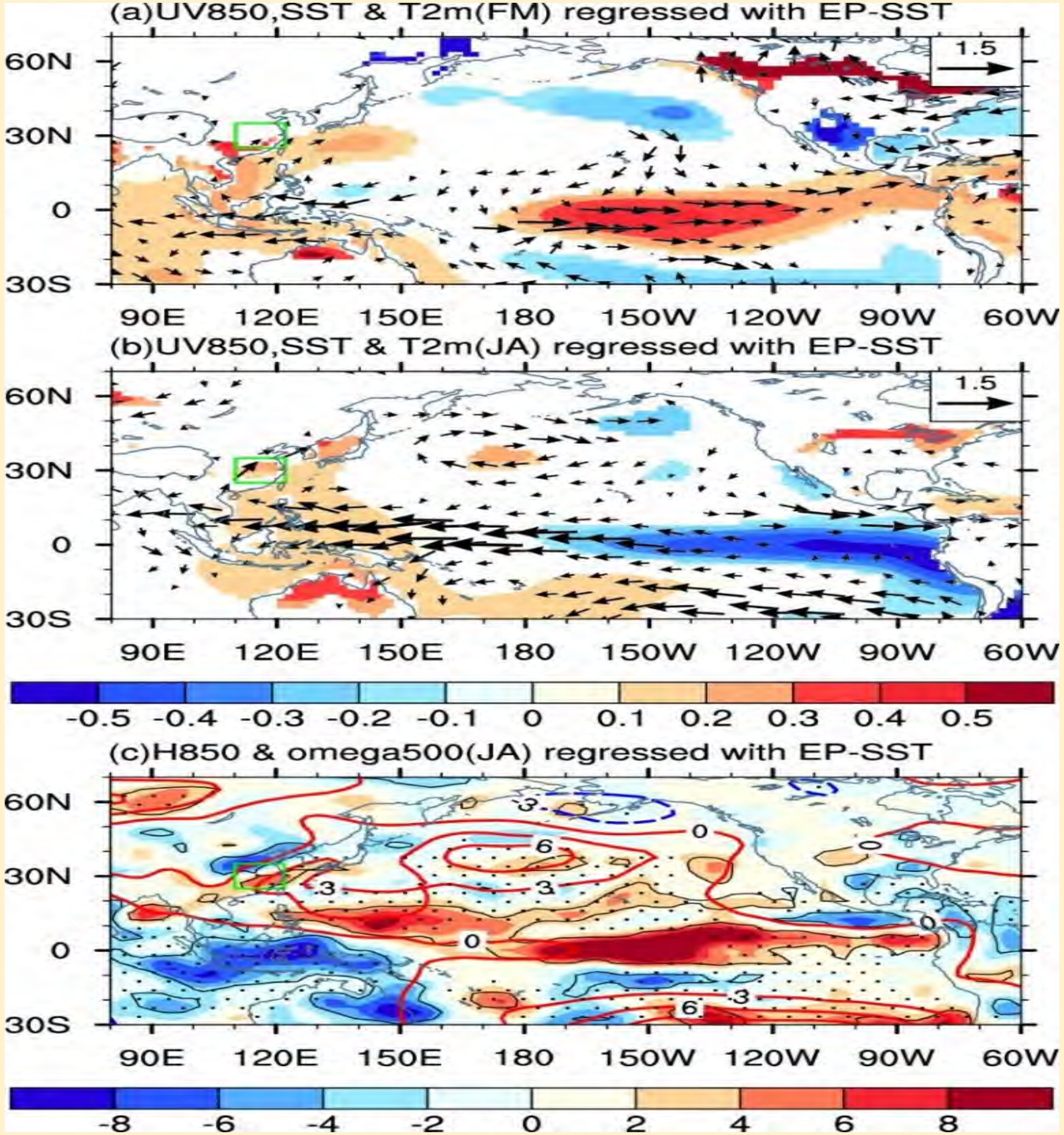
- Zonal dipole SST tendency in Pacific, EP-SST
- Meridional tripole SST over North Atlantic, NAO-SST

The correlation coefficients between predictand and predictors

Cor.	HWDs	EP-SST	NAO-SST
HWDs		**0.53**	**0.54**
EP-SST			**0.39**
NAO-SST			

The bold numbers denote statistically significant at 99% confidence level

EP-SST Predictor
Zonal dipole SST tendency in Pacific



Decaying
CP-El Niño
in early spring

Developing
EP-La Niña
in late summer

Modifies Walker circulation

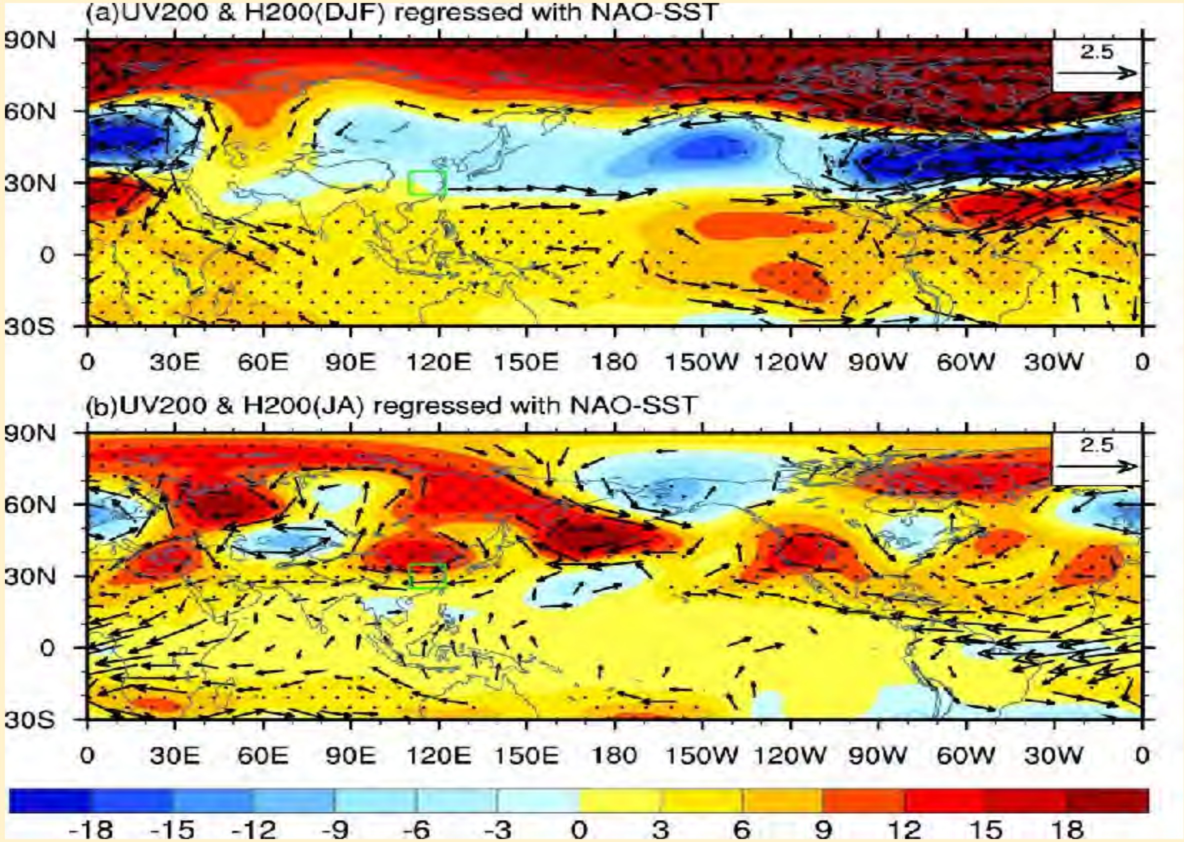
Enhances maritime continent convection, induces P-J teleconnection

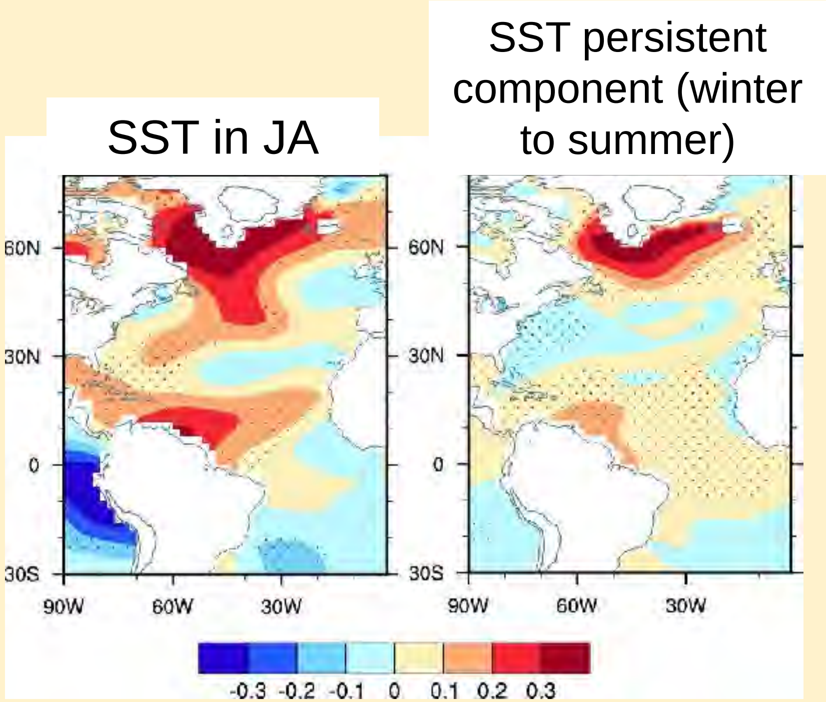
Reinforces equatorial CP convection, induces Rossby wave responses

(Nitta 1987; Wang et al. 2013)

NAO-SST Predictor

Meridional tripole SST over North Atlantic





Tripole SST over North Atlantic in winter

Persists to the following summer through positive air-sea feedback and ocean memory effect

Excites CGT

(Ding and Wang 2005; Pan 2005; Wu et al. 2009; Ding et al. 2011)

Data and Methodology

☐Data(1961-2015)

✓Daily

CN05.1 (0.25° × 0.25°)

✓Monthly

NCEP/NCAR Reanalysis (2.5° × 2.5°)

Hindcast of 5 ENSEMBLES project models initiated from May 1st (1961-2005)

☐Methodology

✓Physics-based empirical model (PEM)

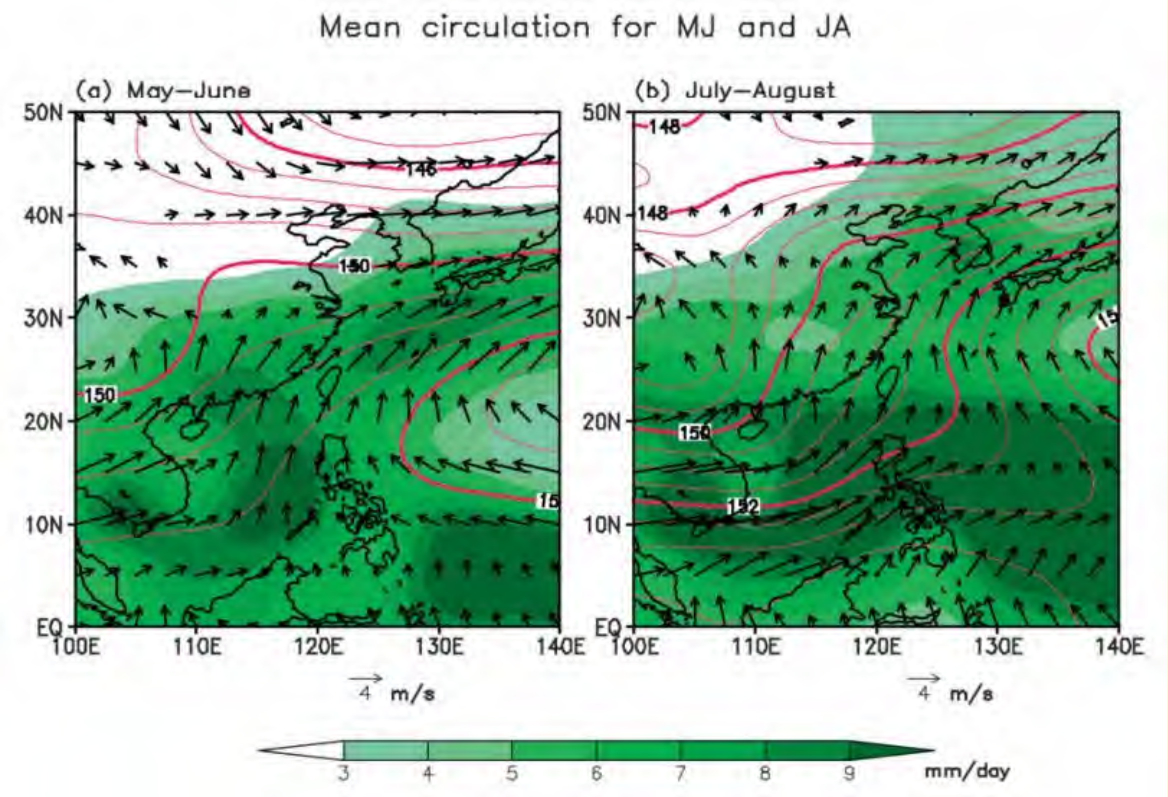
✓Detrend

Target Season

July-August

- JA is the peak season of HW events characterized by high humidity over eastern China (Ding & Ke 2015; Gao et al. 2017).

- The northward migration of western North Pacific subtropical high in JA provides a robust large scale circulation background for the HW occurrence over YHRB.



（Wang et al. 2009）

4. How to build the Physics-based Empirical model ?

Physics-based Empirical model (Wang et al., 2015) is based on understanding of the physical linkages between the predictors and predictand.

- Searching for the predictors :

1. Principle : physical meaning
2. Three fields : SST/2mT/SLP
3. Two types of precursory: persistent signals & tendency signals

- Stepwise regression -> significance & independency

To what extent are the total summer extreme precipitation days (EPDs) over eastern China predictable?

- Understanding the **origins of the predictability** of summer EPDs is the first step
- Take **physical mechanisms** into account can help increase the forecast skill
- **Physics-based empirical (P-E) model** has been successfully applied to seasonal predictability studies of a variety of meteorological phenomena (Xing et al. 2014; Yim et al. 2014; Wang et al. 2015; Grunseich and Wang 2016; Li and Wang 2016).

An EOF based PEM pattern prediction approach

General procedure (Wang et al. 2014)

STEP 1

Performing EOF analysis to NWC summer rainfall

Derive frequently observed patterns; Reconstruct the total variation.

STEP 2

Understanding the origin of the EOF patterns; Exploring the physical processes.

If the EOF patterns are physical meaningful, we will use it as **potentially predictable patterns**.

STEP 3

Predicting the PCs by establishing a set of **P-E prediction models**.

If a PC can be predicted skillful, the corresponding EOF is considered as **predictable mode**.

STEP 4

Predicting the rainfall anomaly pattern by using the predictable modes.

Use observed EOF patterns and predicted PCs to **predict total rainfall anomaly pattern and estimate potential predictability**

Establishment of P-E prediction models (Wang et al. 2015)

- Only two predictor fields: SST/2m air temperature over land and SLP anomalies——Reflecting ocean and land surface anomalous conditions
- Only two types of signals in the lower boundary anomalies:

a) ***persistent*** signals from the previous seasons to the pre-forecaster season

reflect local positive feedback processes which may help maintain the lower boundary anomalies.

a) ***tendency*** signals from the previous seasons to the pre-forecaster season :

denote changes before the pre-forecast season that often tip off the direction of subsequent evolution.

Table. Definitions of predictors for EPDs-NC and EPDs-SC

Predictor	Definition
NC-a	May-June minus December-January east-west dipole SST averaged over tropical Pacific(10S-10N, 120E-80W)
NC-b	May-June minus December-January 2mT averaged over northern Europe (35N-60N, 35E-90E)
SC-a	March-April mean SLP averaged over western Pacific (40S-20N, 100E-160W)