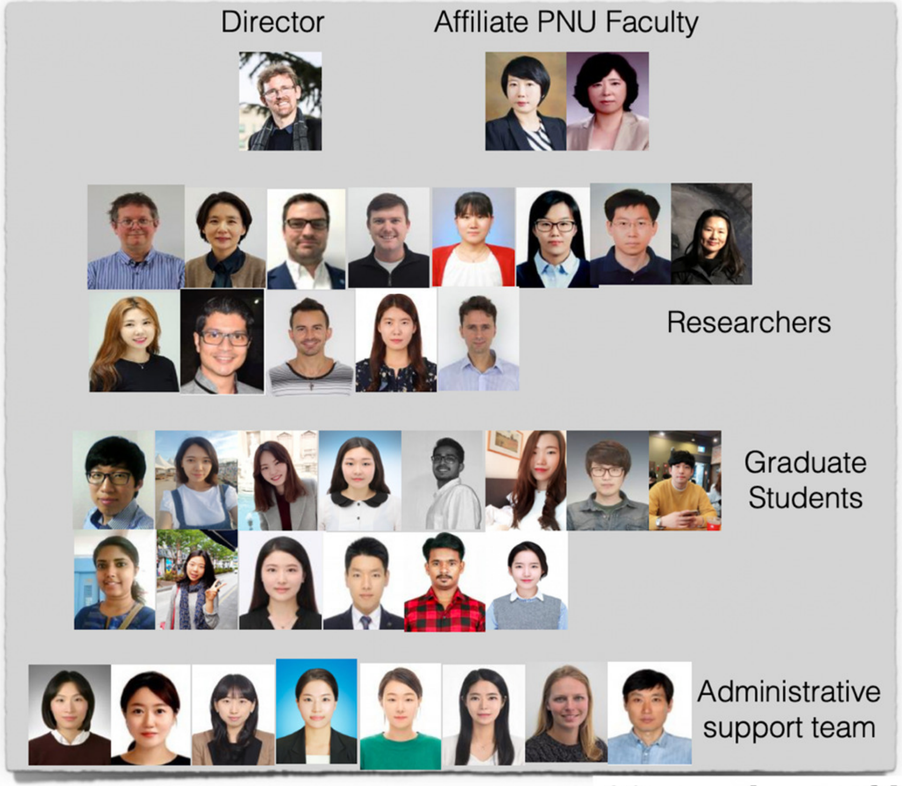
Subseasonal to Multi-year Predictability and Prediction

June-Yi Lee

1. Institute for Basic Science (IBS) Center for Climate Physics (ICCP), Busan, South Korea
2. Research Center for Climate Sciences and Department of Climate System, Pusan National University, Busan, South Korea

May 30th, 2019, CITES-2019 School

Introduction on IBS Center for Climate Physics (ICCP)



38 members of ICCP

1 Director, 2 affiliate PNU faculty, 13 researchers, 14 students, 8 support team members

Introduction on IBS Center for Climate Physics (ICCP)

Scientific breakthroughs

Train next generation of earth system scientists

Climate Knowledge

Earth System Dynamics	Hydroclimate	Earth System Predictability	Physical Oceanography
Sensitivity to radiative forcing, climate modes, abrupt climate change, climate-vegetation coupling, human interactions, sea level rise	Extreme events, subtropical expansion, mega-droughts, and East Asian Monsoon systems	Predictions of soil water, productivity, nutrients, forest fire, longterm migration stress, sea-ice and vegetation	Polar oceanography, ice-sheet ocean interactions, inverse modeling, ocean-carbon cycle feedbacks, high resolution ocean modeling tracers

Director (Earth System Dynamics, Hydroclimate, Earth System Predictability)

Associate Director (from 2020) (Physical Oceanography)

Postdoctoral Fellow Positions are open for

Earth System Predictability
East Asian paleo summer monsoon
Paleo climate-genomics in Africa
Climate/Human migration modeling.

Detail info:

https://www.iccp.ibs.re.kr/jobs

RCCS
RESEARCH CENTER FOR CLIMATE SCIENCES

Content

Part I. Introduction on Seamless Prediction Framework

Part II. Subseasonal Predictability and Prediction

Part III. Seasonal Predictability and Prediction

Part IV. Multi-year Predictability and Prediction

Basic Concepts

- ## Climate prediction (or forecast)

A climate prediction is the result of an attempt to produce (starting from a particular state of the climate system) an estimate of the actual evolution of the climate in the future, for example, at subseasonal, seasonal, interannual or decadal time scales. Because the future evolution of the climate system may be highly sensitive to initial conditions, such predictions are usually probabilistic in nature.

A climate prediction typically proceeds by integrating the governing equations forward in time from observation-based initial conditions.

- ## Climate predictability

Climate predictability indicates the extent to which even minor imperfections in the knowledge of the current state or of the representation of the system limits knowledge of subsequent states. Formally, predictability in climate science is a feature of the physical system itself, rather than of our 'ability to make skillful predictions in practice'

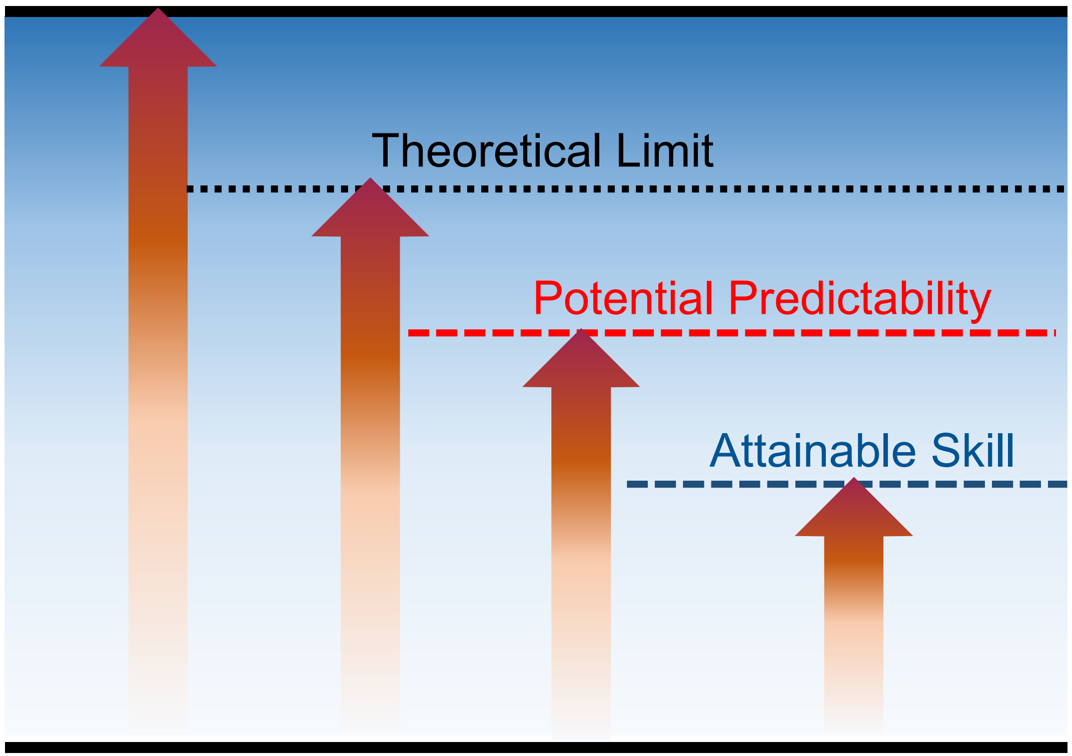
- ## Climate projection

A climate projection is the simulated response of the climate system to a scenario of future emission or concentration of greenhouse gases and aerosols, generally derived using climate models.

*Definition from IPCC AR5

Basic Concepts

Perfect Prediction



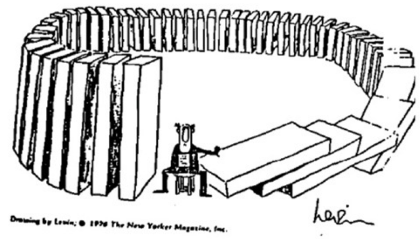
Internal chaotic process

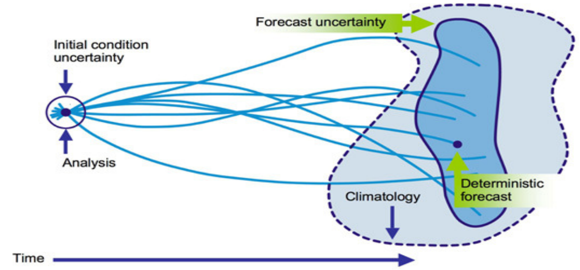
Quality of IC & BC

Model quality

Model's internal dynamics

Internal feedback

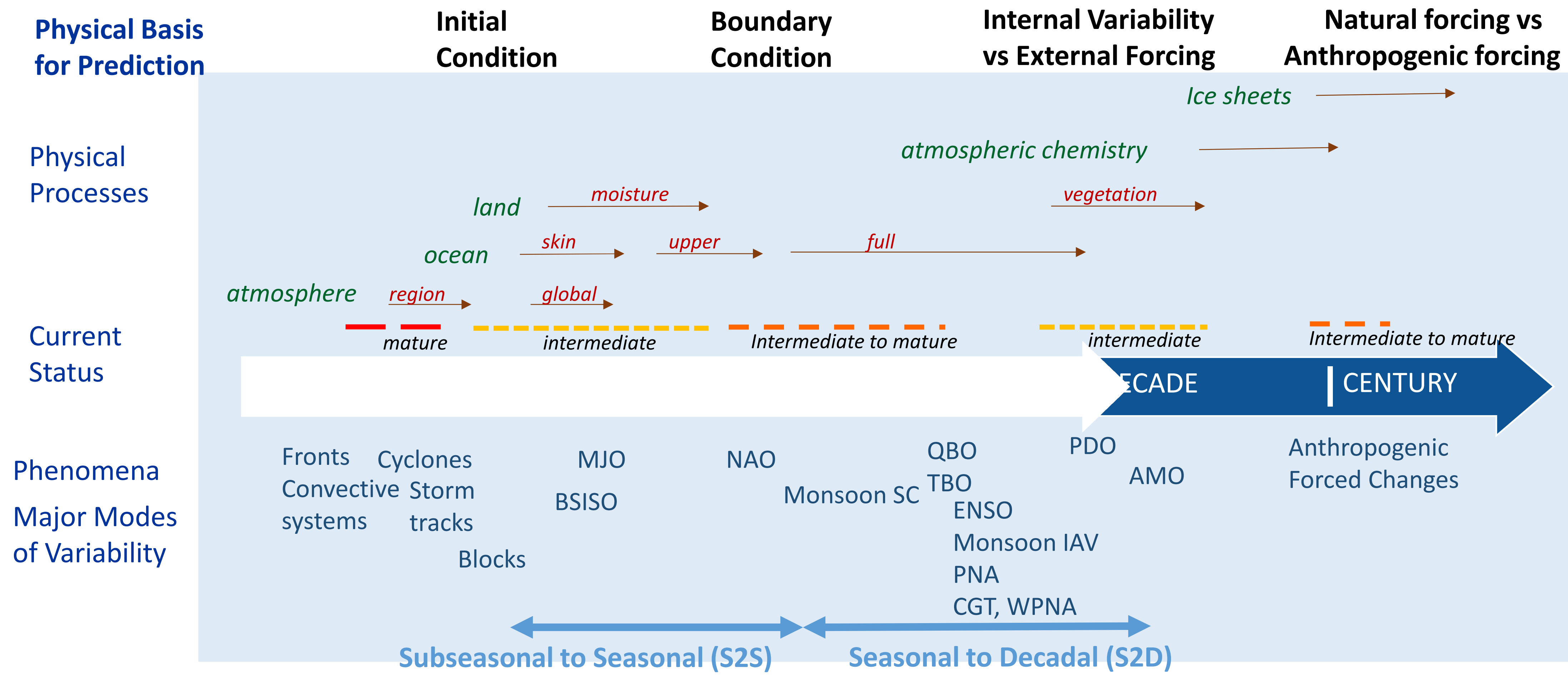




Very Complex

* Sources: Prof. In-Sik Kang and Dr. Young-Min Yang

The Seamless Weather-Climate Prediction Problem



Modified version of Figure 1 in Hoskins (2012; QJRM)

International Intercomparison Projects on S2S & S2D Prediction

AGCM prediction with Perfect SST

AOGCM prediction

A-O-L-SI Coupled Prediction

ESM Prediction

1995 — 2000 — 2010 — 2015 — 2017

Europe	PROVOST	DEMETER	ENSEMBLES	EUROSIP	
USA	DSP		NMME		
Asia-Pacific	AAMIP	CliPAS			PNU/ICCP
Global		UH/IPRC	ISVHE; S2S; CMIP5 Decadal Prediction		CMIP6+ Seamless Prediction

CliPAS — *Major outcome: Predictable Mode Analysis*

Major outcome: Boreal Summer Intraseasonal Oscillation Index

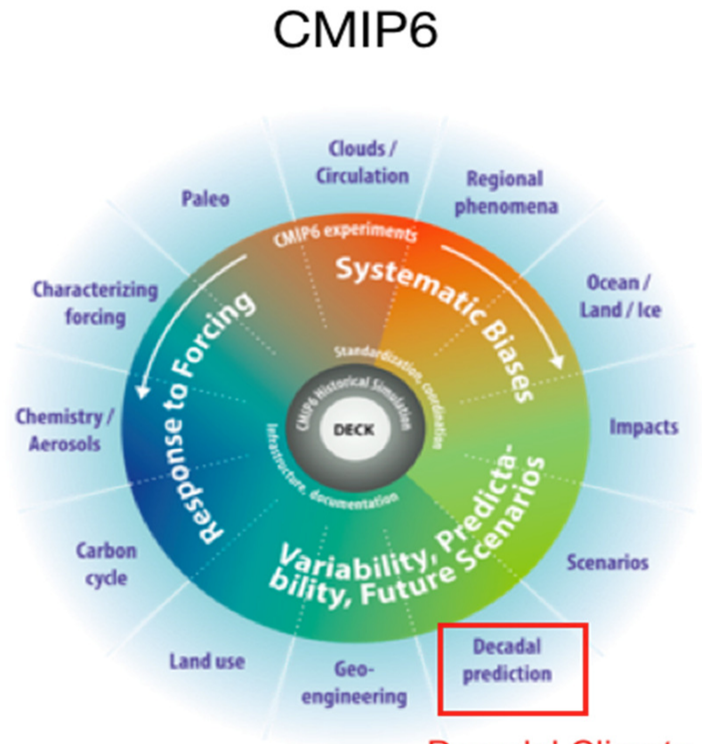
UH/IPRC

PNU/ICCP

CMIP6+ Seamless Prediction

International Efforts on S2D

Near-Term Climate Prediction (**NTCP**)



Decadal Climate Prediction Project (**DCPP**)

Content

Part I. Introduction on Seamless Prediction Framework

Part II. Subseasonal Predictability and Prediction

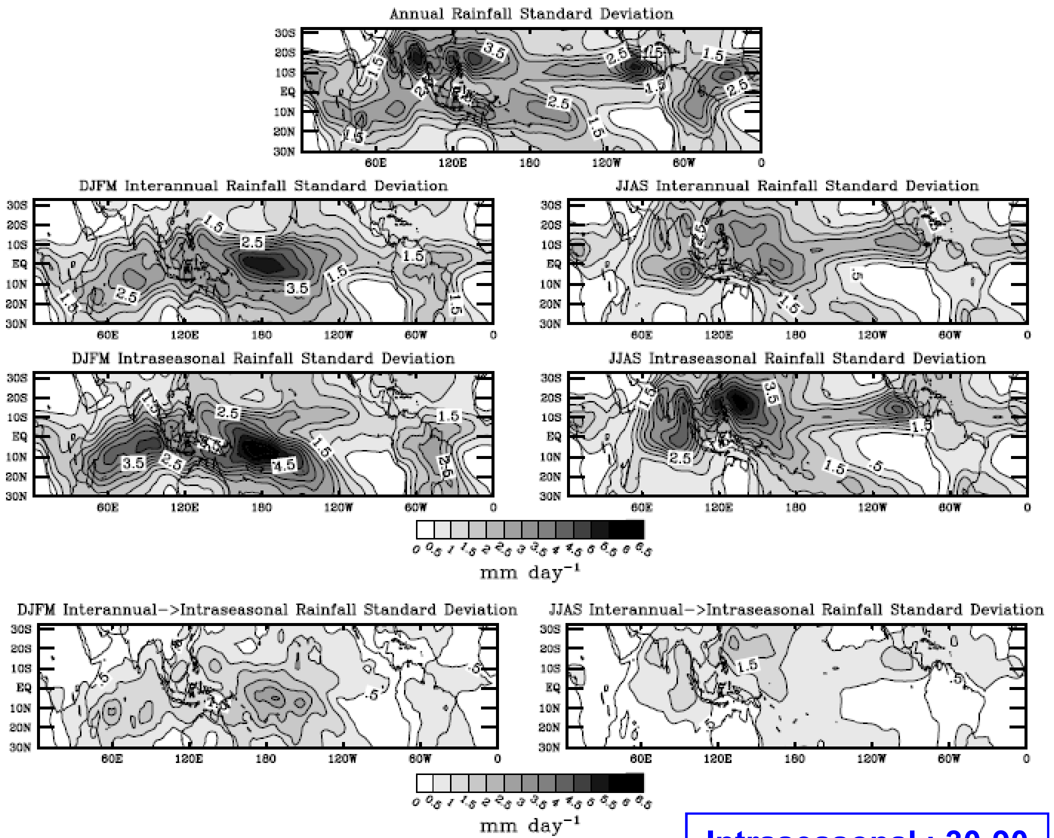
- What we expect to predict on subseasonal timescales

Part III. Seasonal Predictability and Prediction

Part IV. Multi-year Predictability and Prediction

Subseasonal Variability compared with Interannual variability

CMAP Rainfall



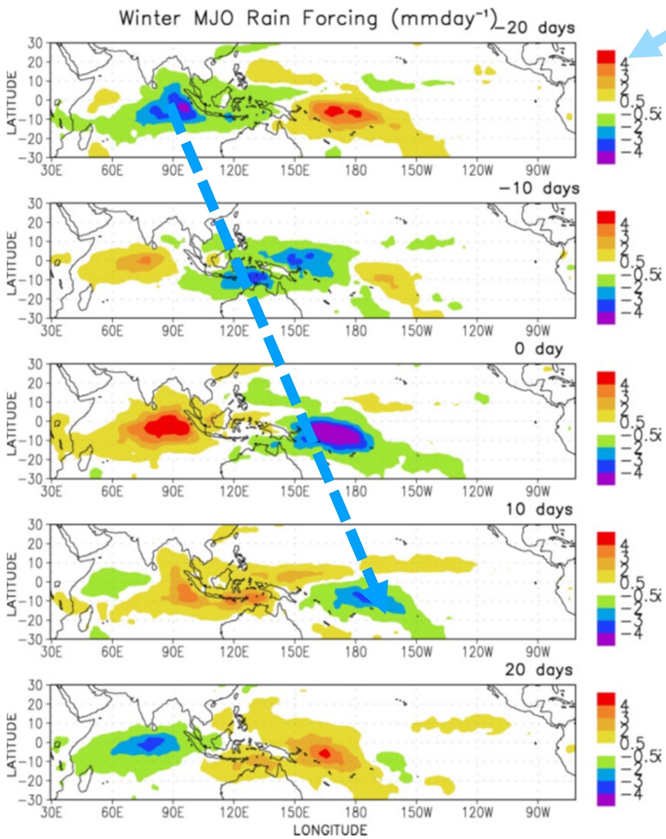
Waliser (2006 in *the Asian Monsoon*)

Intraseasonal : 30-90
Interannual : > 90

- **While the defining variability of a monsoon system is its seasonal character, its variability about its typical seasonal evolution is often of most interest and importance. In the case of the Asian and Australian summer monsoons, their intraseasonal character is especially prominent and unique.**
- **The annual standard deviation exhibits strong variability on either side of the equator, which is a depiction of the annual meridional migration of the tropical rainfall band – a fundamental manifestation of the monsoon.**
- **The IAV, particularly in boreal winter, emphasizes the connection to ENSO-related SST variability.**
- **The intraseasonal variability (ISV) is as large or larger than the interannual variability (IAV).**
- **The ISV tends to be relatively most prominent in the Asian monsoon sector during boreal summer and in the Australia monsoon sector during austral summer.**

Subseasonal Variability: MJO and BSISO

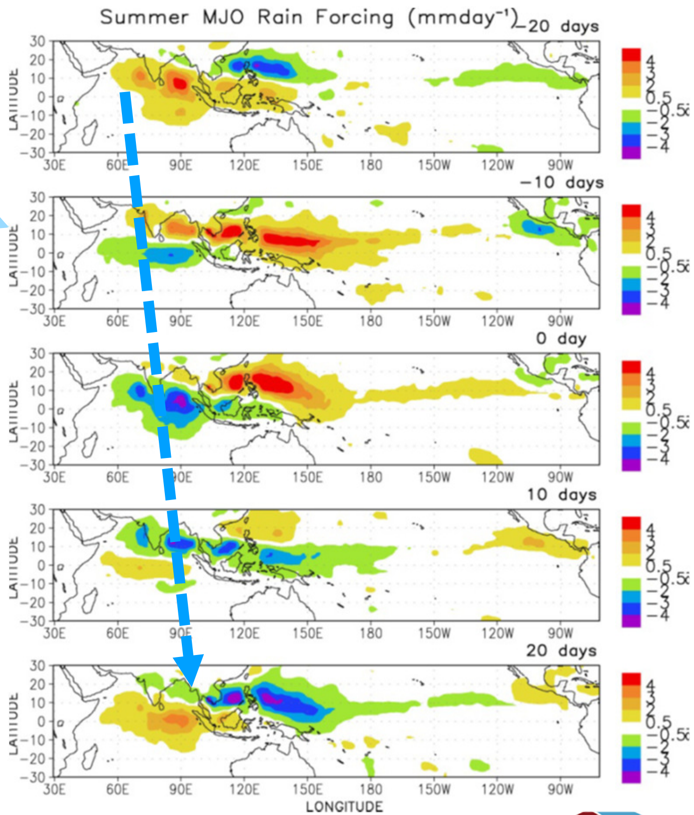
Madden-Julian Oscillation (MJO)



- **Boreal winter** mode
- **30-60-day** time scale
- Dominant **eastward** propagation along the equator
- Realtime Multivariate MJO (**RMM**) index (Wheeler and Hendon 2004)

- **Boreal summer** mode
- **30-60-day** & **biweekly** time scale
- **Northward/northwestward** propagation
- Affecting **monsoon onsets** (Wang and Xie 1997), **active/break phases** of monsoon (Annamalai and Slingo 2001), **monsoon seasonal mean** (Krishnamurthy and Shukla 2007)
- Possible source for **seasonal climate predictability** for precipitation (Lee et al. 2010) and extratropical atmospheric circulation (Ding and Wang; Lee et al. 2011)
- Realtime **BSISO indices** (Lee et al. 2013)

Boreal Summer Intraseasonal Oscillation (BSISO)



Figures: MJO working group website

Subseasonal Variability: Real-time BSISO Indices

Lee, June-Yi, Bin Wang, Matthew C. Wheeler, Xiouhua Fu, Duane E. Waliser, and In-Sik Kang, 2013: **Real-time multivariate indices for the boreal summer intraseasonal oscillation over the Asian summer monsoon region**. Climate Dynamics, 40, 493-509

May-Oct daily OLR (outgoing longwave radiation)

May-Oct daily U850 (850-hPa zonal wind)

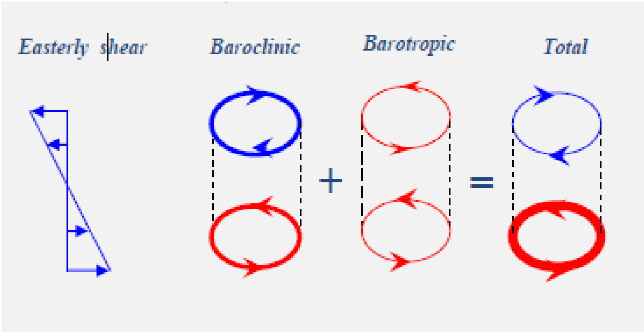
Removal of slow annual cycle & interannual anomalies

Normalization of each field
ASM Standard deviation is 27.58 W m^{-2} for OLR and 3.62 m s^{-1} for U850

Multivariate Empirical Orthogonal Function (EOF)

BSISO1: the first and second EOF modes
Canonical Northward Propagating Mode

BSISO2: the third and fourth EOF modes
The Asian Pre-Monsoon and Onset Mode



$$\frac{D\zeta_+}{Dt} = -v_+ + U_T\left(\frac{DD_-}{Dy} - \frac{D\zeta_-}{Dx}\right)$$

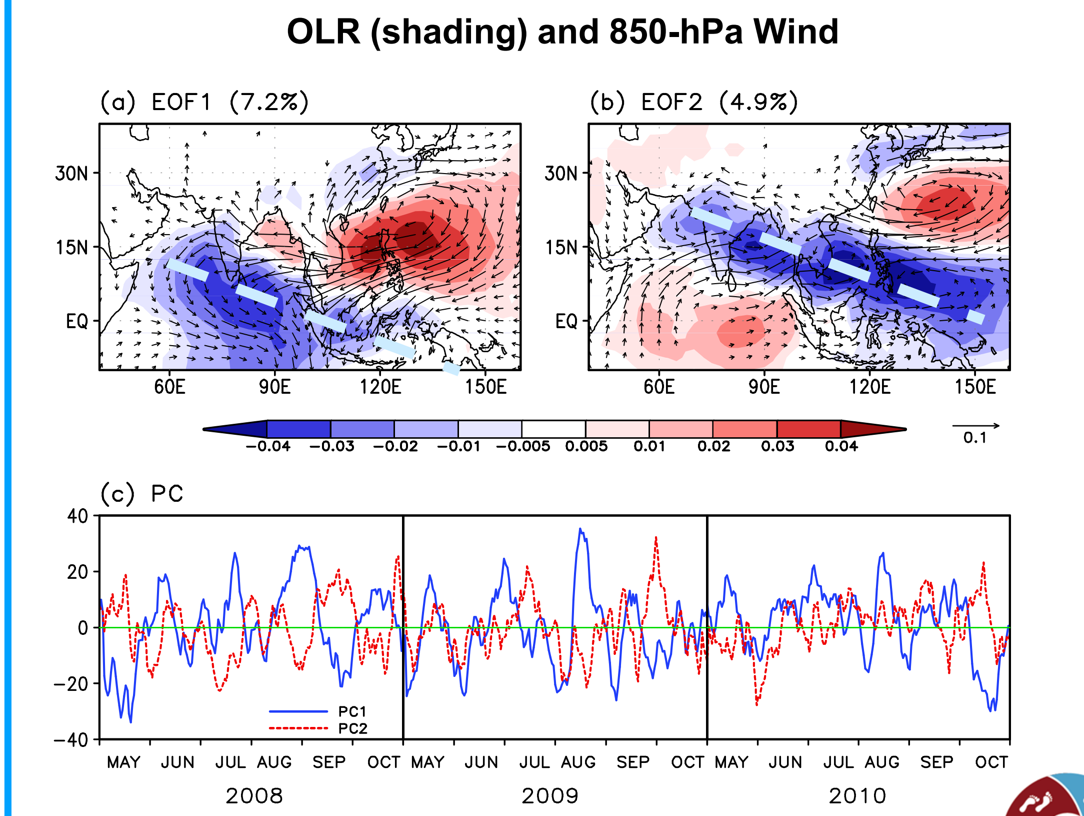
An easterly shear leads to the amplification of Rossby wave (RW) responses in the lower level (Wang and Xie 1996)

*** Filtering is not applied to define BSISO index for real-time monitoring and forecasting purpose.**

BSISO1: Canonical Northward Propagating mode

- **BSISO1, consisting of EOF1 and EOF2**, represents the **canonical northward and north-eastward propagating ISO** over the ASM region **during the entire warm season from May to October** with **quasi-oscillating periods of 30-60 days in conjunction with the eastward propagating MJO**.

- **Spatial Characteristics**: **Rossby wave like pattern** with a **northwest to southeast slope.** Out-of-phase relationship of convection between the ISM and WNPSM. Quadrupole pattern in EOF2.



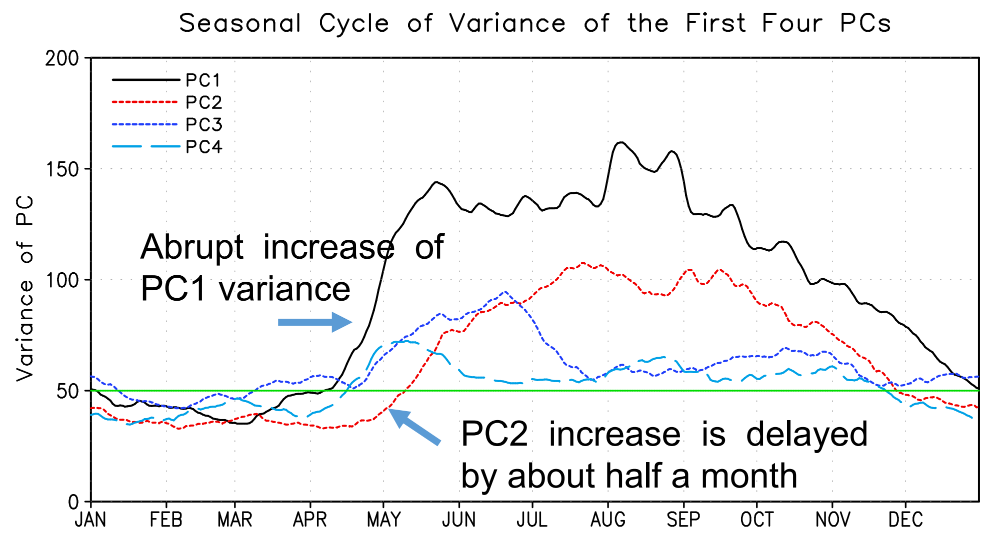
Lee et al. (2013 Clim Dyn)

BSISO1: Canonical Northward Propagating mode

- **BSISO1, consisting of EOF1 and EOF2**, represents the **canonical northward and north-eastward propagating ISO** over the ASM region **during the entire warm season from May to October** with **quasi-oscillating periods of 30-60 days in conjunction with the eastward propagating MJO**.

- **Spatial Characteristics**: **Rossby wave like pattern** with a **northwest to southeast slope.** Out-of-phase relationship of convection between the ISM and WNPSM. Quadrupole pattern in EOF2.

- **Seasonal cycle of variance:** Large overall variance from May to October. The PC1 has an abrupt increase of variance around late April and early May while the PC2 variance tends to be delayed by about half a month.



Lee et al. (2013 Clim Dyn)

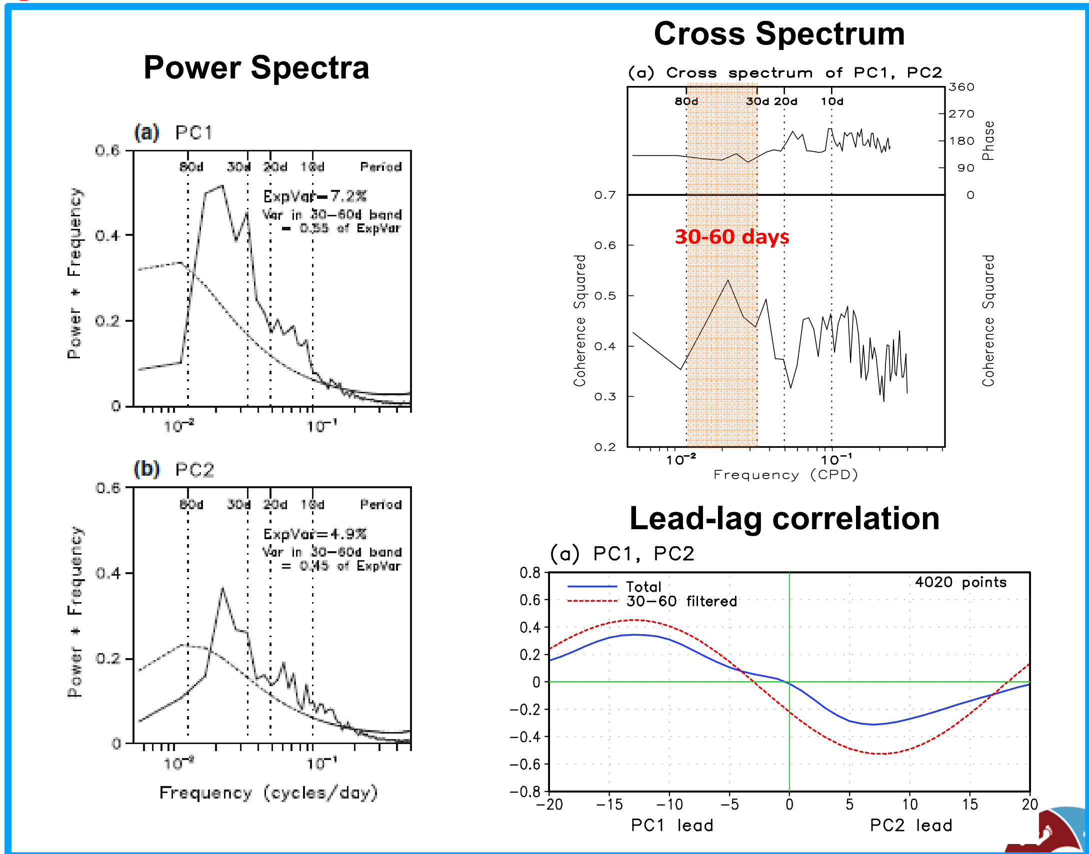
BSISO1: Canonical Northward Propagating mode

- **BSISO1, consisting of EOF1 and EOF2**, represents the **canonical northward and north-eastward propagating ISO** over the ASM region **during the entire warm season from May to October** with **quasi-oscillating periods of 30-60 days in conjunction with the eastward propagating MJO**.

- **Spatial Characteristics**: **Rossby wave like pattern** with a **northwest to southeast slope.** Out-of-phase relationship of convection between the ISM and WNPSM. Quadrupole pattern in EOF2.

- **Seasonal cycle of variance:** Large overall variance from May to October. The PC1 has an abrupt increase of variance around late April and early May while the PC2 variance tends to be delayed by about half a month.

- **Coherence and lead-lag relationship:** The greatest coherence in the 30-60-day range between the PC1 and PC2 with a 90° phase difference, indicating **the PC1 leads PC2 by a quarter cycle**. The PC1 tends to lead PC2 by about 13 days with a maximum correlation of 0.34 for non-filtered data, and 0.45 for 30-60-day filtered data.

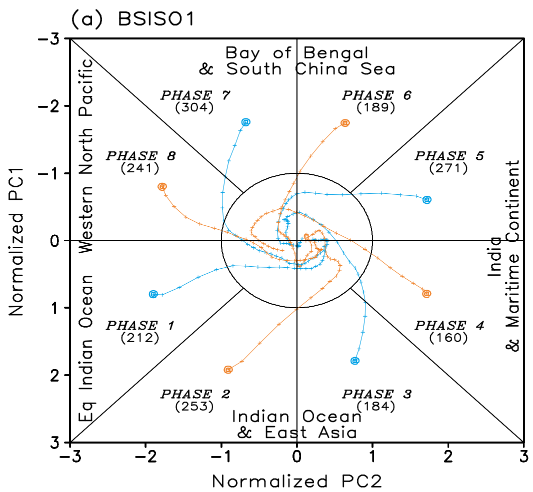


Lee et al. (2013 Clim Dyn)

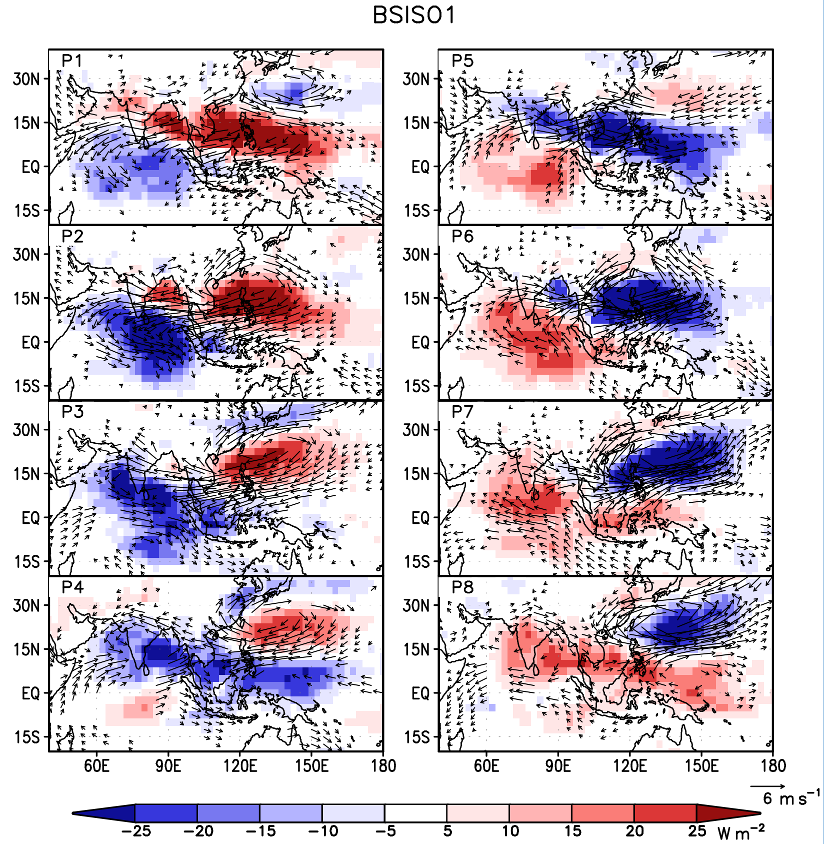
BSISO1: Its Life Cycle

- The BSISO1 convective activity **first appears over the equatorial Indian Ocean** in Phase 1, and then propagates northeastward reaching **the Indian Subcontinent in Phase 3** and **the Bay of Bengal in Phases 4-5**.
- The convection over the equatorial Indian Ocean also propagates eastward from Phase 1 and reaches the **Maritime Continent in Phases 3-4**. Then, the convection propagates northward reaching **the South China Sea in Phase 7**, the **WNP in Phase 8**.
- **Over East Asia, active convection occurs in Phases 3-4.**

Given the strong lead-lag behavior of PC1 and PC2, it is convenient to diagnose the state of BSISO1 as a point in the two-dimensional phase space.



Life cycle composite of OLR (shading) and 850-hPa wind anomalies

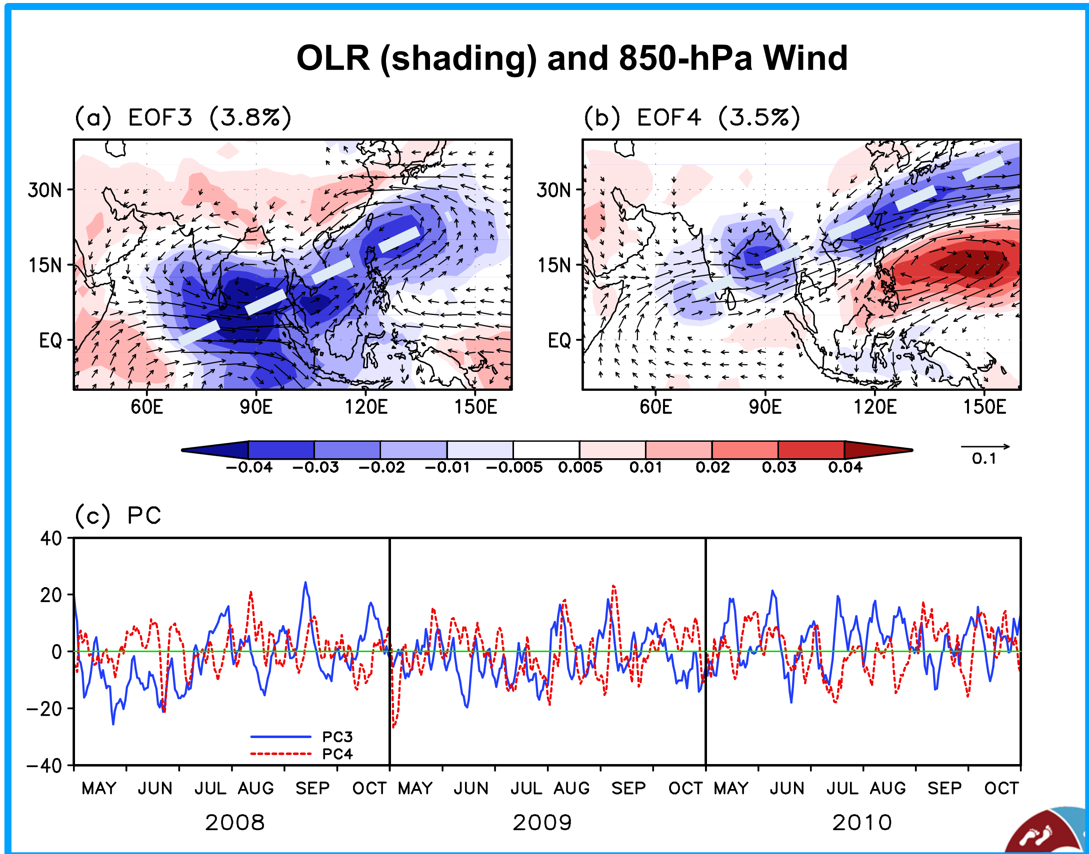


Lee et al. (2013 Clim Dyn)

BSISO2: The Asian Pre-Monsoon and Onset Mode

- **BSISO2, consisting of EOF3 and EOF4**, captures the **northward/northwestward propagating** variability with periods of **10-30 days** during primarily the **pre-monsoon and monsoon-onset season** that is not related with the eastward propagating MJO.

- **Spatial Characteristics**: **Elongated and front-like pattern** with a **southwest to northeast slope**. In-phase relationship of convection between the ISM and WNPSM.



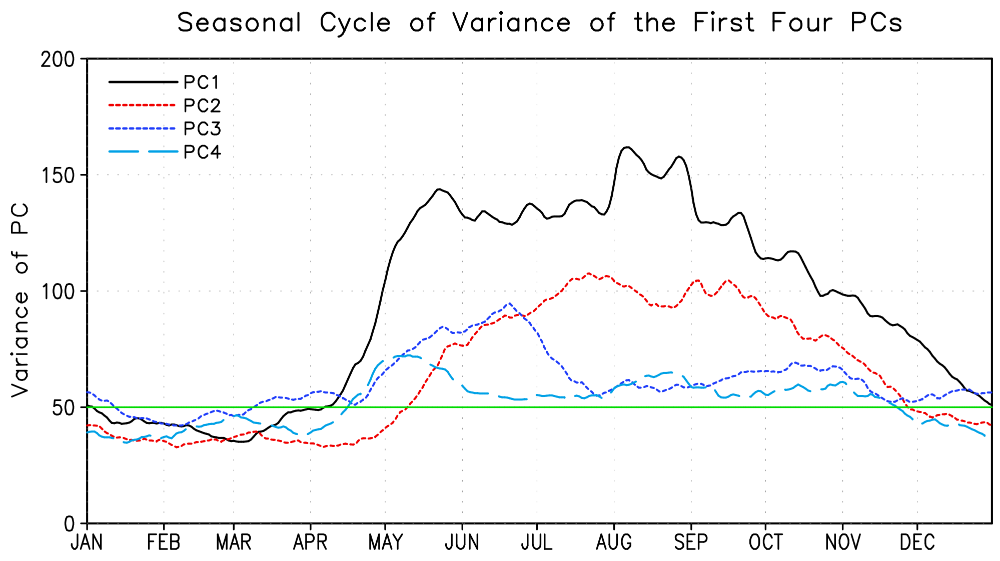
Lee et al. (2013 Clim Dyn)

BSISO2: The Asian Pre-Monsoon and Onset Mode

- **BSISO2, consisting of EOF3 and EOF4**, captures the **northward/northwestward propagating** variability with periods of **10-30 days** during primarily the **pre-monsoon and monsoon-onset season** that is not related with the eastward propagating MJO.

- **Spatial Characteristics**: **Elongated and front-like pattern** with a **southwest to northeast slope**. In-phase relationship of convection between the ISM and WNPSM.

- **Seasonal cycle of variance:** Maximum variance **from late May to early July**, corresponding to the pre-monsoon and onset period.



Lee et al. (2013 Clim Dyn)

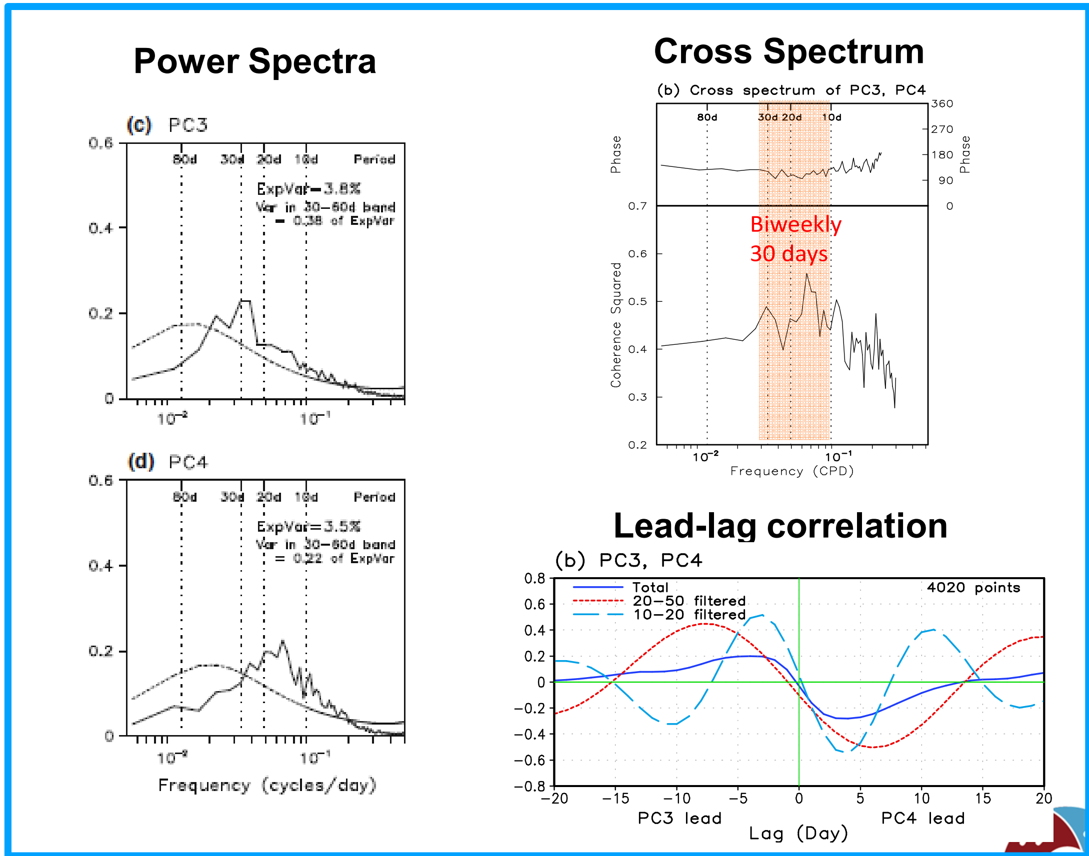
BSISO2: The Asian Pre-Monsoon and Onset Mode

- **BSISO2, consisting of EOF3 and EOF4**, captures the **northward/northwestward propagating** variability with periods of **10-30 days** during primarily the **pre-monsoon and monsoon-onset season** that is not related with the eastward propagating MJO.

- **Spatial Characteristics**: **Elongated and front-like pattern** with a **southwest to northeast slope**. In-phase relationship of convection between the ISM and WNPSM.

- **Seasonal cycle of variance:** Maximum variance **from late May to early July**, corresponding to the pre-monsoon and onset period.

- **Coherence and lead-lag relationship:** High coherence in the 10-20 days (biweekly) range and around 30 days with 90° phase difference between the PC3 and PC4, indicating PC3 leads PC4 by quarter cycle. PC3 tends to lead PC4 by about 3-4 days for 10-20 period and 7-8 days for 30 day period.

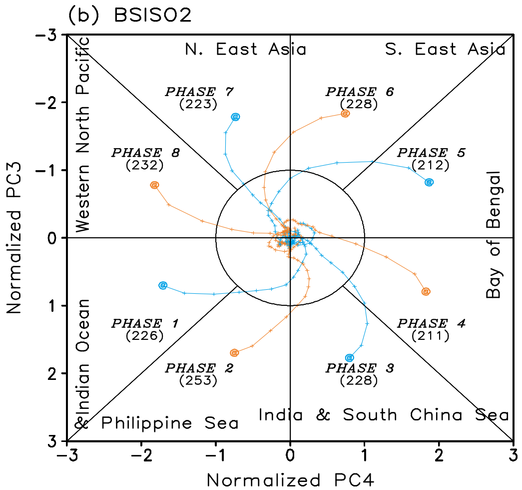


Lee et al. (2013 Clim Dyn)

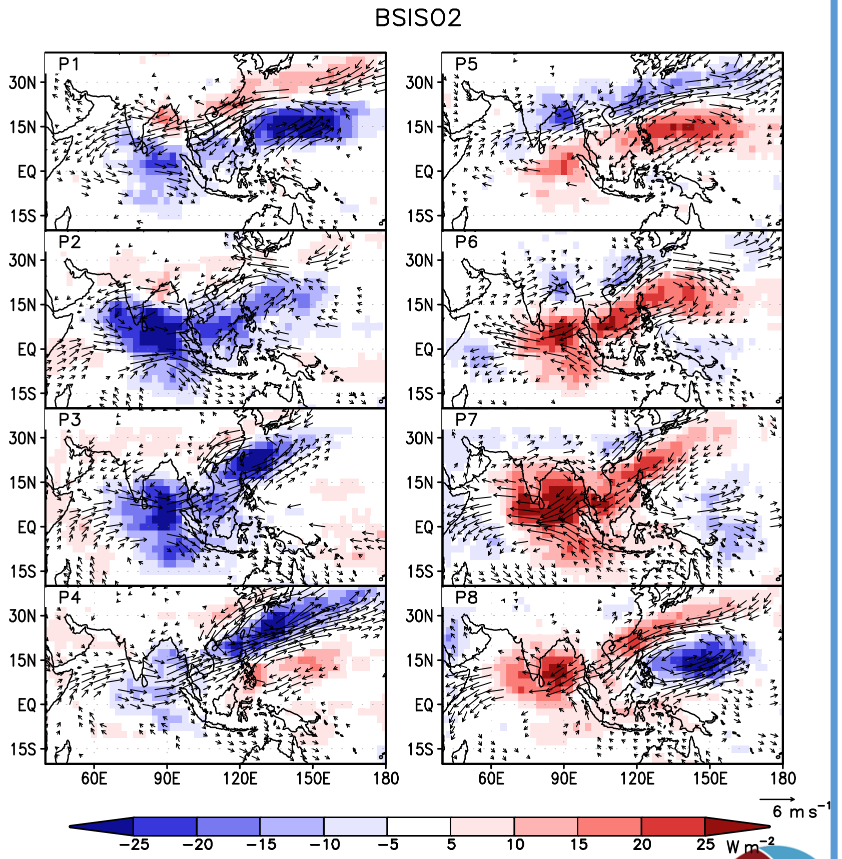
BSISO2: The Life Cycle

- The life cycle of BSISO2 is shorter than BSISO1.
- The BSISO2 **initiates at the equatorial western Pacific**. The convection is located in the equatorial Indian Ocean and **Philippine Sea in Phase 1** and then propagates northwestward over the Indian longitude as well as the WNP-EA region.
- The BSISO2 may represent **stepwise monsoon onset** over the ASM region.

Given the strong lead-lag behavior of PC3 and PC4, it is convenient to diagnose the state of BSISO2 as a point in the two-dimensional phase space.



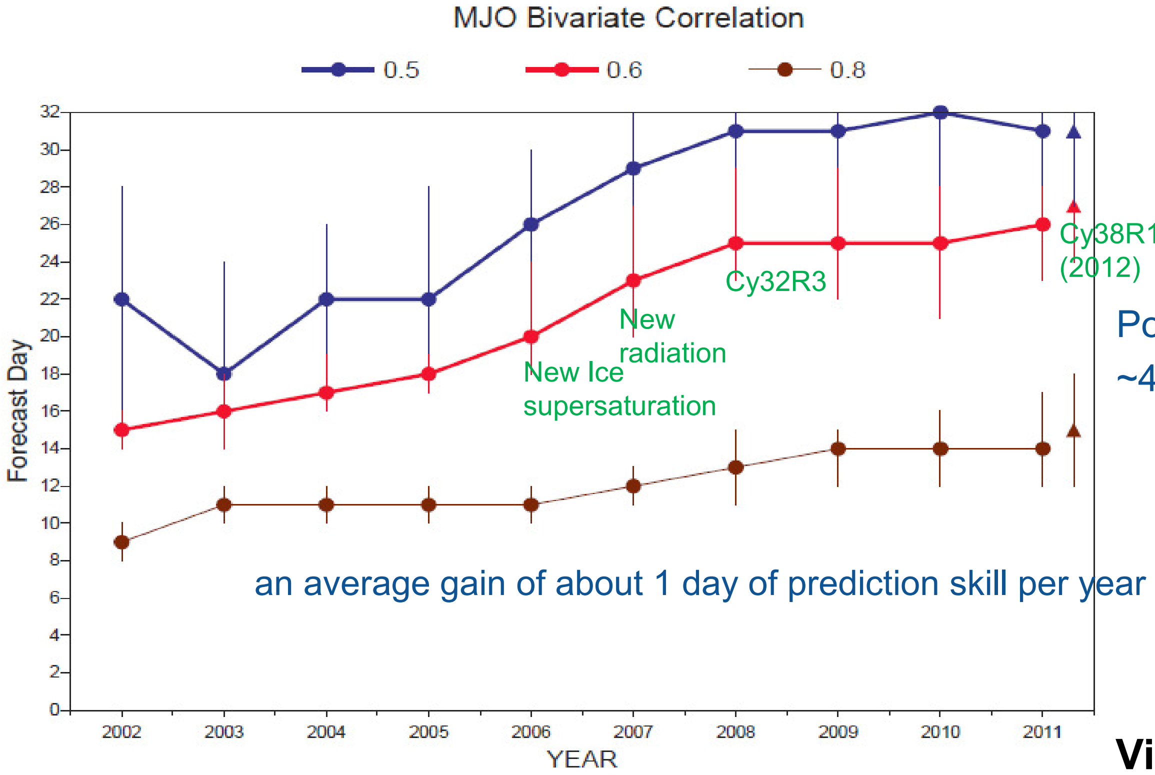
Life cycle composite of OLR (shading) and 850-hPa wind anomalies



Lee et al. (2013 Clim Dyn)

MJO Predictability and Prediction

Evolution of ECMWF MJO Forecast Skill Score



Cy41R1 (2015) ?

Bivariate Correlation Skill

$$\mathrm{COR}(\tau) = \frac{\sum_{i=1}^{N} [a_{1i}(t)b_{1i}(t) + a_{2i}(t)b_{2i}(t)]}{\sqrt{\sum_{i=1}^{N} [a_{1i}^2(t) + a_{2i}^2(t)]}\sqrt{\sum_{i=1}^{N} [b_{1i}^2(t) + b_{2i}^2(t)]}},$$

Potential predictability: ~45 days

Vitart (2014 QJRMS)

Reforecast period: 1995 – 2011

BSISO1 Predictability and Prediction

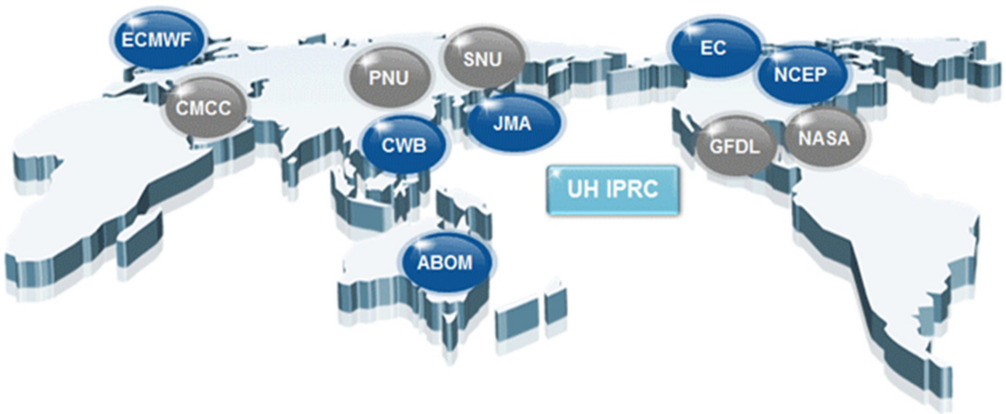
Description of Models and Experiments in ISVHE

ISVHE

The ISVHE Project

Intraseasonal Variability Hindcast Experiment

The **ISVHE** is a coordinated multi-institutional ISV hindcast experiment supported by **APCC, NOAA CTB, CLIVAR/AAMP, YOTC/MJO TF, and AMY.**



ONE-TIER SYSTEM

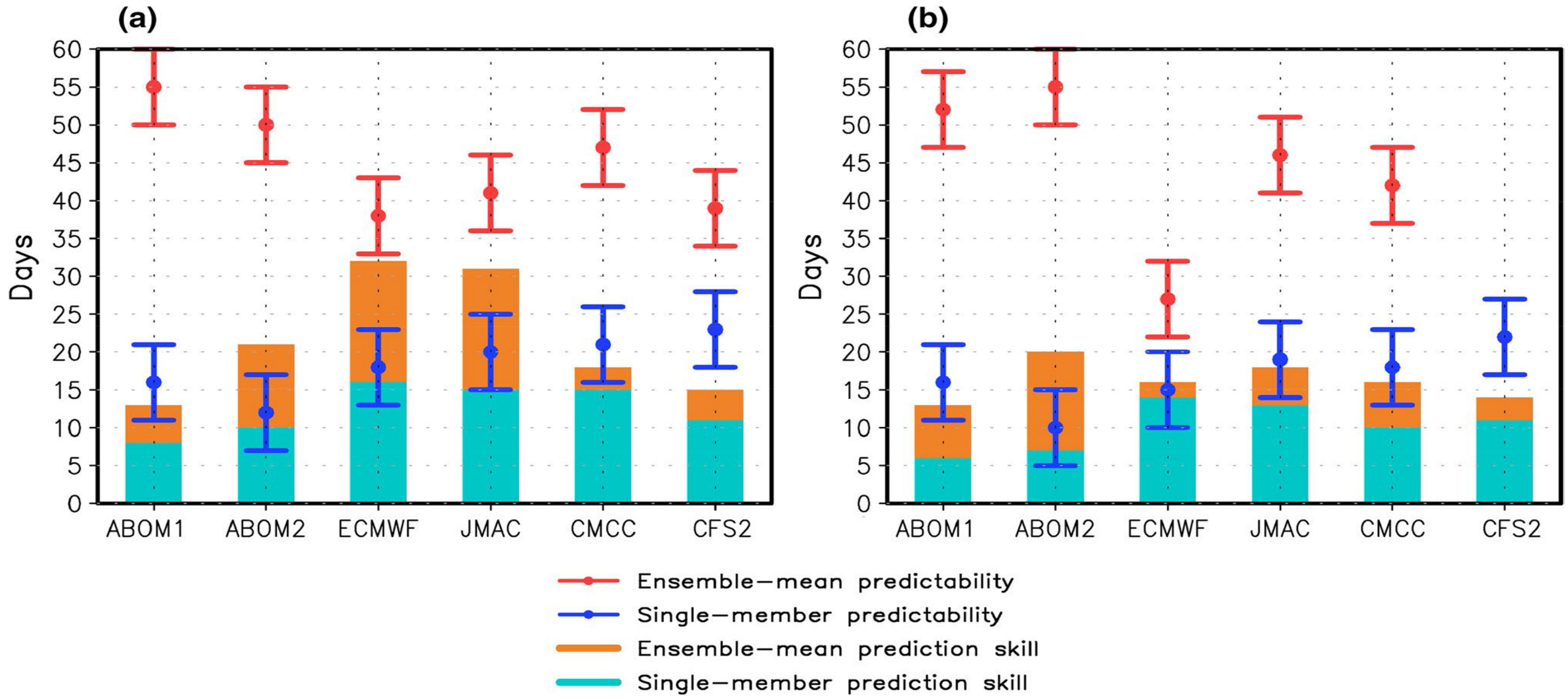
	Model	Control Run	ISO Hindcast		
			Period	Ens No	Initial Condition
ABOM	POAMA 1.5 & 2.4 (ACOM2+BAM3)	CMIP (100yrs)	1980-2006	10	The first day of every month
CMCC	CMCC (ECHAM5+OPA8.2)	CMIP (20yrs)	1989-2008	5	Every 10 days
ECMWF	ECMWF (IFS+HOPE)	CMIP(11yrs)	1989-2008	15	Every 15 days
GFDL	CM2 (AM2/LM2+MOM4)	CMIP (50yrs)	1982-2008	10	The first day of every month
JMA	JMA CGCM	CMIP (20yrs)	1989-2008	6	Every 15 days
NCEP/CPC	CFS v1 (GFS+MOM3) & v2	CMIP 100yrs	1981-2008	5	Every 10 days
PNU	CFS with RAS scheme	CMIP (13yrs)	1981-2008	3	The first day of each month
SNU	SNU CM (SNUAGCM+MOM3)	CMIP (20yrs)	1989-2008	1	Every 10 days
UH/IPRC	UH HCM	CMIP (20yrs)	1994-2008	6	Every 10 days

TWO-TIER SYSTEM

	Model	Control Run	ISO Hindcast		
			Period	Ens No	Initial Condition
CWB	CWB AGCM	AMIP (25yrs)	1981-2005	10	Every 10 days
MRD/EC	GEM	AMIP (21yrs)	1985-2008	10	Every 10 days

BSISO1 Predictability and Prediction

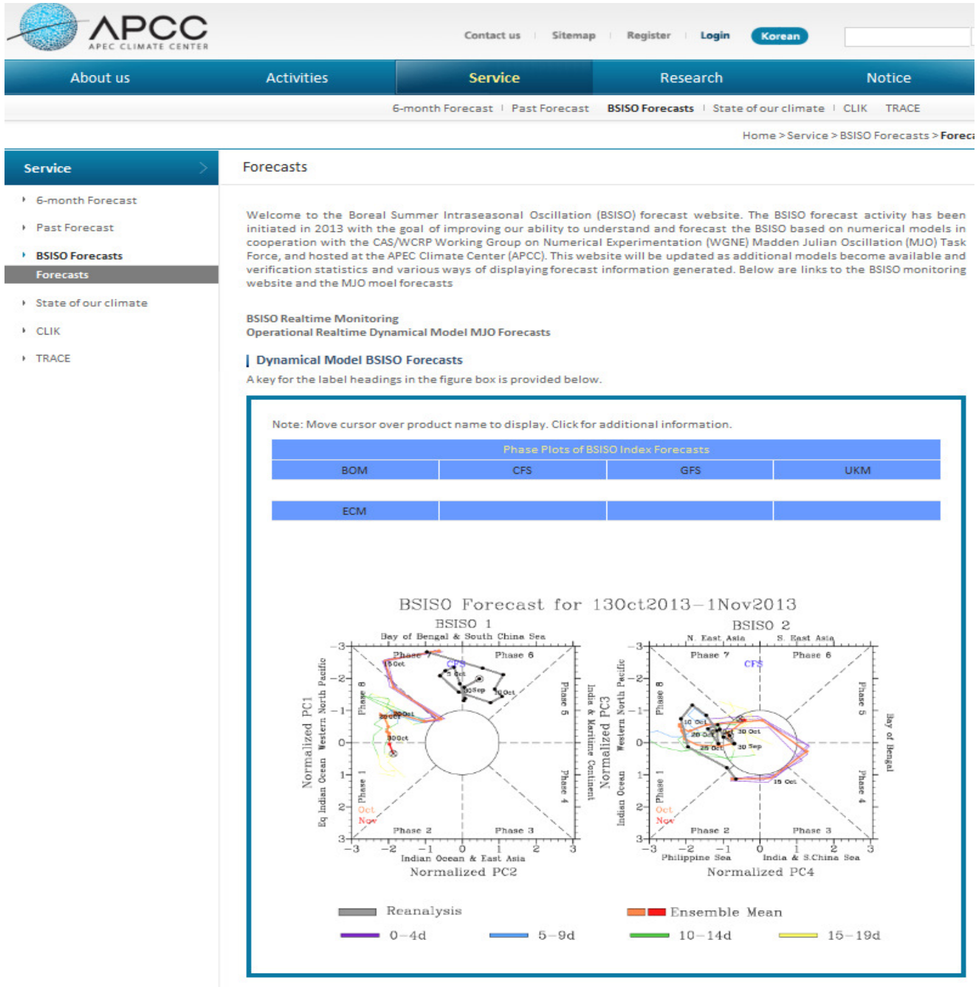
The Predictability and prediction skill in BSISO in (a) strong and (b) weak BSISO initial condition



	Strong BSISO IC	Weak BSISO IC
Prediction skill	~ 3 weeks	~2 weeks
Predictability	~ 6weeks	~6 weeks

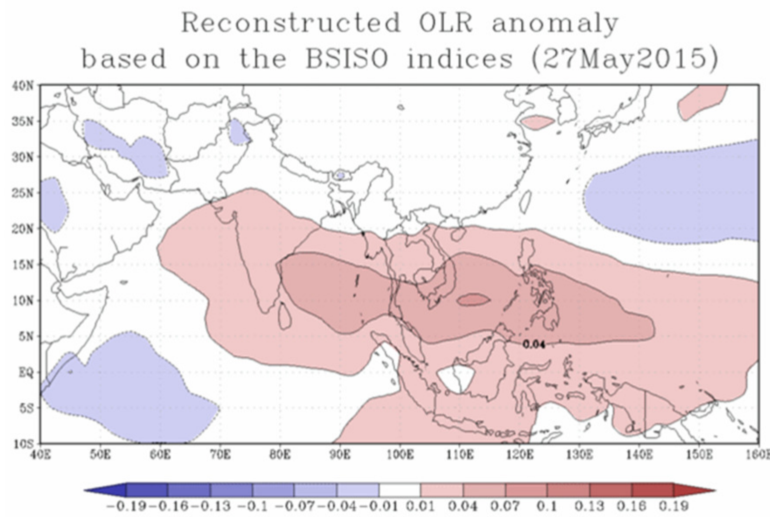
Lee et al. 2015 Clim Dyn
Based on Intraseasonal Hindcase Experiment (ISVHE)

BSISO Real-time Monitoring and Forecast at APCC



BSISO Monitoring and Real-time forecast hosted by APCC and endorsed by WMO WGNE and MJOTF

Forecast are from five operational models in ECMWF and UKMO in Europe, NCEP in USA, and CWB in Taiwan



BSISO Real-time Monitoring and Forecast at APCC

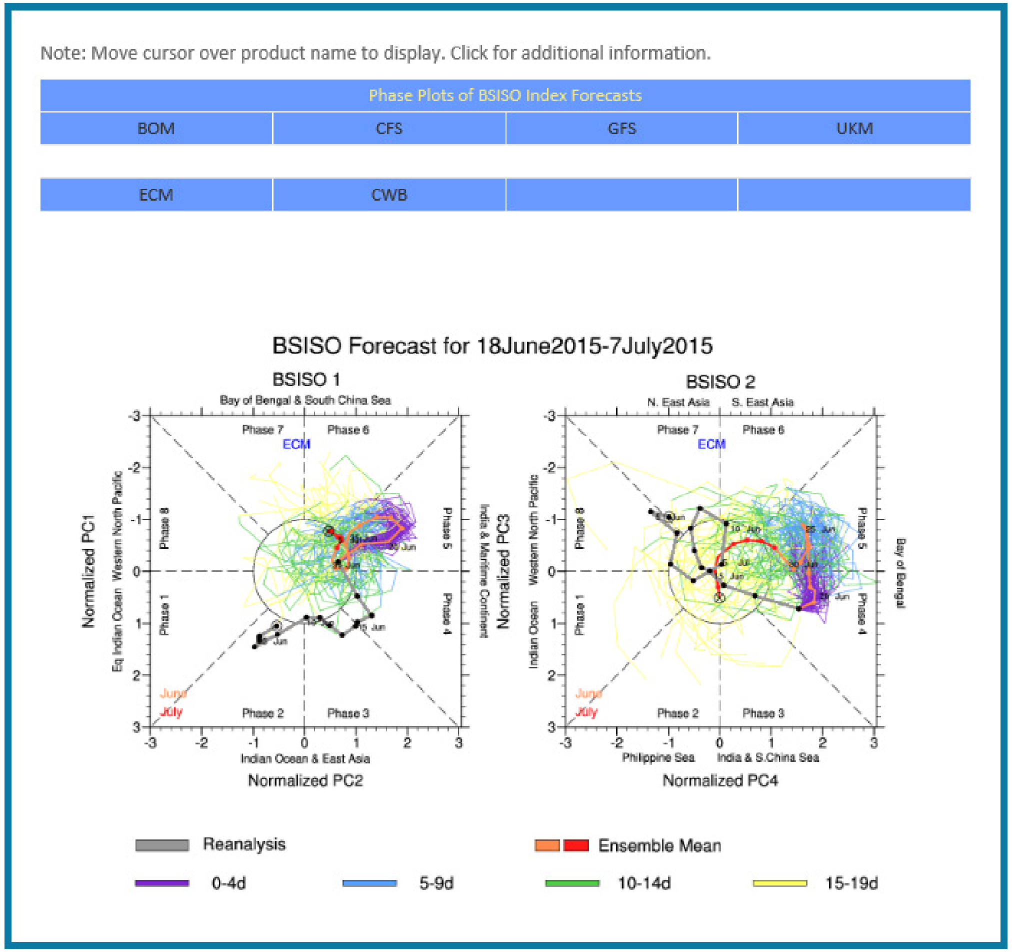
In cooperation with the WGNE MJO TF, APCC has hosted real-time monitoring and forecast of BSISO indices since 2013 summer.

Participating Institutes

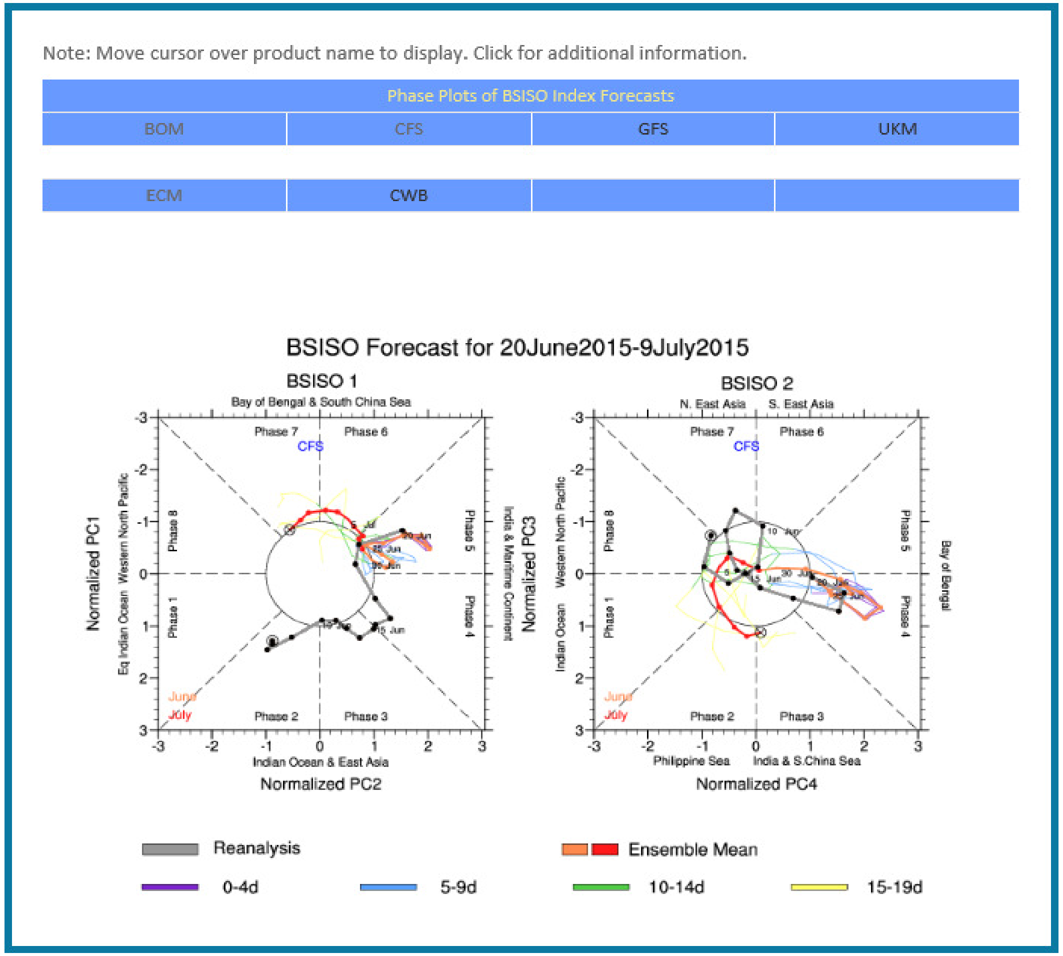
Institute	Model	Ensemble Size	Forecast Period	Update frequency	Resolution
NCEP	Climate Forecast System	4	40 days	Once a day	T126 L64
	Global Forecast System	1	16 days	Once a day	T574, T190 L64
	Global Ensemble Forecast System	20	35 days	ASAP	
Australia	POAMA 2.4 multi-week model	33	40 days	Twice per week	T47 L17
ECMWF	ECMWF Ensemble Prediction System	51	32 days	Twice per week	T639, T319 L62
UK Met Office	MOGREPS-15	24	15 days	Once a day	60km L70
Taiwan CWB	*CWB EPS T119*	*1*	*40 days*	*From 2015*	
CMC	*GEMDM_400x200*	*20*	*15 days*	*ASAP*	

BSISO Real-time Monitoring and Forecast at APCC

ECMWF Forecast

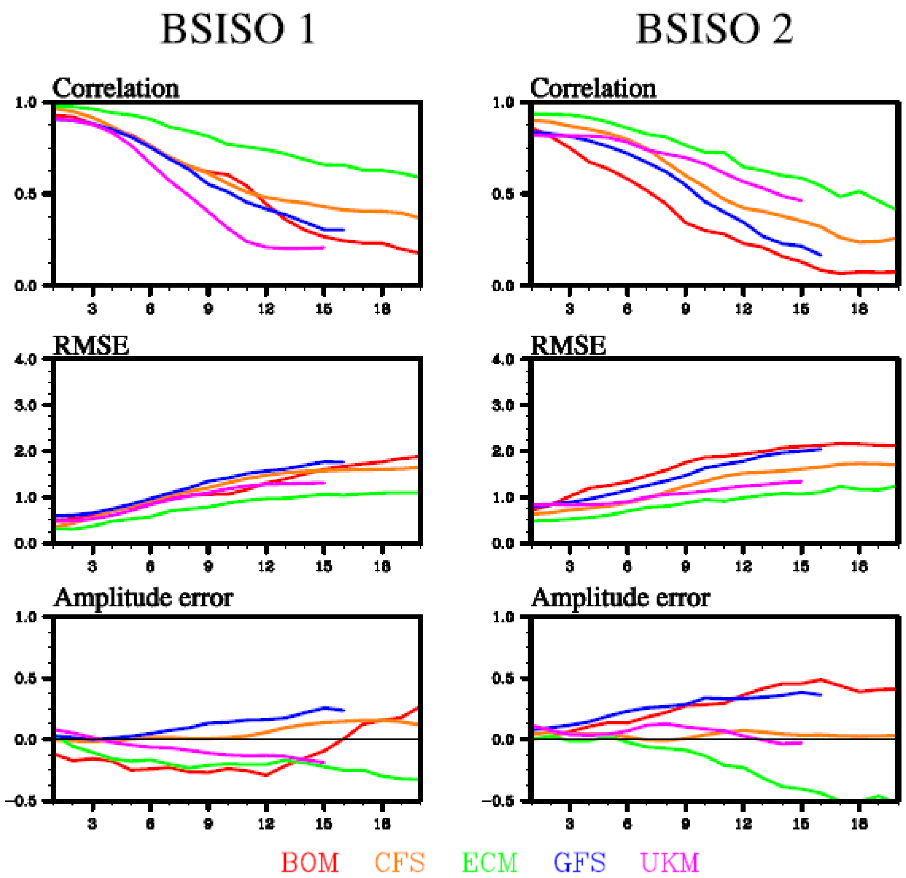


NCEP CFS Forecast



BSISO Real-time Monitoring and Forecast at APCC

Assessment of real-time forecast skill for the BSISO1 and BSISO2 during May-October for 2013-2014



Models have a useful forcast skill of 0.5 for BSISO1 (BSISO2) up to 10-20 days (10-16 days) for the two years of 2013-2014.

Summary of Part II

- Given the extreme importance of the BSISO, we have made an effort to define new indices to assist in real-time monitoring and forecast applications of the BSISO. The BSISO indices proposed in this study were designed to better represent fractional variance and the observed northward/northwestward propagating ISO over the ASM region than the RMM index.

- **BSISO1, consisting of EOF1 and EOF2**, represents **the canonical northward and north-eastward propagating ISO over the ASM region** during the entire warm season from May to October with quasi-oscillating periods of 30-60 days in conjunction with the eastward propagating MJO.

- **BSISO2, consisting of EOF3 and EOF4**, captures **the northward/northwestward propagating variability with periods of 10-30 days** during primarily the pre-monsoon and monsoon-onset season.

- The ISVHE has been coordinated to better understand the physical basis for prediction and determine predictability of ISO. Analysis of ISVHE data indicates that the **BSISO1 is predictable up to 6 weeks** but the state-of-the-art coupled models have a useful skill of 0.5 for **the BSISO1 and BSISO2 up to 15-20 days and 10-15 days**, respectively.

Content

Estimation of Predictability

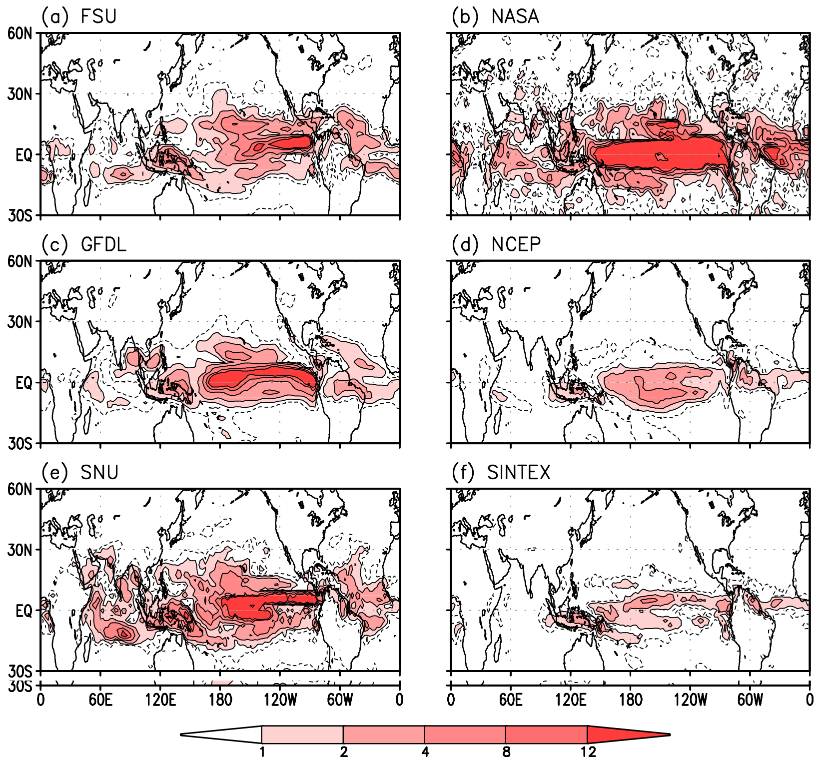
How to determine **predictability** of seasonal climate anomalies remains an unresolved issue!

We propose a new way to estimate seasonal climate predictability based on the **Predictable Mode Analysis (PMA)**, an **integral approach combining empirical analysis, physical reasoning and prediction** (Wang et al. 2007, 2013, 2015; Lee et al. 2011, 2013; Lee and Wang 2012; Lee and Ha 2015; and many others).

1. Conventional S/N Ratio Approach using One Model

The conventional signal-to-noise ratio approach is highly model-dependent (Charney and Shukla 1981; Shukla 1998; Rowell et al. 1998; Kang et al. 2004; Kang and Shukla 2006 and many others).

Signal-to-noise ratio for JJA Precipitation



✓ **Total Var = Signal Var (σ^2_{SST}) + Noise Var (σ^2_{INR})**

$$\sigma^2_{SST} = \sigma^2_{EN} - \frac{1}{n}\sigma^2_{INR} \qquad \sigma^2_{EN} = \frac{1}{N-1}\sum_{i=1}^{N}(\overline{x_i} - \overline{\overline{x}})^2$$

$$\overline{\overline{x}} = 1/(Nn)\sum_{i=1}^{N}\sum_{j=1}^{n} x_{ij}$$

$$\sigma^2_{INR} = \frac{1}{N(n-1)}\sum_{i=1}^{N}\sum_{j=1}^{n}(x_{ij} - \overline{x_i})^2$$

✓ **Signal-to-noise ratio**
= Signal Var / Noise Var

2. Mean Square Error (MSE) method based on multi models

(Kumar et al. 2007, J Climate)

Predictability limits for seasonal climate variability depend on **the fraction of external and internal variability**. *From the observed data alone, separation of the total seasonal variance into its external and internal components remains difficult and controversial issue*.

- **Basic Idea**: **The expected value of MSE** is the sum of three terms: **the observed internal variability**, the internal variability of the ensemble mean of model simulations, and a term that is the error in model's anomaly prediction. We can find the minimum value of MSE irrespective of which model it came from at each geographical location, and **the spatial map of the minimum value of MSE is the best estimate for the observed internal variability.**

$$MSE = (M - O)^2 = \sigma_{oi}^2 + \sigma_{mi}^2 + < (\mu_m - \mu_o)^2 >$$

- **Limitation**: **Since models have large anomaly errors related to slowly varying boundary forcing, the estimation always underestimates predictability.**

3. Predictable Mode Analysis (PMA) method

(Wang et al. 2007, 2013, 2015; Lee et al. 2011, 2013; Lee and Wang 2012; Lee and Ha 2015; and many others)

The **PMA** is an **integral approach combining empirical analysis, physical reasoning and prediction**.

- **The empirical analysis detects most important patterns**
- **The understanding of physical processes governing these patterns establishes their physical basis**
- **The empirical and dynamical models' predictions determine predictable modes.**

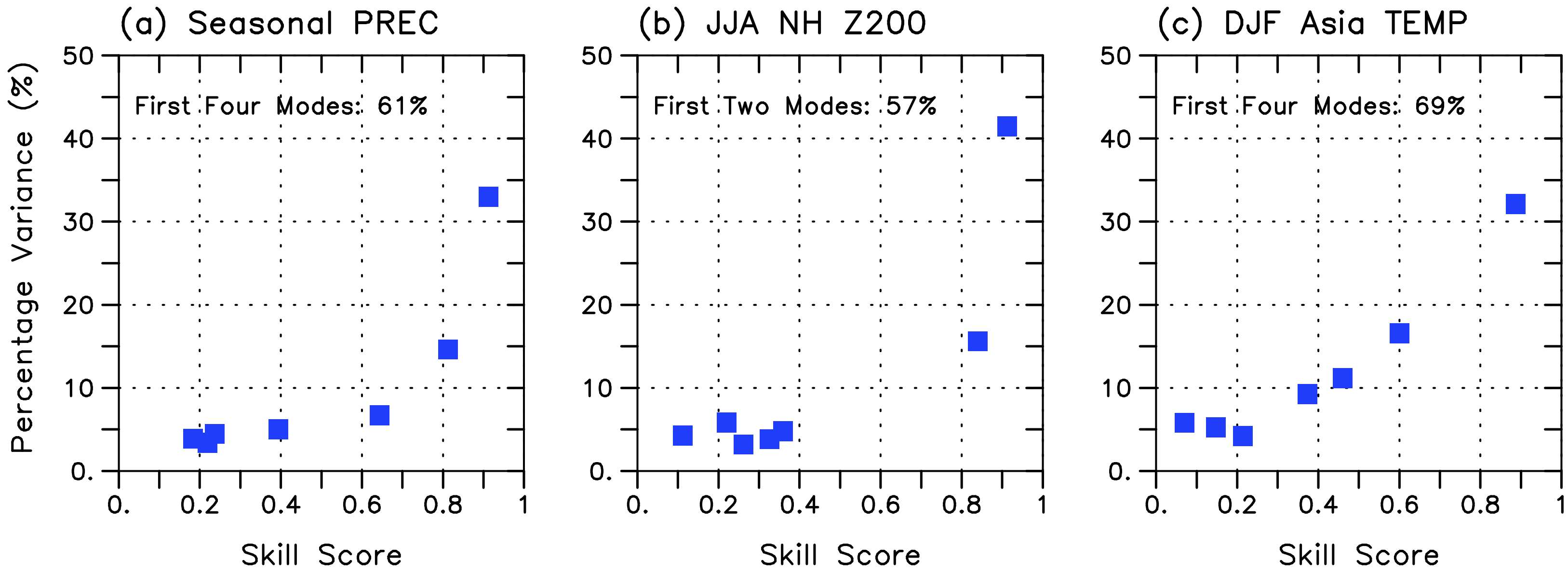
► **The potential predictability can then be estimated by the fractional variance accounted for by the "predictable" modes.**

► **Limitation:** The method depends on the identification method of predictable modes and models' quality for capturing major modes of the observed variability.

Application of the PMA

(Wang et al. 2007, 2013, 2015; Lee et al. 2011, 2013; Lee and Wang 2012; Lee and Ha 2015; and many others)

The percentage variances that are accounted for by the observed first 7 modes and the skill score on predicting the modes by one-month lead MME.



Wang et al. (2007, CLIVAR)
Wang et al. (2015 Clim Dyn)

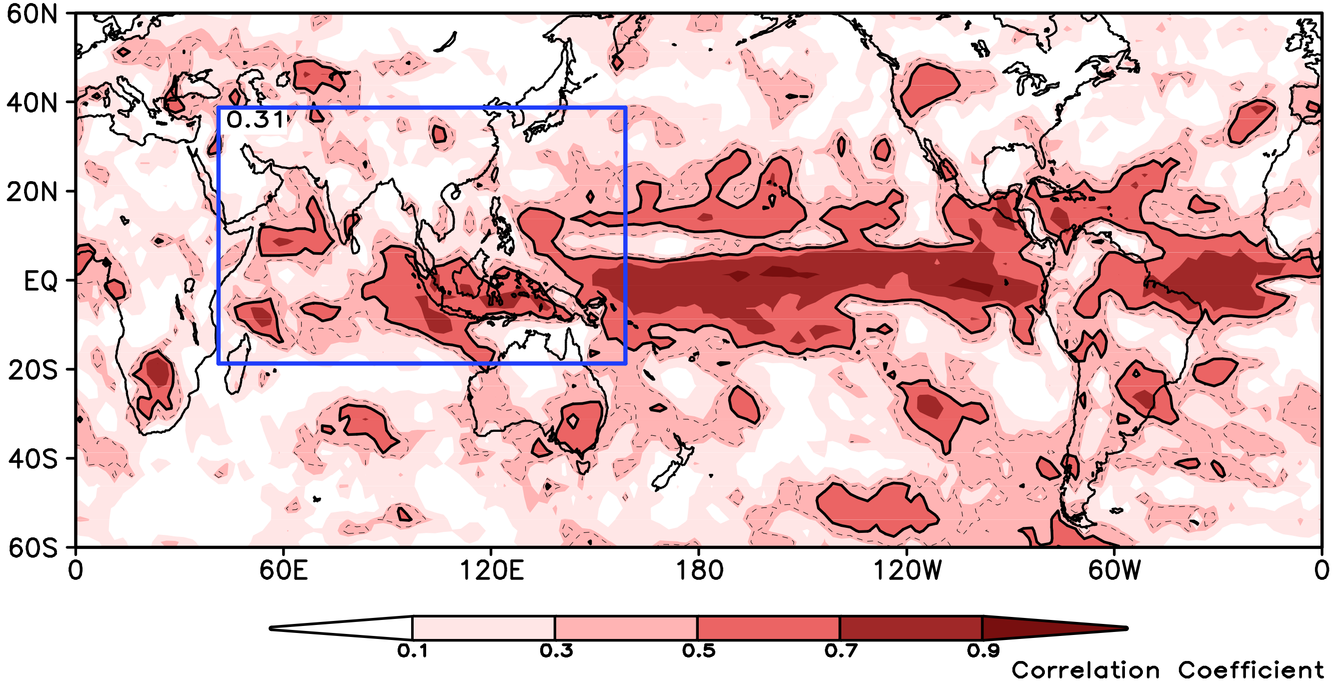
Lee et al. (2011 Clim Dyn)

Lee et al. (2013 Clim Dyn)

Application of the PMA to Asian Summer Precip Predictability

The temporal correlation coefficient (TCC) skill of MME for JJA precipitation

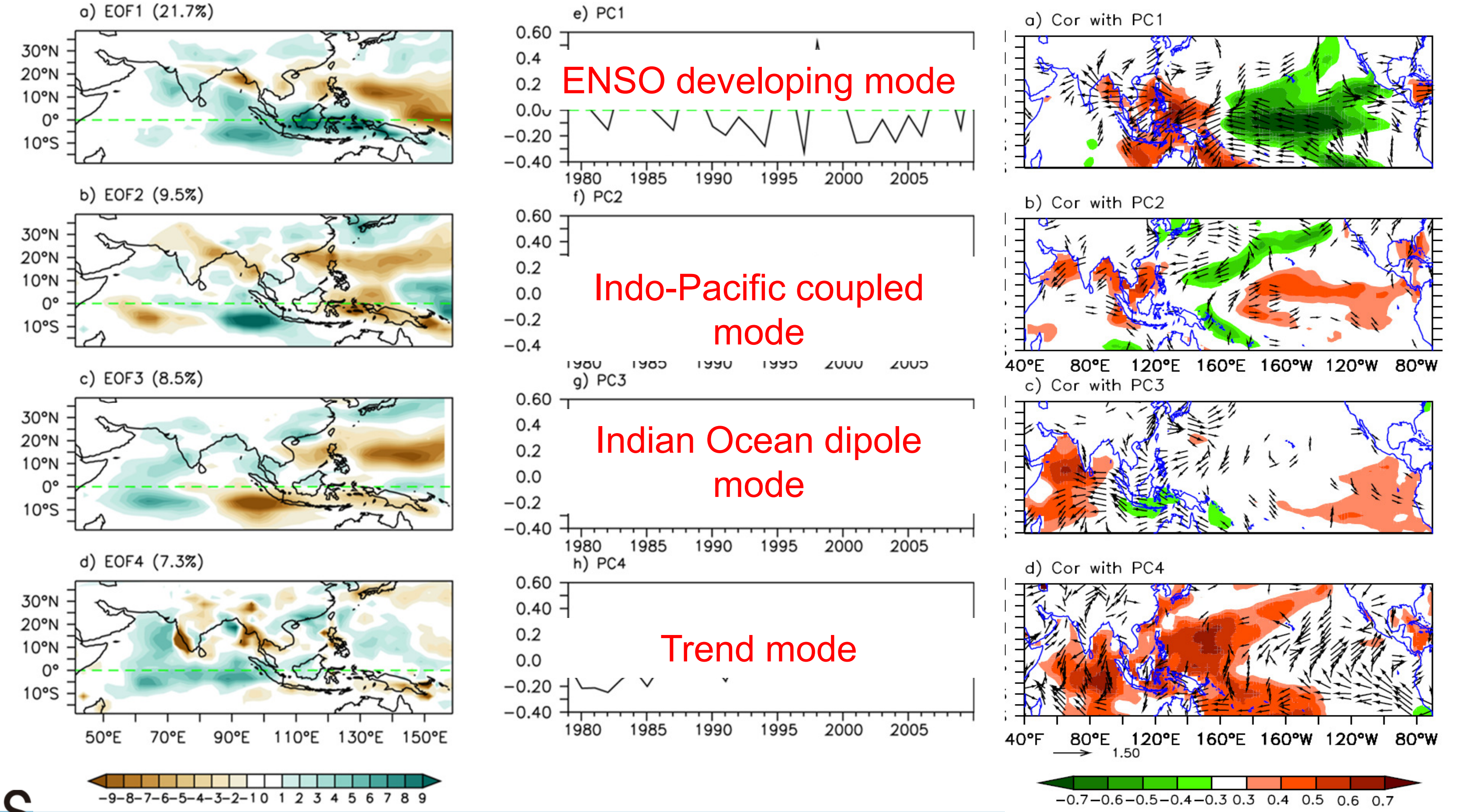
Initiated from June 1st for 1979 - 2010



The TCC skill for JJA precipitation prediction using the four coupled models' multi-model ensemble (MME) initiated from the first day of June for the 32 years of 1979-2010. Blue box indicates the Asian Summer monsoon (ASM) region used in this study (20°S-40°N, 40°E-160°E) and the number in the upper-left corner of the blue box is the averaged TCC skill over the AAM region.

Application of the PMA to Asian Summer Precip Predictability

- The empirical analysis detects **the four major modes of ASM precipitation variability.**
- The understanding of physical processes governing these patterns establishes **their physical basis**

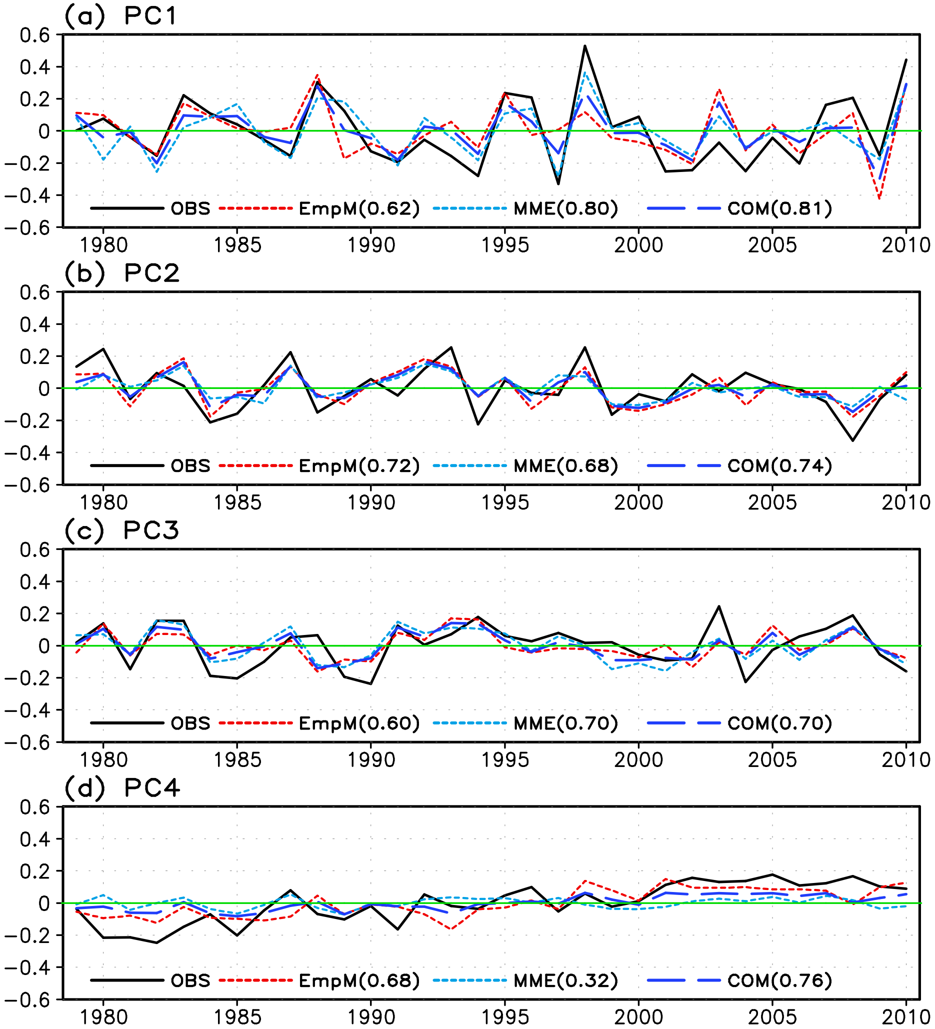


Wang et al. (2015 Clim Dyn)

Application of the PMA to Asian Summer Precip Predictability

- **The four major modes** can be predicted reasonably well by a physical-empirical prediction model as well as the atmosphere-ocean coupled models' multi-model ensemble (MME).

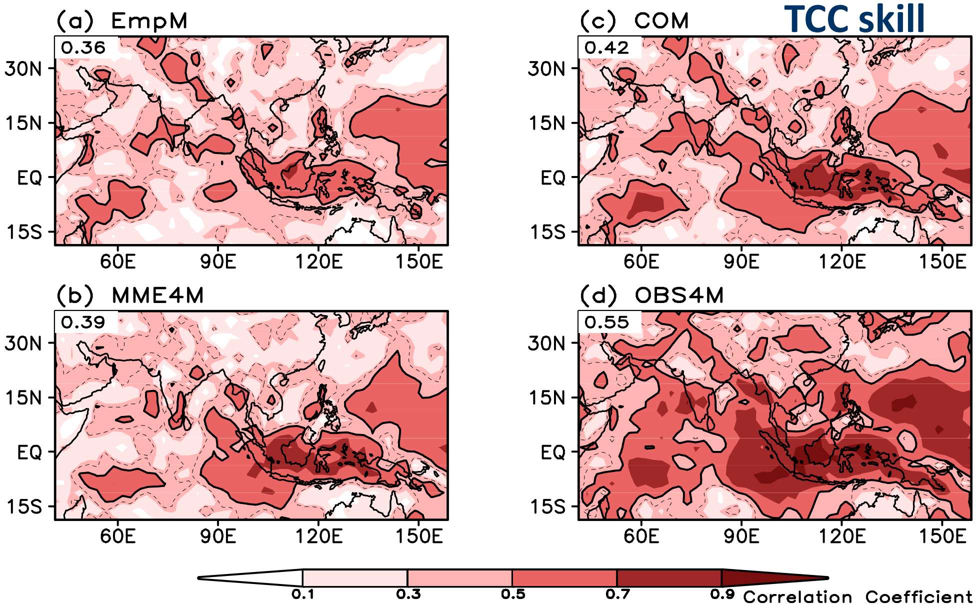
- The empirical and dynamical coupled models have comparable prediction skills and complementary strengths in predicting the ASM precipitation.



Application of the PMA to Asian Summer Precip Predictability

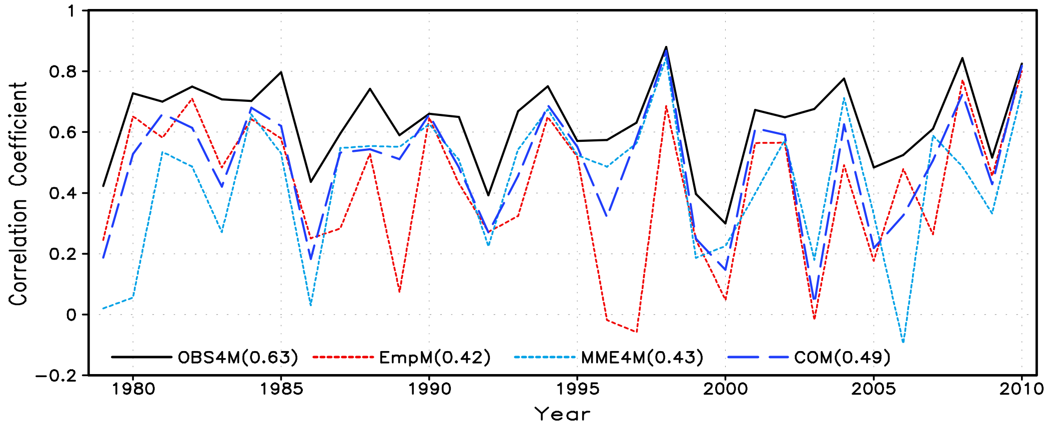
The temporal correlation coefficient (TCC) skill for JJA precipitation

Realized TCC skill



Attainable TCC skill

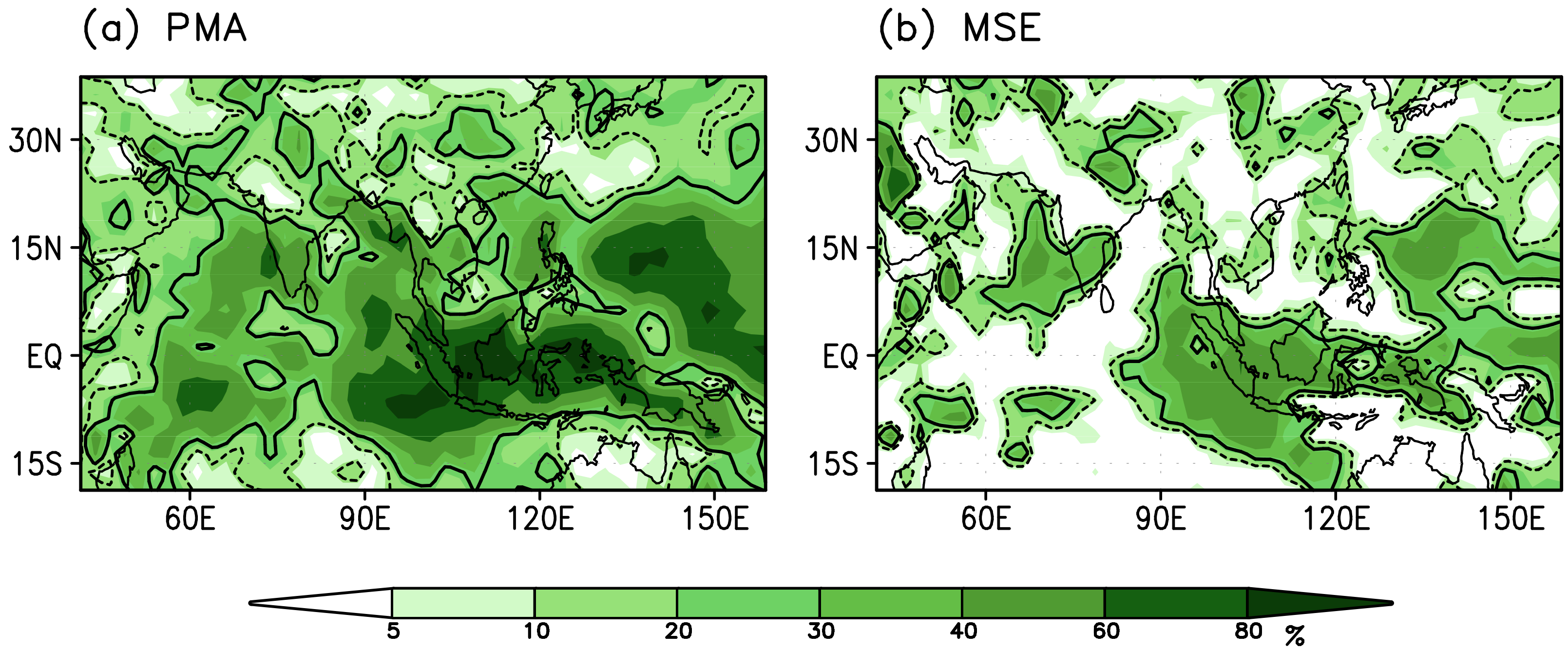
The pattern correlation coefficient (PCC) skill for JJA precipitation



Wang et al. (2015 Clim Dyn)

Predictability for JJA Precip Estimated by the PMA and MSE Method

Fractional signal variance (the predictable part of total variance)
1979-2010

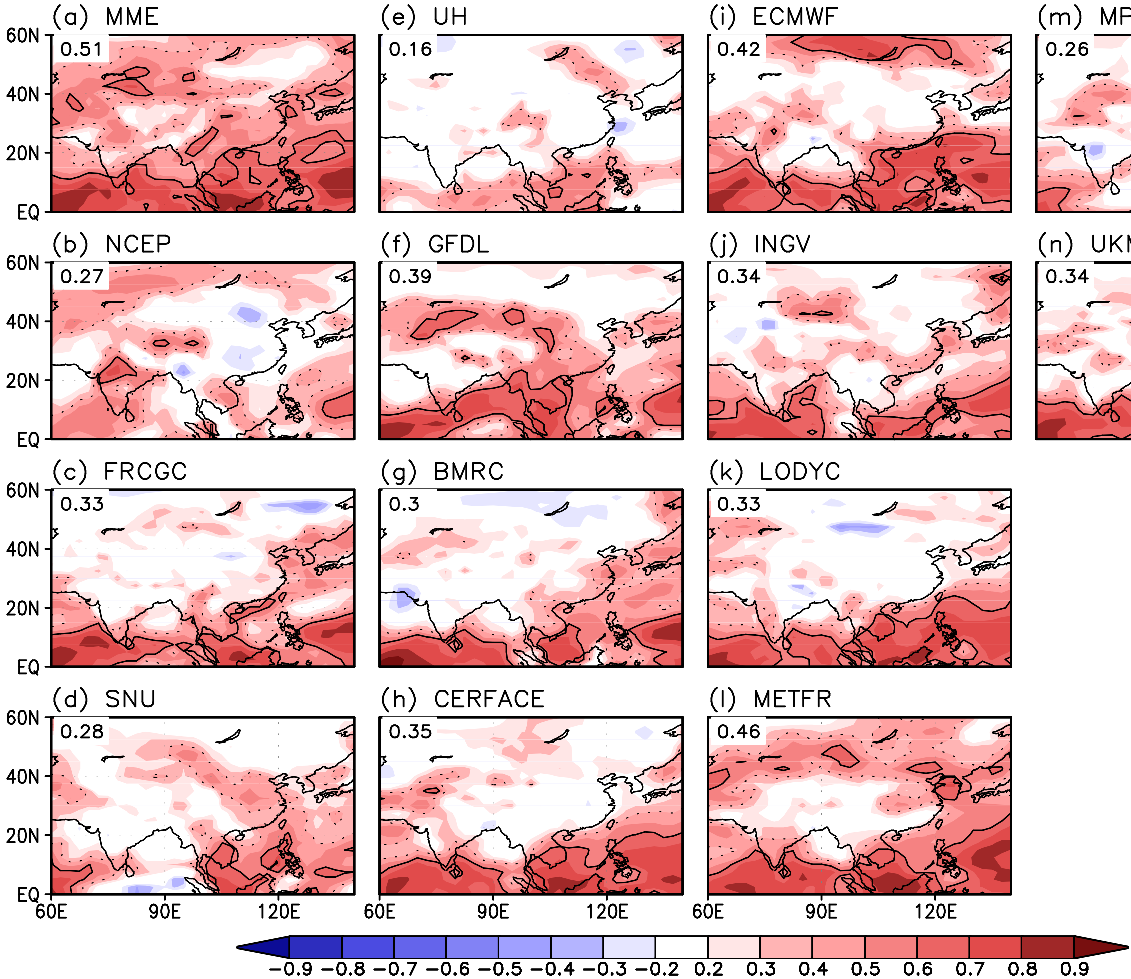


The dashed (solid) contour represents 12 % (25%) that are corresponding to the TCC of 0.35 (0.5).

Wang et al. (2015 Clim Dyn)

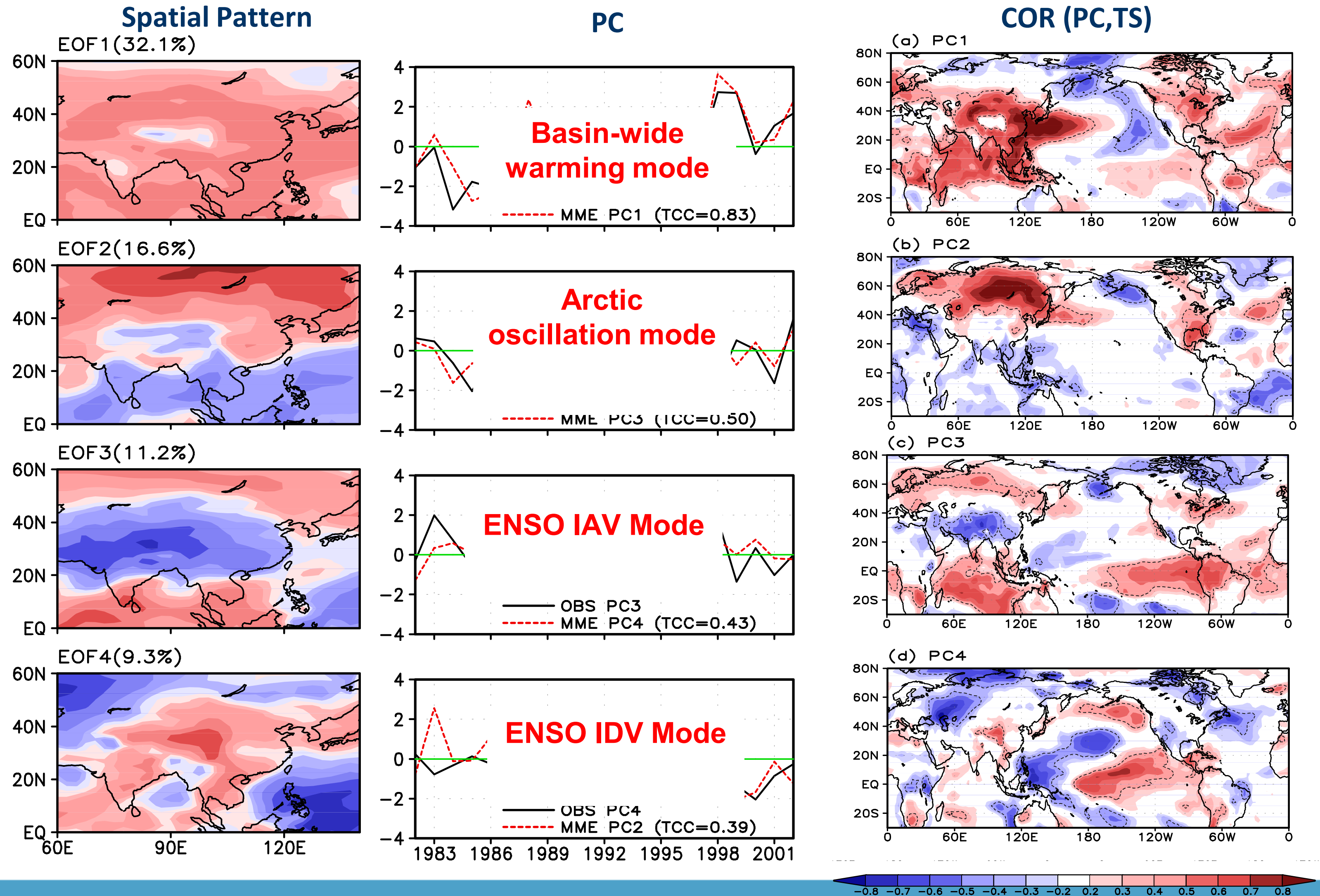
Application of the PMA to Asian Winter Temperature Predictability

The TCC skill of 13 coupled models and their MME for DJF Sfc Temp
Initiated from Nov 1st for 1982 - 2002

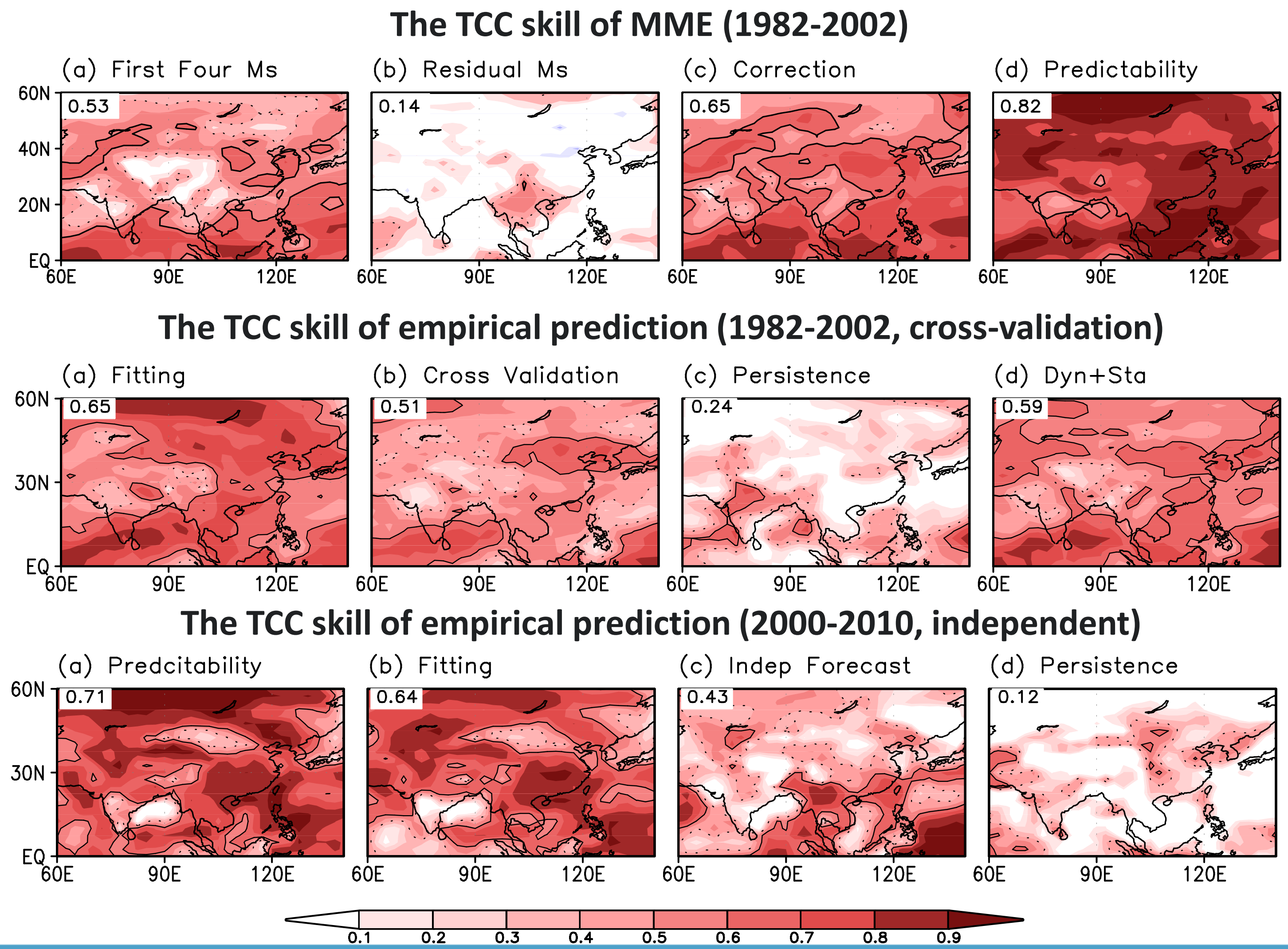


Lee et al. (2013 Clim Dyn)

Application of the PMA to Asian Winter Temperature Predictability



Application of the PMA to Asian Winter Temperature Predictability



Attainable TCC skill

Realized TCC skill

Lee et al. (2013 Clim Dyn)

Summary of Part III

- We introduce a Predictable Mode Analysis (PMA) method to estimate the seasonal climate predictability. The PMA is an integral approach combining empirical analysis, physical reasoning and prediction.

- The empirical analysis detects most important patterns; the understanding of physical processes governing these patterns establishes their physical basis; and the empirical and dynamical models' predictions determine predictable modes. The potential predictability can then be estimated by the fractional variance accounted for by the "predictable" modes.

- For the Asian summer monsoon precipitation variability, we identify four major modes of variability by analysis of the 1979-2010 observation: (1) El Niño and Southern Oscillation (ENSO) developing mode, (2) Indo-Pacific coupled mode which is sustained by a positive thermodynamic feedback with the aid of background mean flows and mean precipitation, (3) the Indian Ocean dipole (IOD) mode, and (4) trend mode. If these four modes are perfectly predicted, about 47% of the total variance can be captured over the entire Asian summer domain base on the PMA

Summary of Part III

- **The first four observed EOF modes of DJF TS variability explain 69% of the total variability and are statistically separated from other higher modes. We identify these as predictable modes, because they have clear physical meaning and the MME and empirical model reproduce them with acceptable criteria. The MME skill basically originates from the models' ability to capture the predictable modes.**

- **The MME shows better skill for the first mode, represented by a basin-wide warming trend, and for second mode related to the Arctic Oscillation. However, the statistical model better captures the third and fourth modes, which are strongly related to ENSO variability on interannual and interdecadal timescales, respectively. Independent statistical forecasting for the recent 11-year period further reveals that the first and fourth modes are highly predictable. The second and third modes are less predictable due to lower persistency of boundary forcing and reduced potential predictability during the recent years. In particular, the notable decadal change in the monsoon–ENSO relationship makes the statistical forecast difficult.**

Content

Purpose of the Current Study in ICCP

- This study aims to assess multi-year predictability for total soil water and wildfire occurrence over the Globe using the multi-year dynamical prediction system based on the Community Earth System Model and to better understand sources of their predictability.

Description of Data, Model and Experiments

- CPC Soil Moisture v2 (1958-2015)
- Palmer Drought Severity Index (PDSI) (1958-2014)
- Fire Weather Index (FWI) from GFWED (Field et al 2015) (1982-2015)
- Natural & anthropogenic radiative forcing

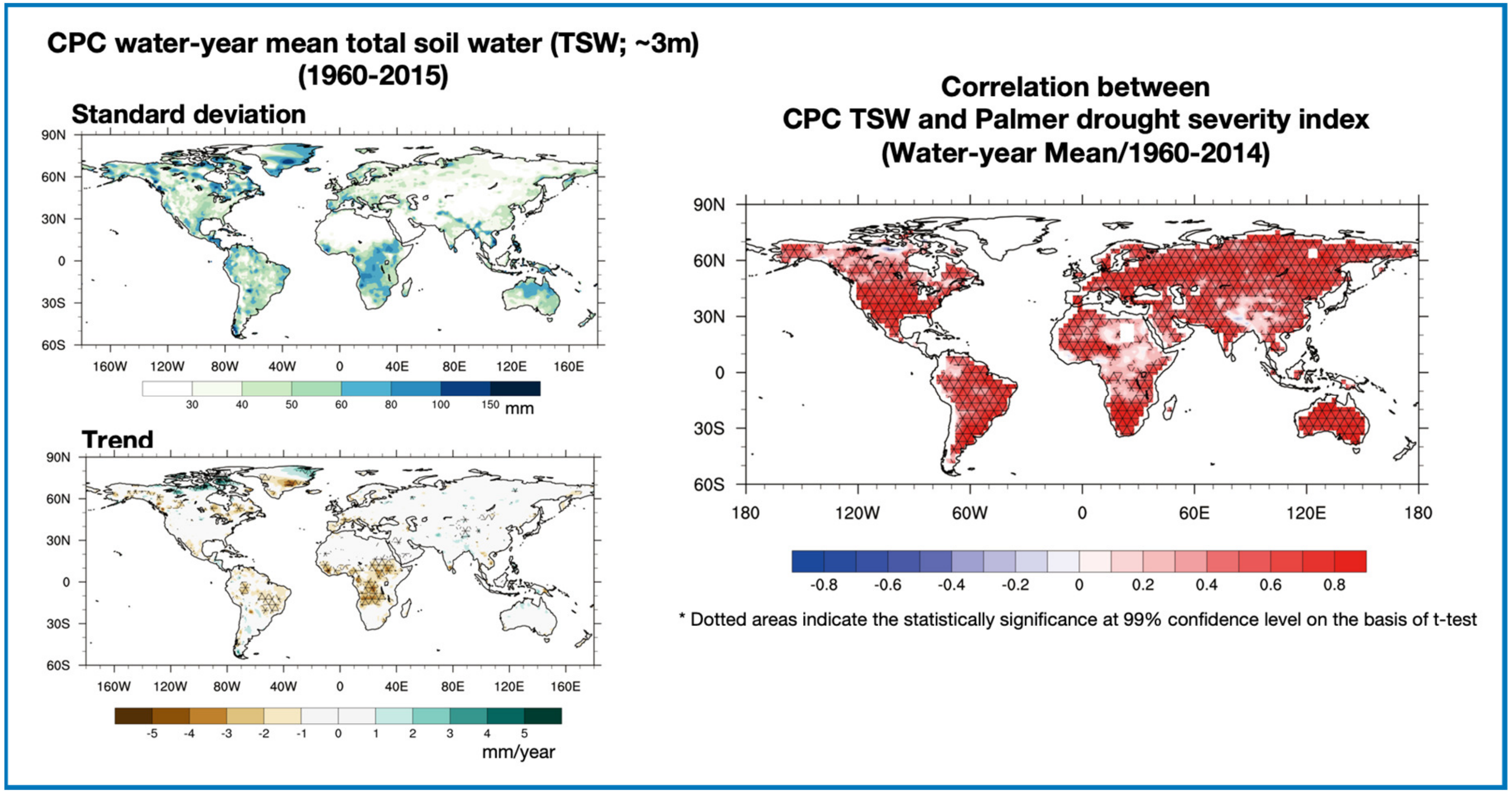
ATM: H3.75°/L26
OCN: H3°/L60
LAND: H3.75°/L10

- AR with global 3-D ocean temperature & salinity fields from ECMWF ORA-S4 (1958-2015)
- 10 ensemble runs initialized once a year (Jan 1st) from AR for 10-year long integration (1958-2015)
- Historical run (1850-2005)
- IPCC RCP 4.5 run (2006-2030)

- Definition of water year: October of the previous year to September
- Data analysis period: 1960-2015

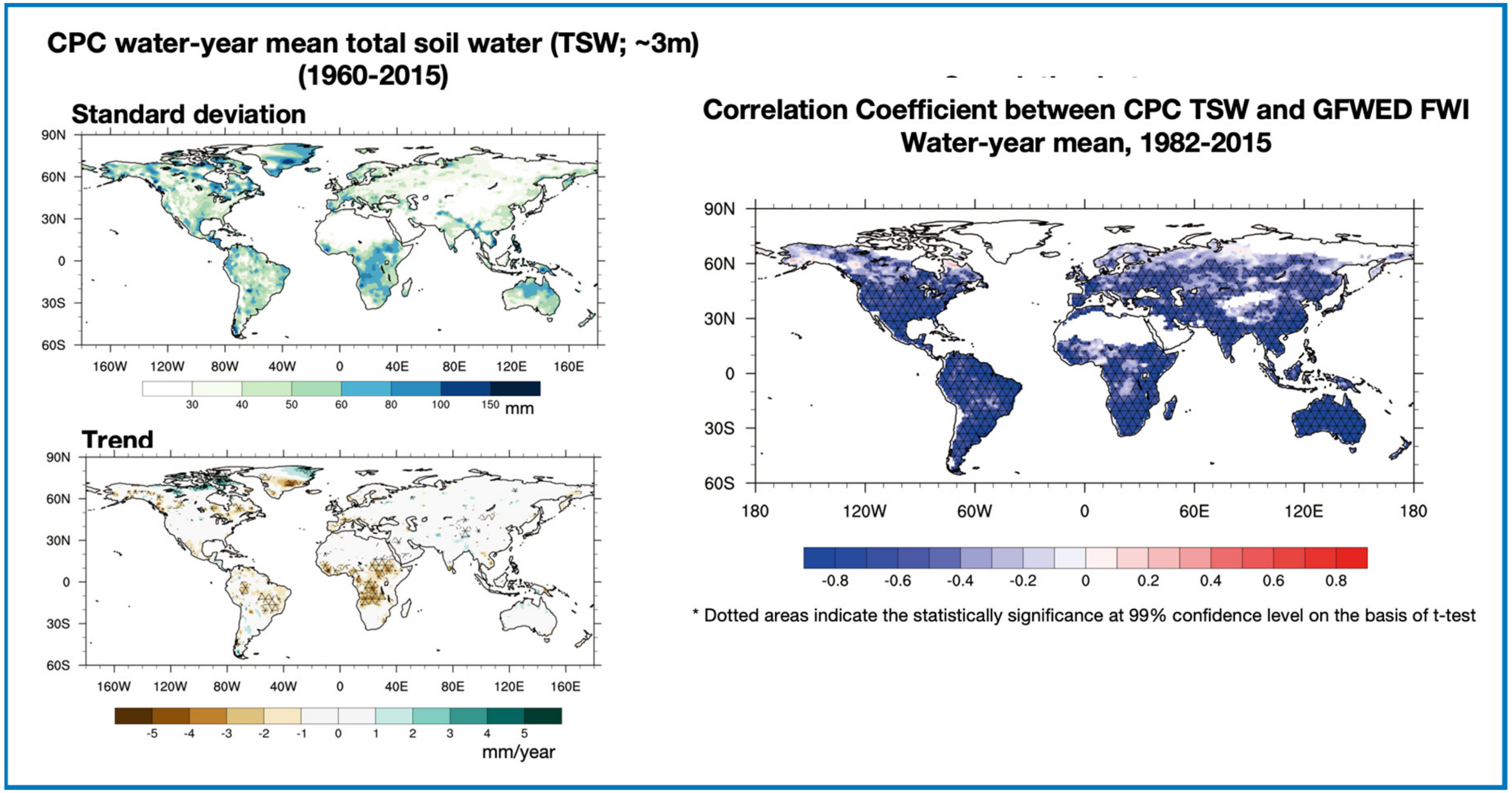
Variability and Trend of Total Soil Water

- There are significant interannual to interdecadal variability and long-term trend in total soil water averaged from surface to 3-m depth over the many parts of the globe.
- There is a significant negative correlation between the TSW and Drought Severity.



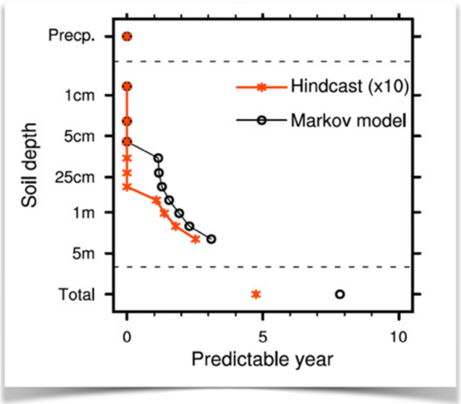
Variability and Trend of Total Soil Water

- There are significant interannual to interdecadal variability and long-term trend in total soil water averaged from surface to 3-m depth over the many parts of the globe.
- There is a significant negative correlation between the TSW and Fire Weather Index.



Sources of Multi-year Predictability

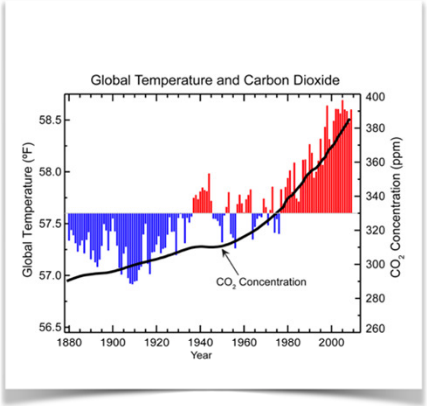
- **The important sources for multi-year predictability of TSW include the low-pass filtering characteristics of soils, the anthropogenic radiative forcing, and the Trans-basin variability (TBV) between the Atlantic and Pacific SST.**



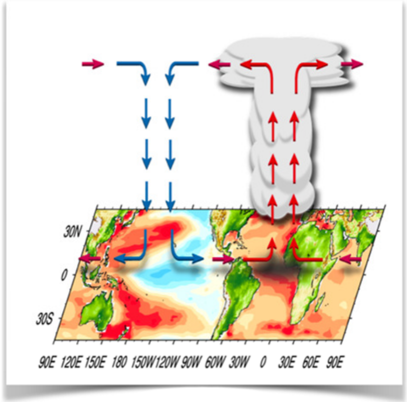
Natural Low-pass Filtering Characteristics of Soil

$$\frac{dW_T}{dt} = -\lambda \, W_T(t) + P(t)$$

Predictability due to the damped persistence



Anthropogenic Radiative Forcing

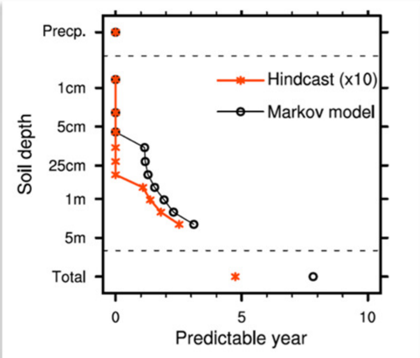


Transbasin Variability (TBV) between the Pacific and Atlantic SST

Chikamoto et al. (2015, 2017)

Sources of Multi-year Predictability

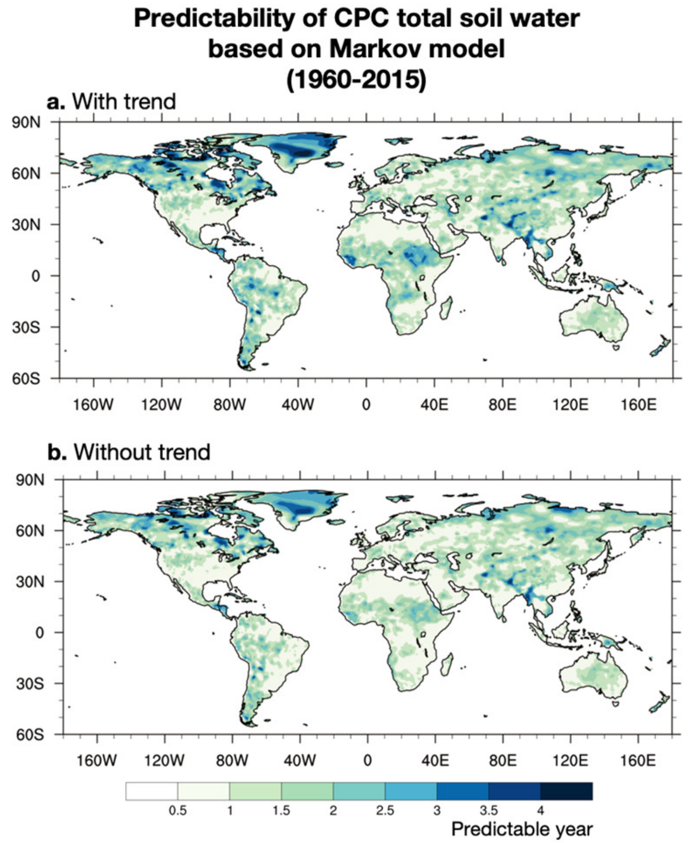
- Soils act as an **integral and natural low-pass filter** of white noise precipitation



Natural Low-pass Filtering Characteristics of Soil

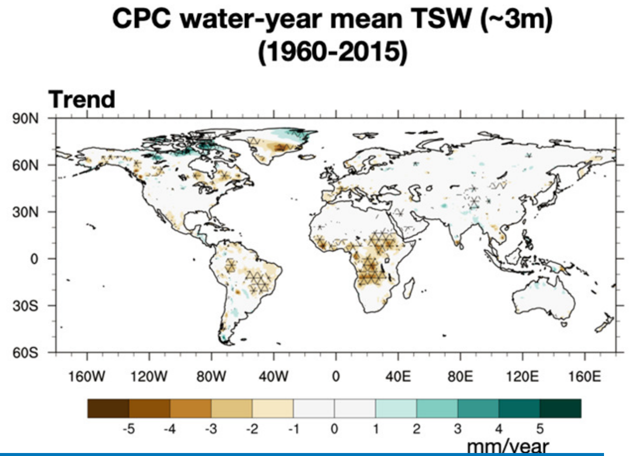
$$\frac{dW_T}{dt} = -\lambda\, W_T(t) + P(t)$$

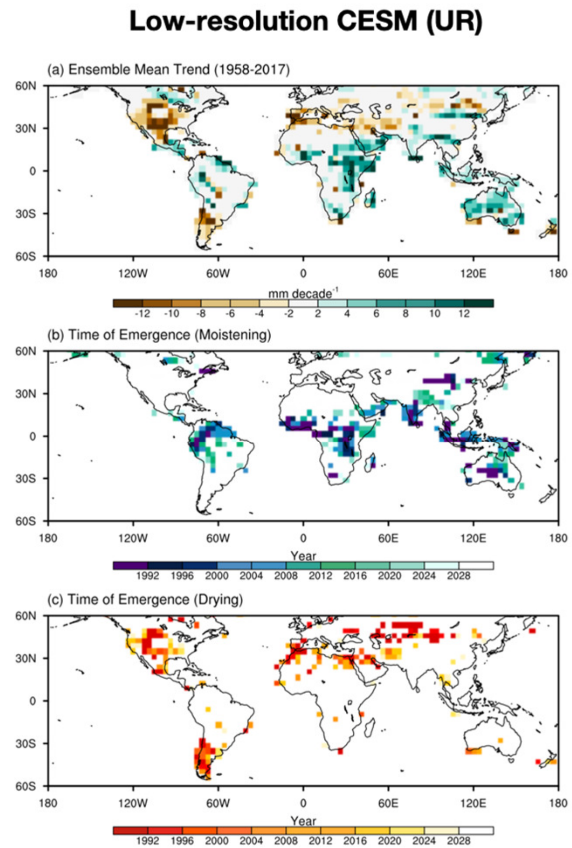
Predictability due to the damped persistence



Sources of Multi-year Predictability

- Long-term trend also provides near-term predictability





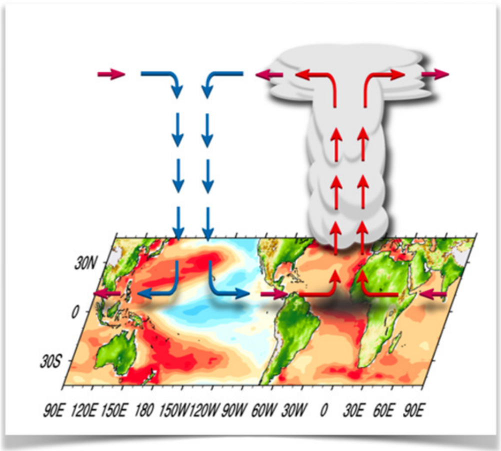
What causes the discrepancy between the observed and simulated trend?

- Model deficiency
- Natural long-term variation
- Quality of the reconstructed soil water data

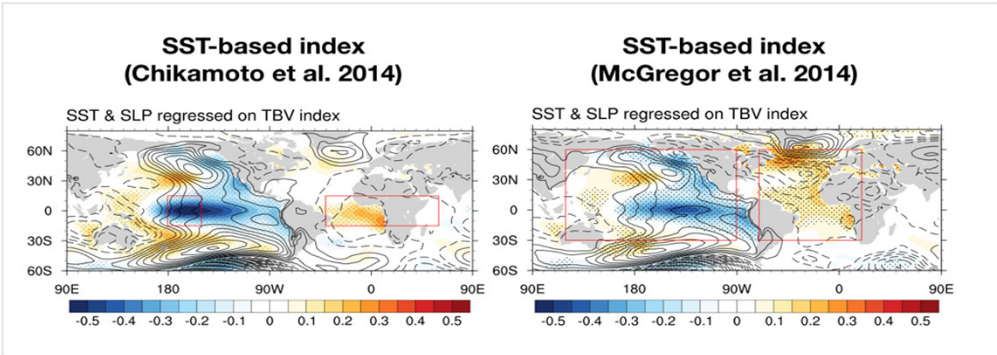
Anthropogenic Radiative Forcing

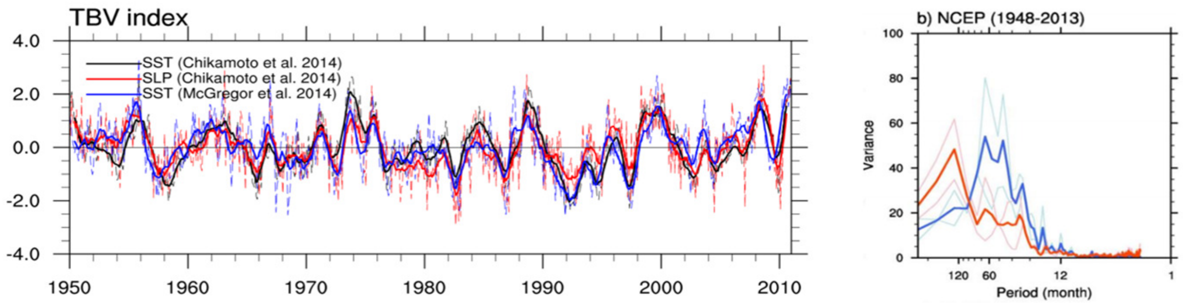
Sources of Multi-year Predictability

- The **Trans-basin variability (TBV)** between the Atlantic and Pacific SST is the key source of multi-year predictability for water-year mean TSW over the many parts of the globe.



The positive TBV phase: the relatively warmer SST over the Atlantic than the Pacific





Dominant Periods

Blue line for ENSO: 2~7 years

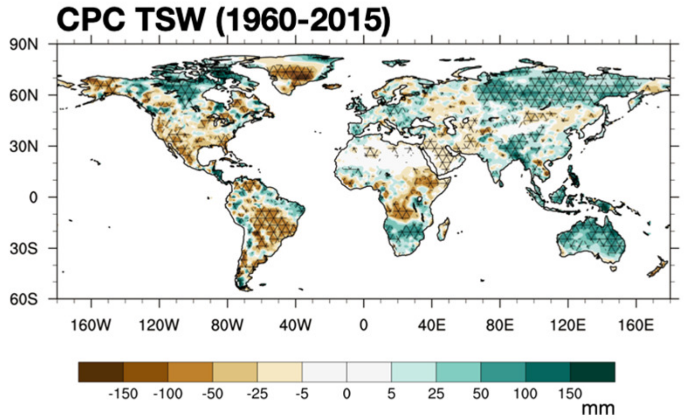
Red line for TBV: 10~20 years

Chikamoto et al. (2014, 2017)

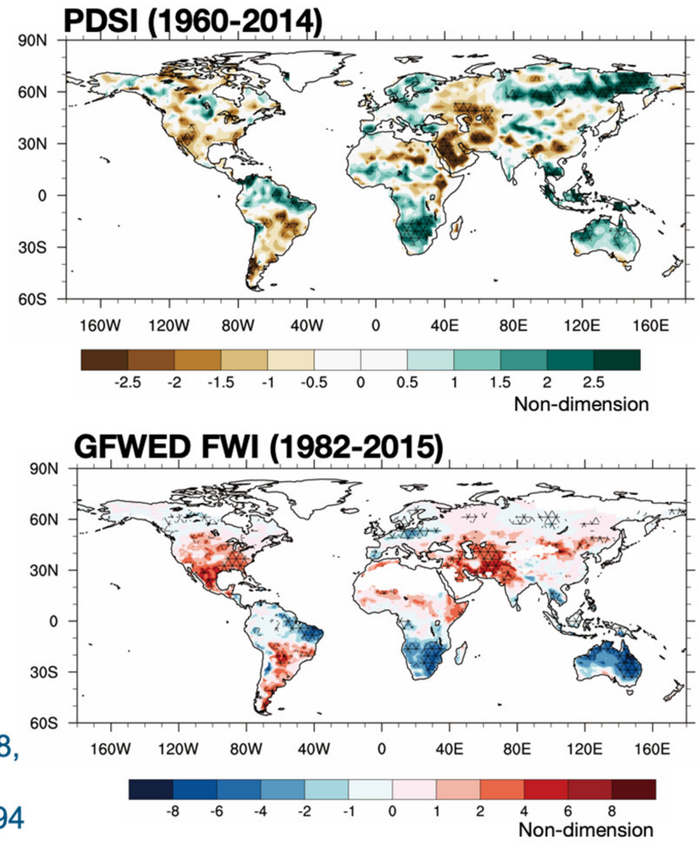
Sources of Multi-year Predictability

- The Trans-basin variability (TBV) between the Atlantic and Pacific SST is the key source of multi-year predictability for water-year mean total soil moisture over the many parts of the globe.

TBV Composite Difference
(Water-year mean)



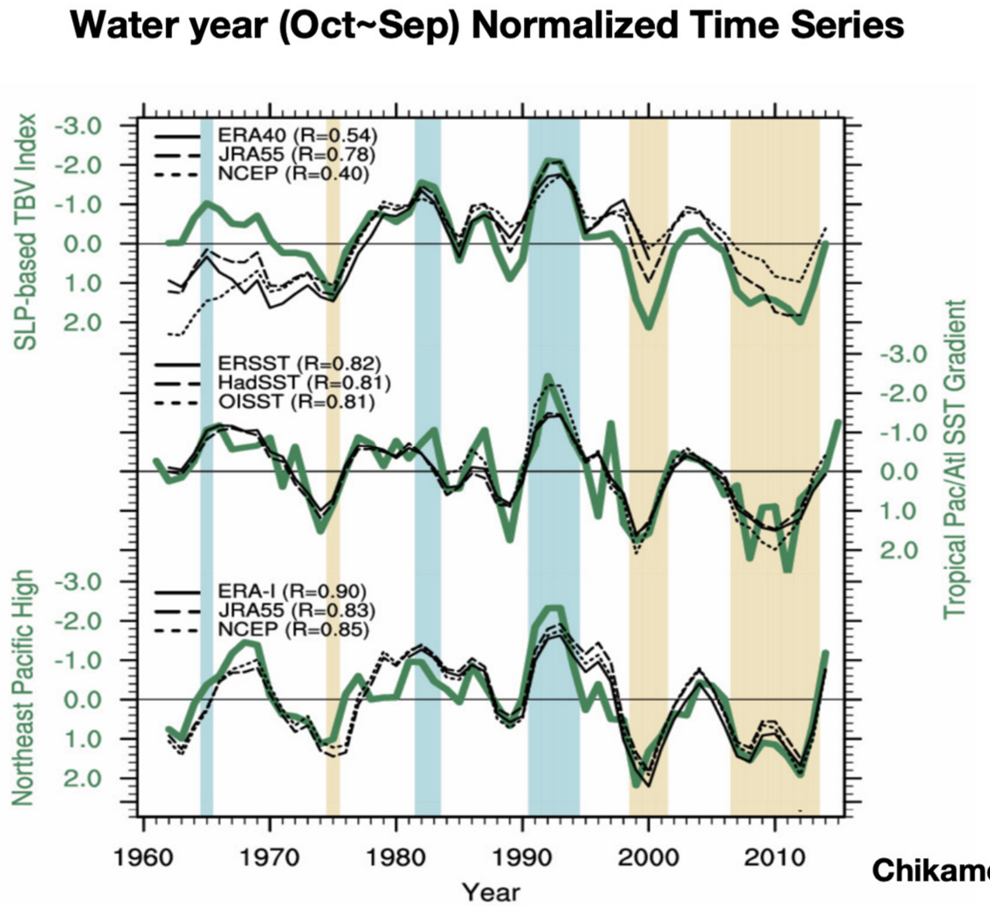
* Areas with a slant line indicate the statistically significance at 90% confidence level on the basis of two-tail Student's *t*-test



- Positive TBV years: 1975, 1999, 2000, 2001, 2007, 2008, 2009, 2010, 2011, 2012, 2013
- Negative TBV years: 1965, 1982, 1983, 1991, 1993, 1994

Assimilation Results: TBV Impacts

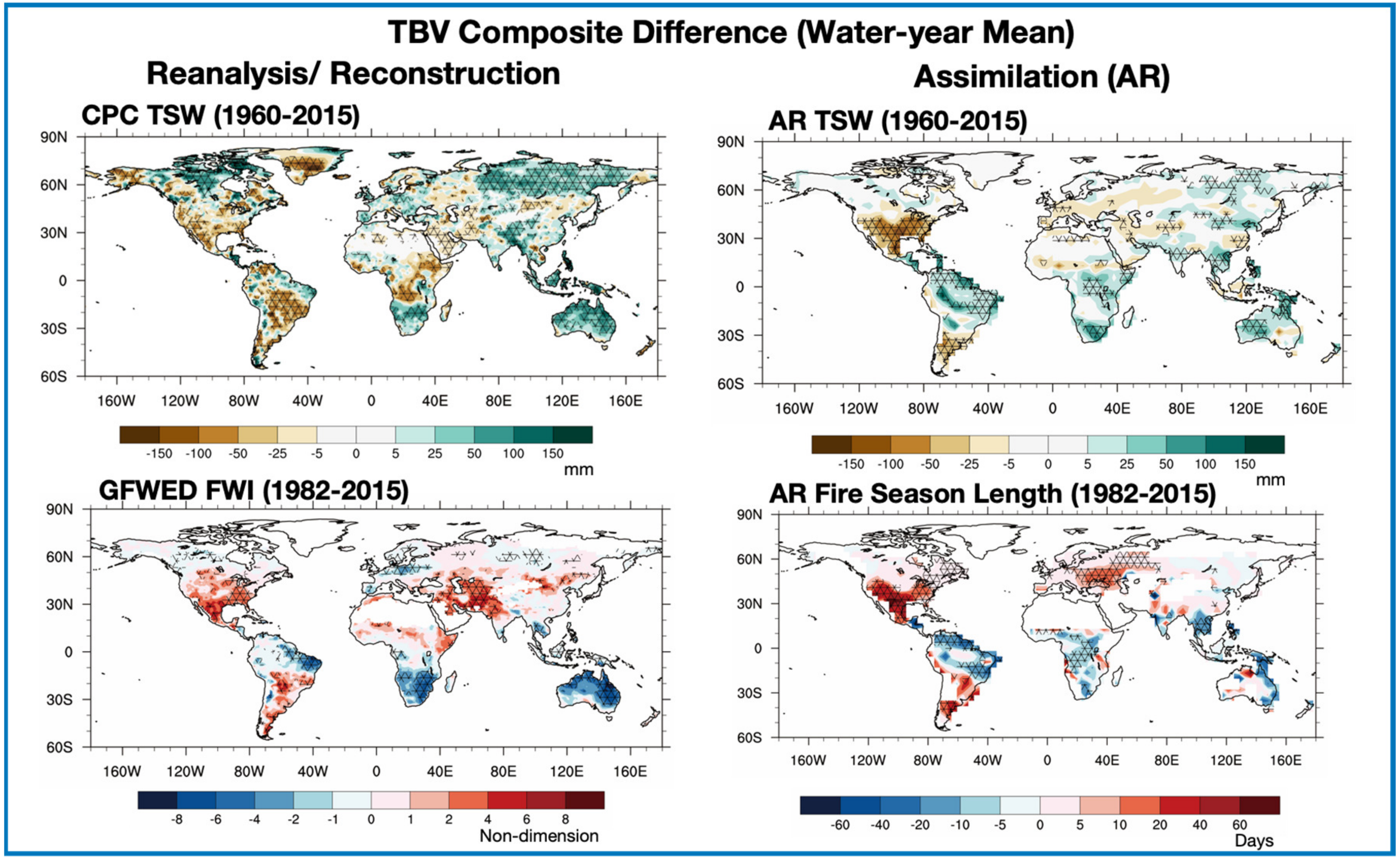
- Assimilation (AR) with global SST using CESM well captures the observed TBV variation.



Chikamoto et al. (2017)

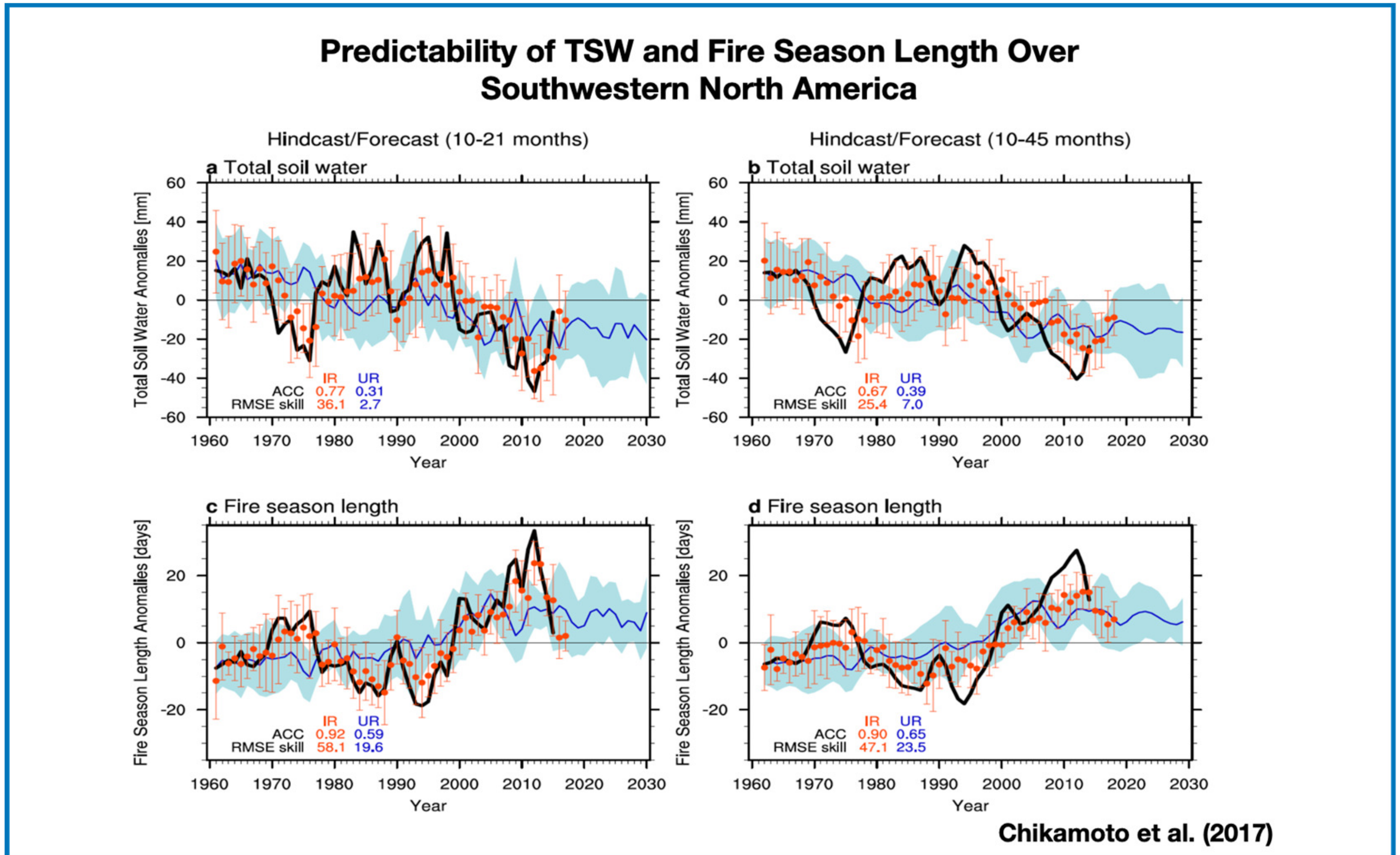
Assimilation Results: TBV Impacts

- Assimilation (AR) with global SST using CESM is capable of captures the global impact of TBV



Potential Multi-Year Prediction Skills (IR)

- The dynamical prediction system is capable of capturing TSW and fire season length anomalies 2~4 years ahead particularly over southwestern North America. Antrhopogenic radiative forcing also contributes to the recent long-term trend of two variables.



Summary of Part IV

- Severe drought and increased change in wildfire occurrence have significant impacts to a wide range of sectors such as agriculture, energy, food security, forestry, drinking water and tourism. **This study aims to assess multi-year predictability for total soil water and wildfire occurrence over the Globe using the multi-year dynamical prediction system based on the Community Earth System Model and to better understand sources of their predictability.**

- **The important sources of multi-year predictability for soil water include the the low-pass filtering characteristics of soils, the anthropogenic radiative forcing and Trans-basin variability (TBV) between the Atlantic and Pacific SST.** In particular, the positive phase of TBV, characterized by the relatively warmer SST over the Atlantic than the Pacific, is favorable for less precipitation, less soil water, drought, and more wildfire occurrence over the southern part of North and South America, the northern part of South Africa and many parts of Europe and Asia.

- **The dynamical prediction system has a high potential skill in forecasting total soil water and fire season length up to 2~4 year lead time over many parts of the Globe.** However, the actual skill of the system is very limited yet with respect to reanalysis/reconstruction data.

IBS Center for Climate Physics

Thank you very much!

Any Question?