Advance of Dynamical Seasonal Prediction:

Assessment of the APCC/CliPAS 14-Model Ensemble Retrospective Seasonal Prediction (1980-2004)

APCC/CliPAS team

Presented by Bin Wang

Department of Meteorology and IPRC

University of Hawaii

APCC Symposium August 19-21 2008 Lima

CliPAS

Climate Prediction and Its Application to Society

A Joint International Research Project in Support of APEC Climate Center (APCC)

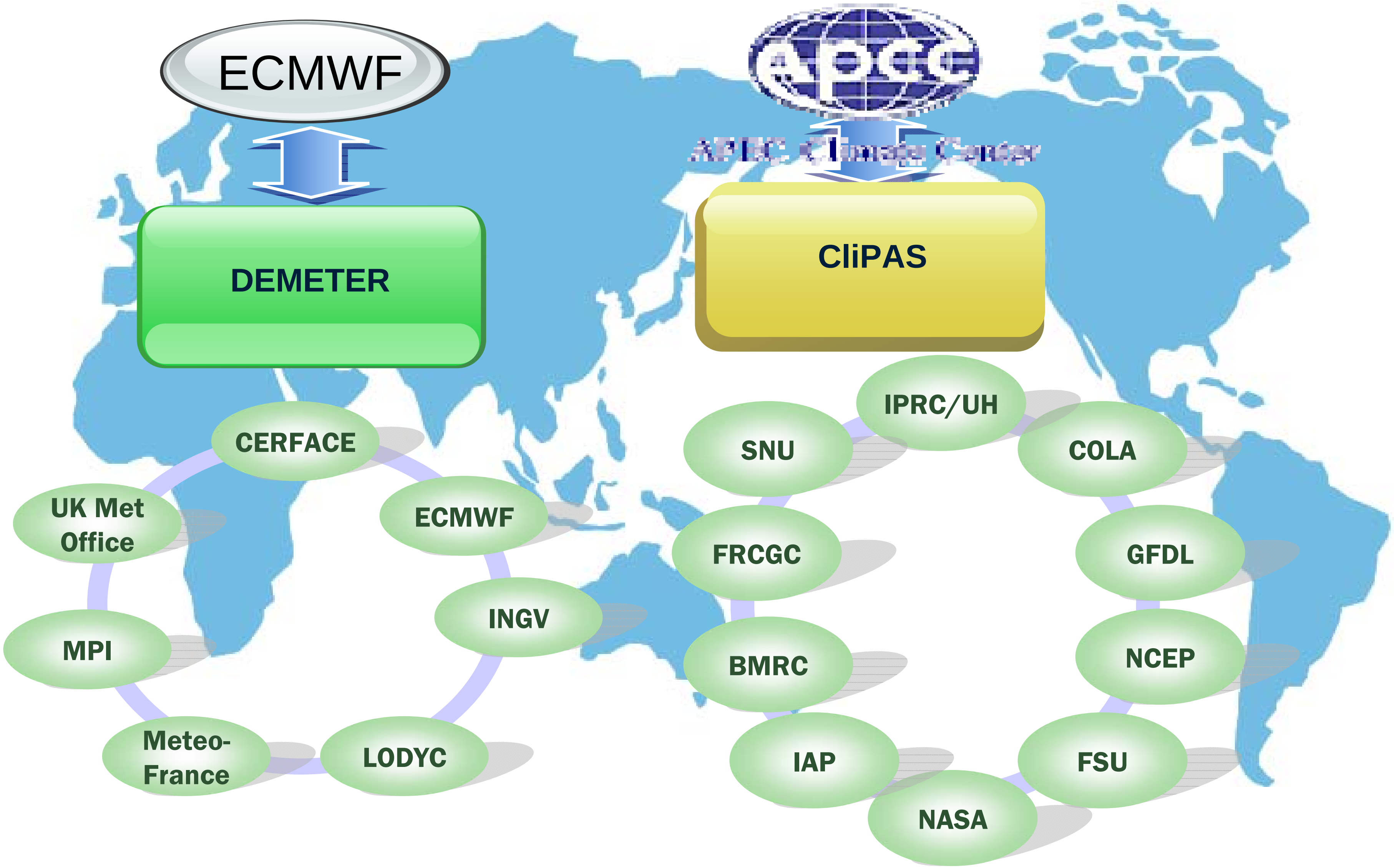
Missions

Address key scientific problems on multi-model ensemble (MME) climate prediction

Establish well-validated MME prediction systems for intraseasonal to interannual prediction

Develop economic and societal application models.

International Cooperation for Climate Prediction



APCC/CliPAS Team

UH/IPRC: B. Wang (PI), J.-Y. Lee, P. Liu, X. Fu

COLA/GMU: J. Shukla (Co-PI), B. Kirtman, J. Kinter, K. Jin

SNU: I.-S. Kang (Co-PI), J.-S. Kug

NASA/GSFC: S. Schubert, M. Suarez, W. Lau

NOAA/GFDL: N.-C. Lau, T. Rosati, W. Stern

NOAA/NCEP: A. Kumar ,J. Schemm

FSU: T. Krishnamurti, S. Cocke,

FRCGC/JAMSTEC: J. Luo, T. Yamagata (UT)

IAP/CAS: T. Zhou, B. Wang

BMRC: O. Alves. H. H. Hendon

KMA: W.-T. Yun

CCSR: M. Kimoto

CMC

CliPAS Models Hindcast System (1980-2004)

APCC/CliPAS Tier-1 Models

Institute	AGCM	Resolution	OGCM	Resolution	Ensemble Member	Reference
BMRC	BAM v3.0d	T47L17	ACOM2	0.5-1.5° latx 2° lon L25	10	Zhong et al., 2005
FRCGC	ECHAM4	T106 L19	OPA 8.2	2° cos(lat)x2° lon L31	9	Luo *et al*. (2005)
GFDL	R30	R30L14	R30	R30 L18	10	Delworth et al. (2002)
NASA	NSIPP1	2° lat x 2.5° lon L34	Poseidon V4	1/3° lat x 5/8° lon L27	3	Vintzileos *et al*. (2005)
NCEP	GFS	T62 L64	MOM3	1/3° lat x 1° lon L40	15	Saha *et al*. (2005)
SNU	SNU	T42 L21	MOM2.2	1/3° lat x 1° lon L32	6	Kug *et al*. (2005)
UH	ECHAM4	T31 L19	UH Ocean	1° lat x 2° lon L2	10	Fu and Wang (2001)

APCC/CliPAS Tier-2 Models

Institute	AGCM	Resolution	Ensemble Member	SST BC	Reference
FSU	FSUGCM	T63 L27	10	SNU SST forecast	Cocke, S. and T.E. LaRow (2000)
GFDL	AM2	2° lat x 2.5° lon L24	10	SNU SST forecast	Anderson *et al*. (2004)
IAP	LASG	2.8° lat x 2.8° lon L26	6	SNU SST forecast	Wang et al. (2004)
NCEP	GFS	T62 L64	15	CFS SST forecast	Kanamitsu et al. (2002)
SNU/KMA	GCPS	T63 L21	6	SNU SST forecast	Kang *et al*. (2004)
UH	CAM2	T42 L26	10	SNU SST forecast	Liu *et al*. (2005)
UH	ECHAM4	T31 L19	10	SNU SST forecast	Roeckner *et al*. (1996)

Forecast quality measures

- For the deterministic forecast, MME prediction was made using simple arithmetic average of 14 models' ensemble means.

  Multiple regression and SVD method

  SPPM method (more sophisticated statistical post-processes

- Probabilistic forecast was derived by simple democratic counting using 109 individual realizations from the ten models (5 one-tier and 5-two tier models) after normalizing each simulation with respect to its own mean and standard deviation.

Evaluation of deterministic forecast skills

- Metrics used to measure prediction skill of MME mean forecast include anomaly pattern correlation coefficient (PCC) and root mean square error (RMSE) normalized by the corresponding observed standard deviation.
- Temporal correlation coefficient (TCC) was used for a specific time series of a predictand. For convenience of comparison, we also calculated the time-averaged anomaly PCC and RMSE over a specific region.

Evaluation of Probabilistic Forecast Skill

Brier Skill Score (BSS)

The BSS can be computed as the sum of following three terms (Murphy 1973, Wilks 1995, Stanski et al. 1989)

$$b = b_{rel} - b_{res} + b_{unc}$$

Reliability **measures the bias in predicted probabilities relative to the verified frequency for given event**

Resolution **measures the intrinsic ability of the forecast system to detect (or resolve) situations in which the observed frequency of the event is different from the climatological frequency**

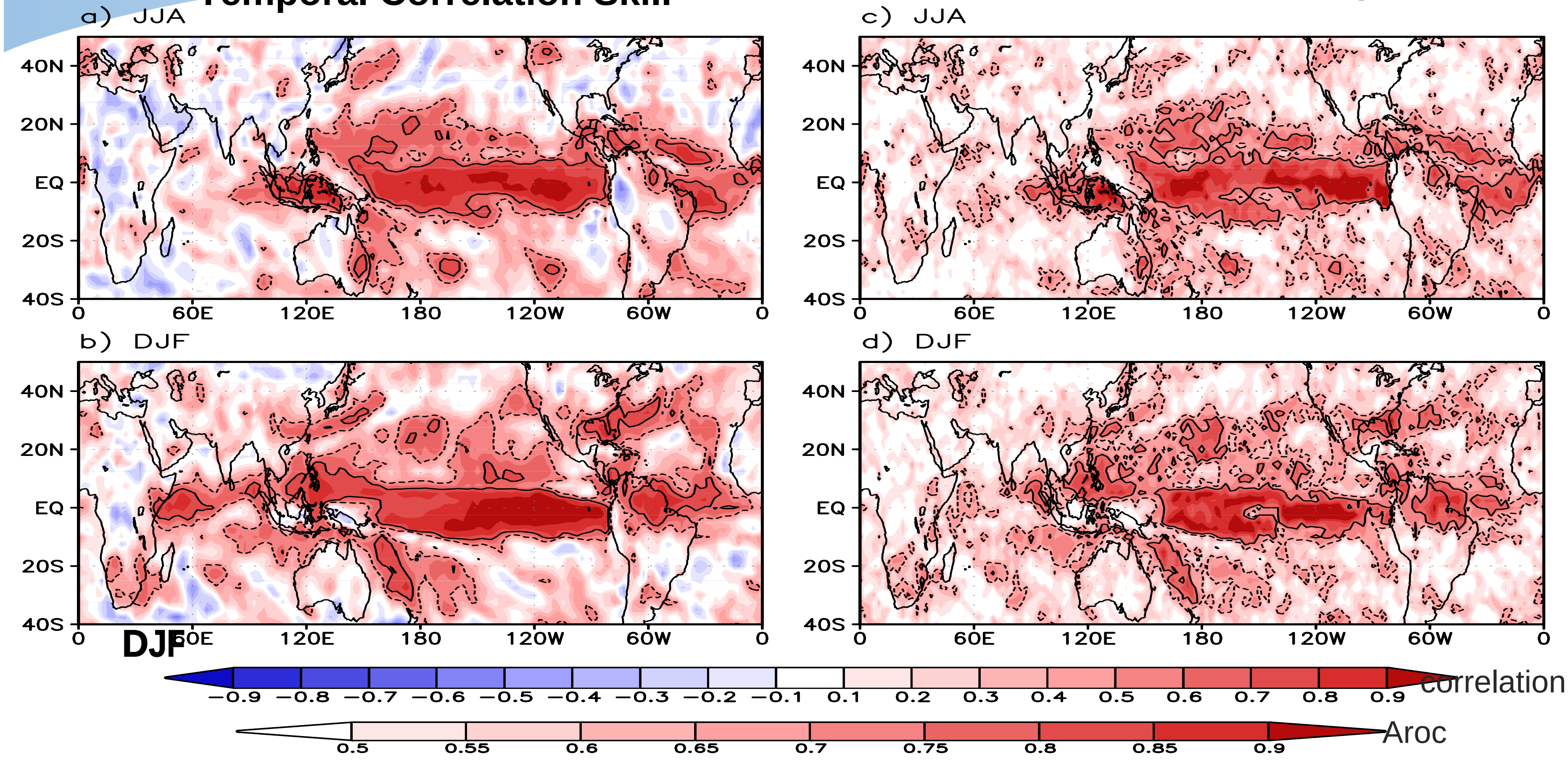
Area under ROC curve (AROC)

Relative operating characteristics (ROC) is a **graph of hit rate against false alarm rate within a range of probability threshold.**

AROC is a way to quantify the ROC by calculating the area beneath the ROC curve (Green and Swets 1966). If the area is less than 0.5 of the whole (unit area), then the model is less skillful than a random or constant forecast.

1. Relationship between Probabilistic and Deterministic prediction skills

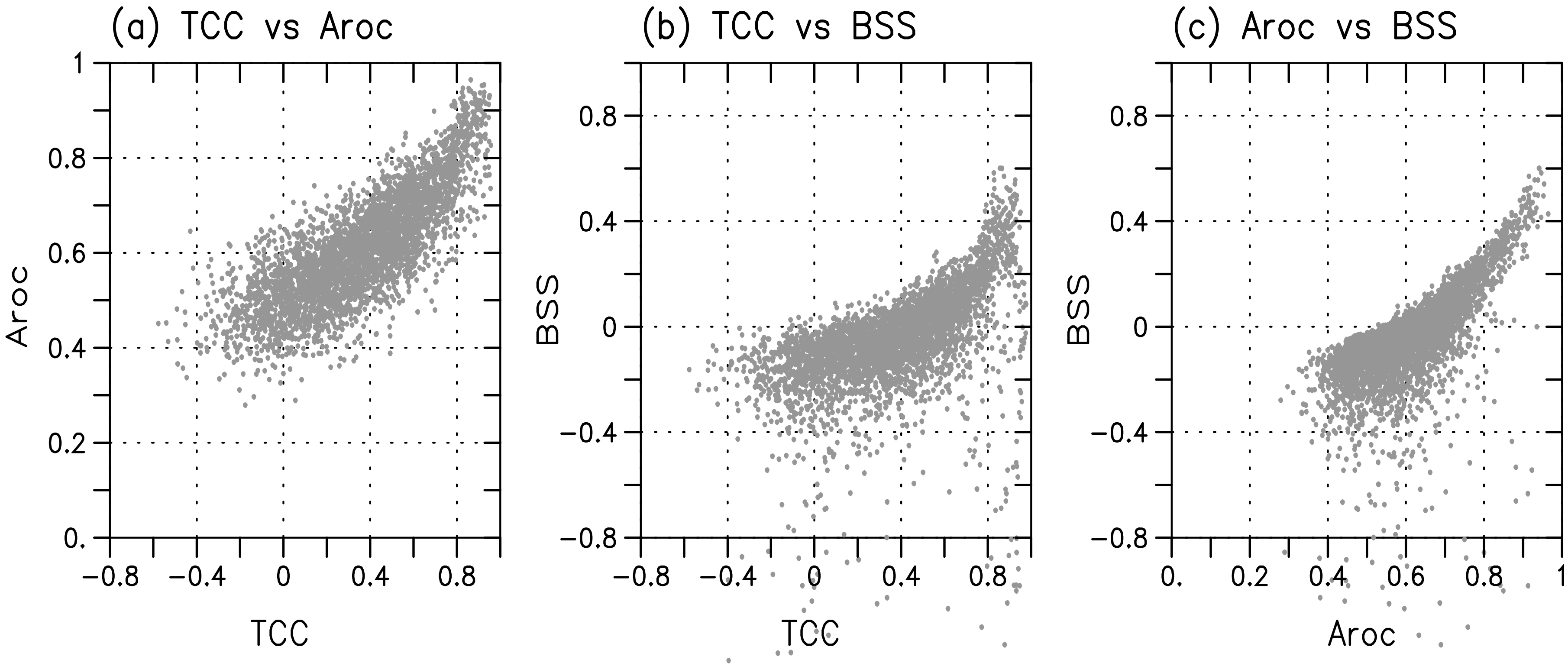
Temporal Correlation Skill | **Aroc skill score for tercile prediction**



Two probabilistic forecast skills, the Brier Skill Score (BSS) and the Area under the Relative Operating Characteristic curve (AROC), display similar spatial patterns as the Temporal Correlation Coefficient (TCC) score of the deterministic MME forecast.

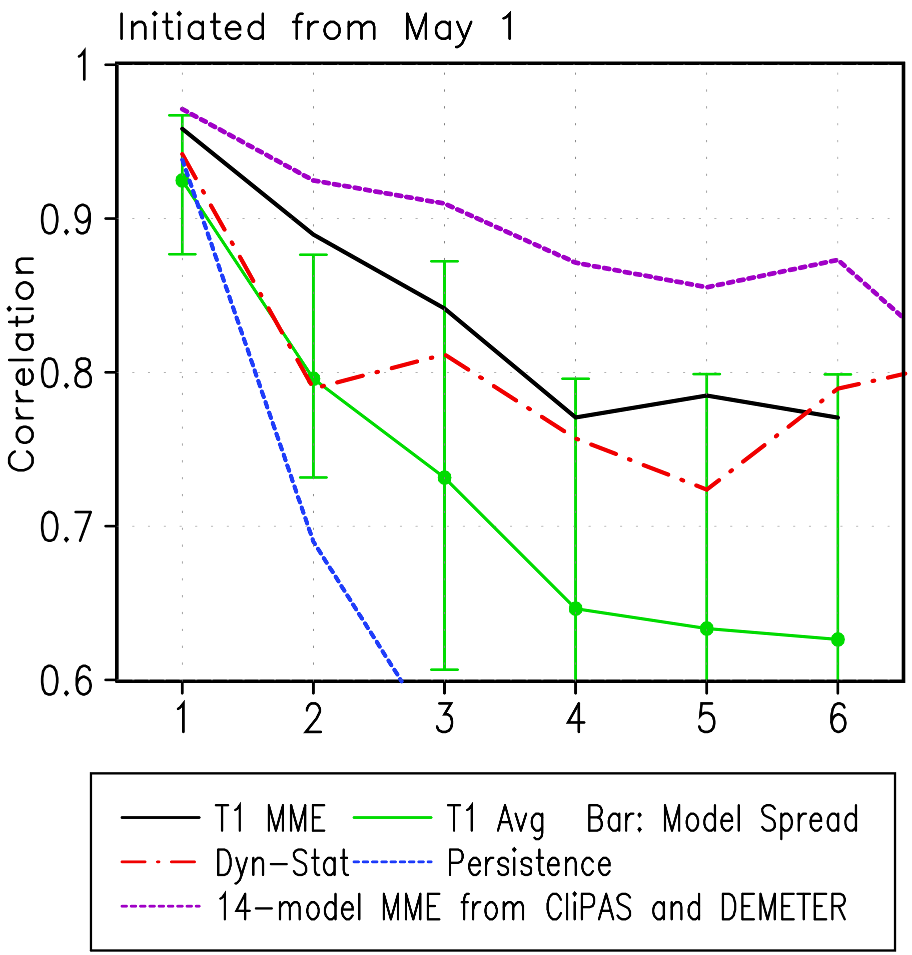
Relationships between probabilistic(AROC, BSS) and deterministic (TCC) measures

APCC/CliPAS MME Skills for DJF Precipitation



While the relationship is nonlinear,
AROC 0.7 ~ BSS 0.1 ~ TCC 0.6
in the CliPAS MME system.

2. Effectiveness of MME: ENSO prediction



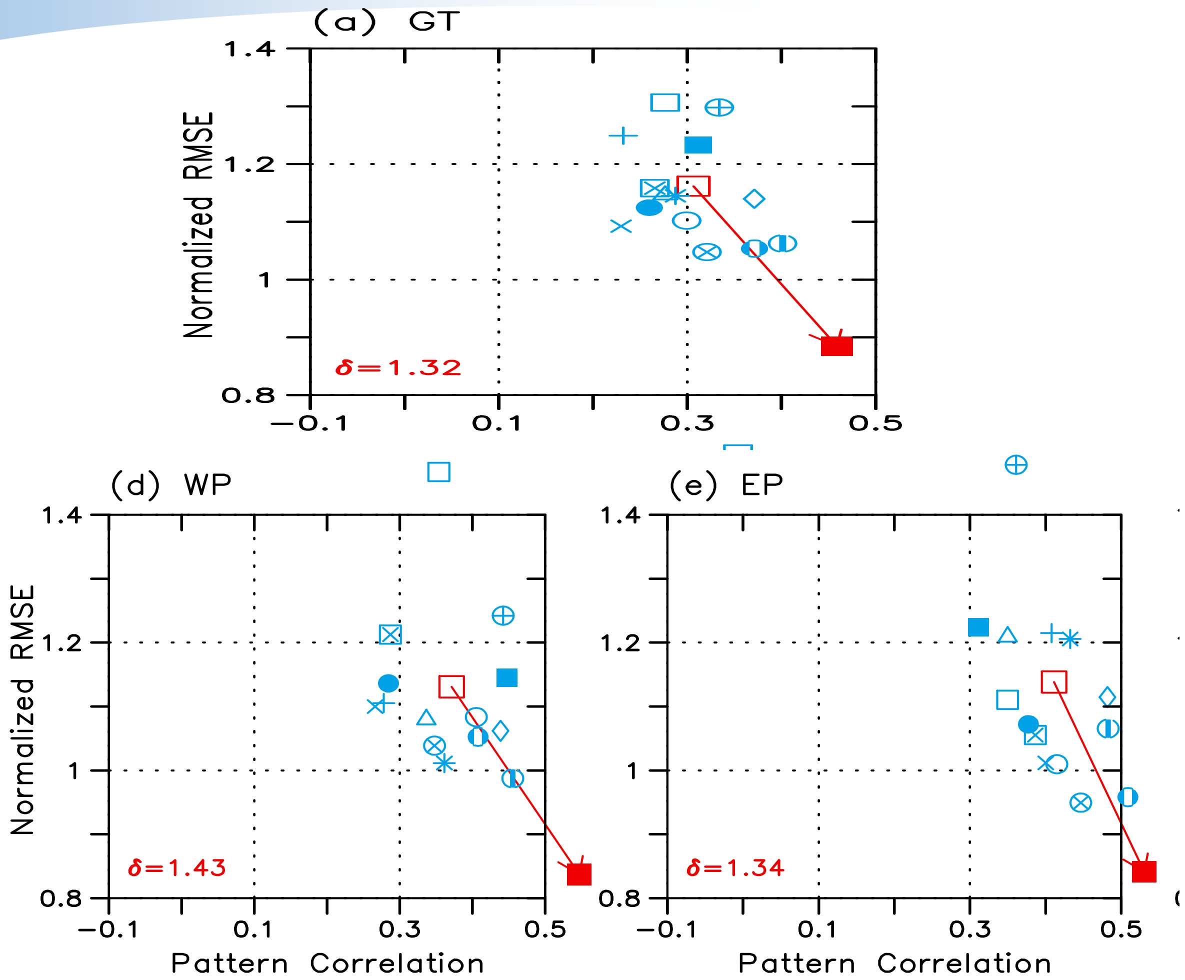
The 6-month lead forecast initiated from May 1

Averaged skill of 7 individual coupled models 0.63.

The MME of 7 CliPAS model: 0.77,

The MME made by 14 CliPAS + DEMETER models 0.87.

2a Effectiveness of MME: Precipitation

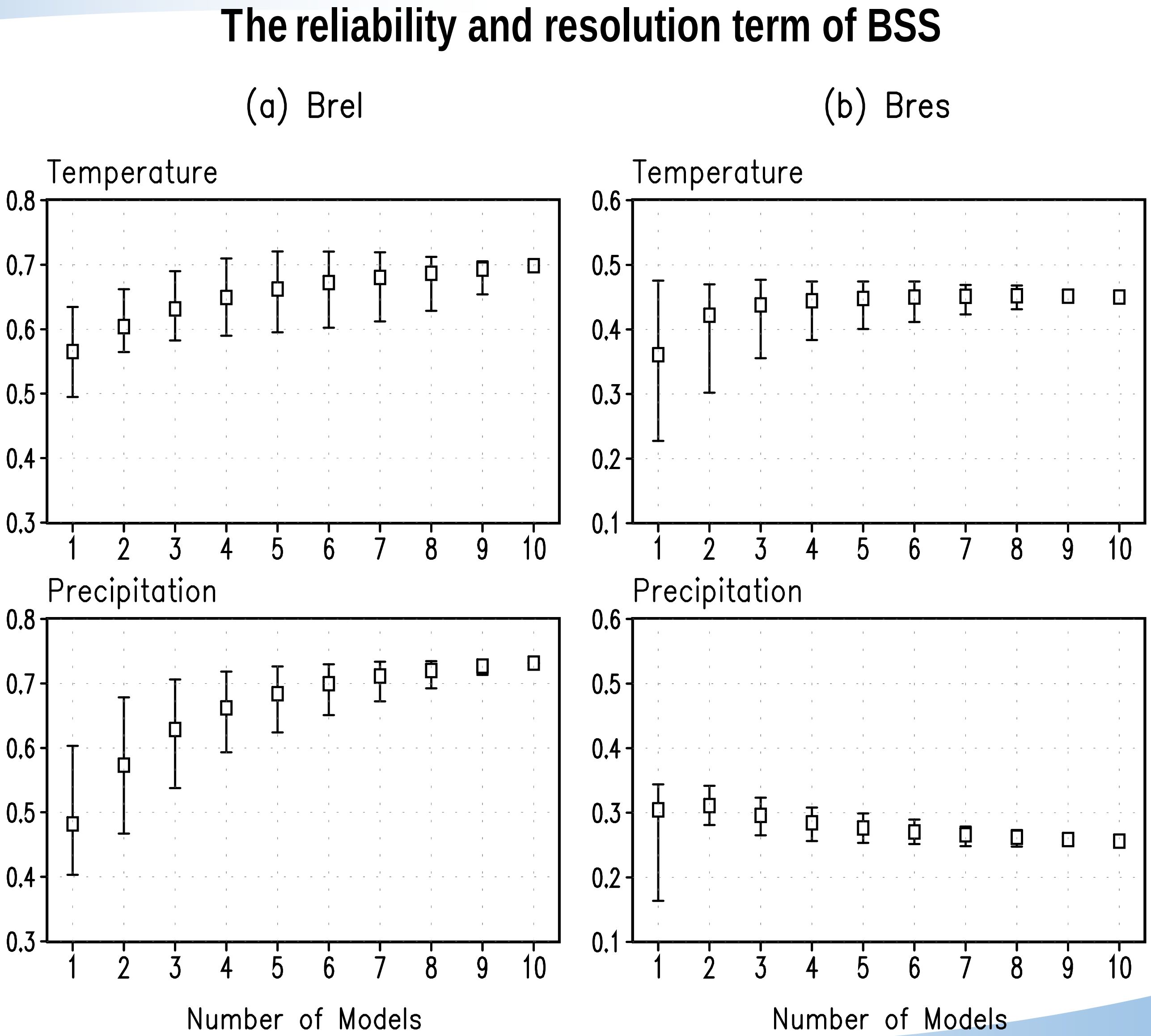


The effectiveness of the MME depends on the averaged skill of individual models and their mutual independency.

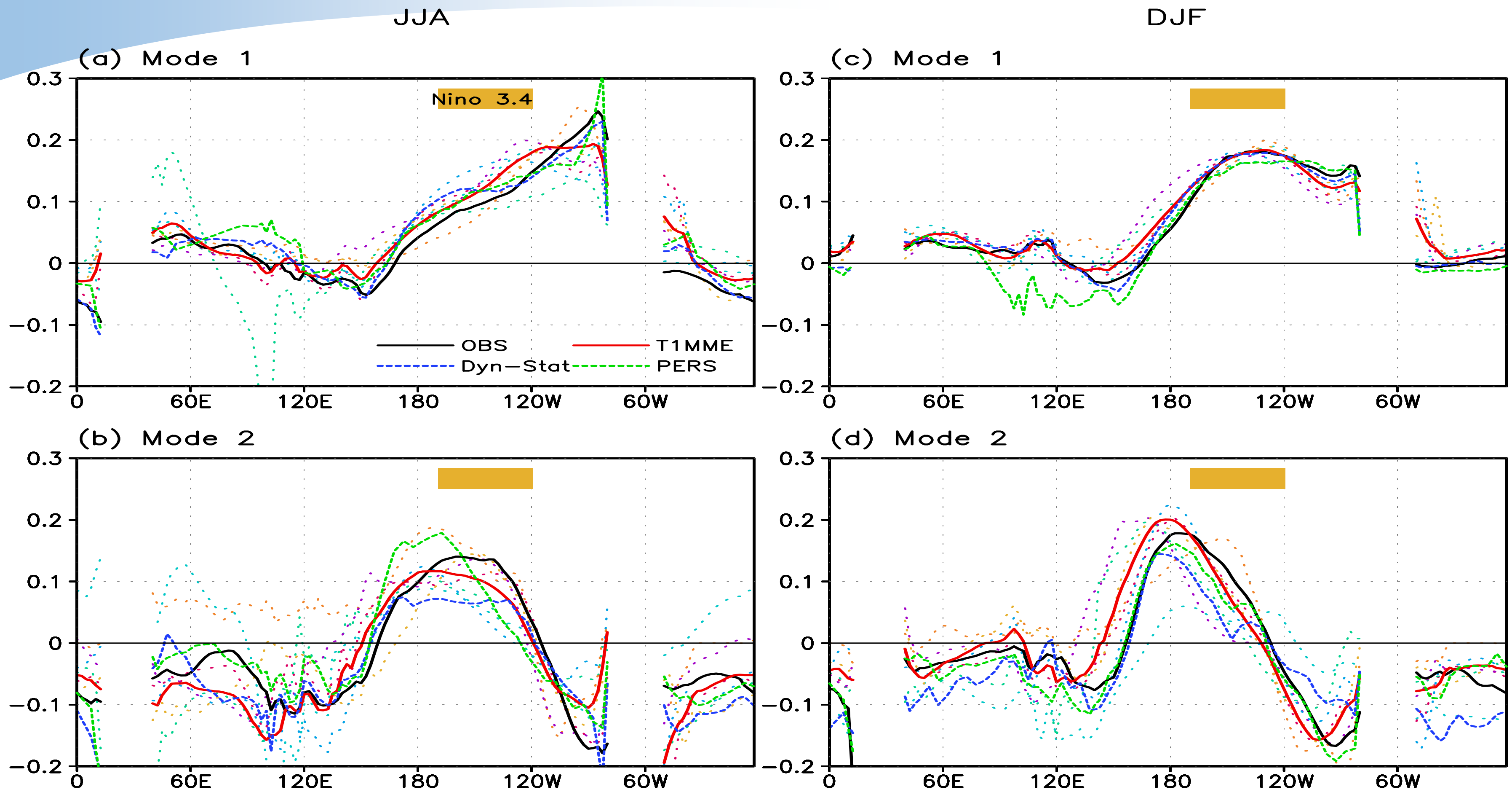
2b Probabilistic forecast :greater advantages

The reliability of BSS score (rain) increases from 0.48 to 0.73 when 10 models are used.

The resolution score also increases for 2 m temperature but slightly decreases for precipitation forecast



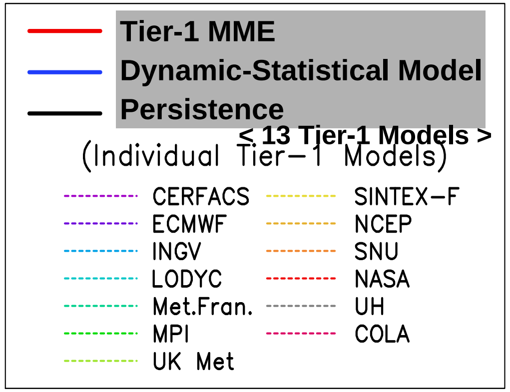
3. Hindcast Equatorial SST [10S-5N]

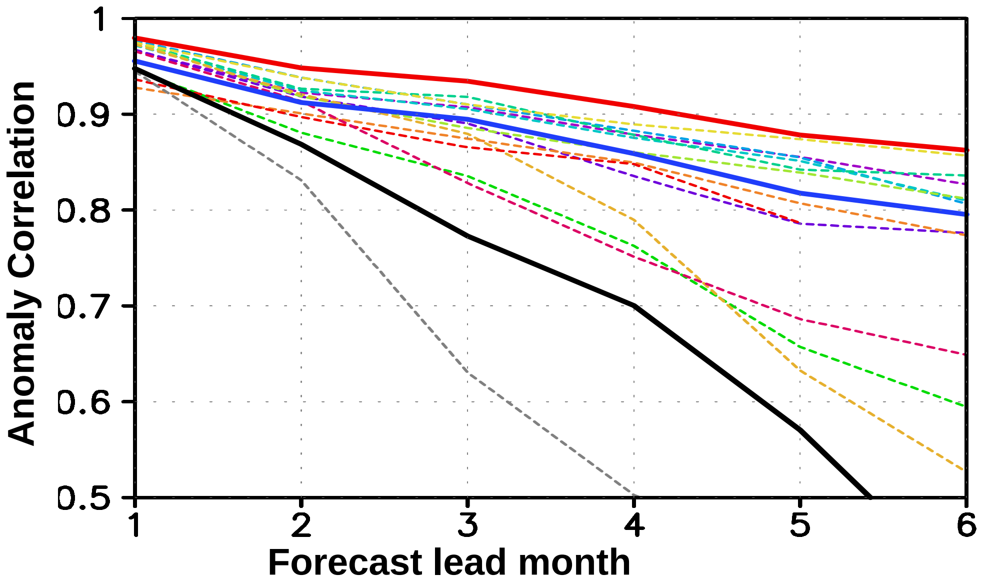


The MME one-month lead hindcast can predict, with high fidelity, the spatial-temporal structures of the first two leading empirical orthogonal modes of the equatorial SST anomalies for both the boreal summer (JJA) and winter (DJF), which account for about 80% to 90% of the total variance. The major bias is a westward shift of the SST anomaly between the dateline and 120°E.

4. Hindcast NINO 3.4 SST

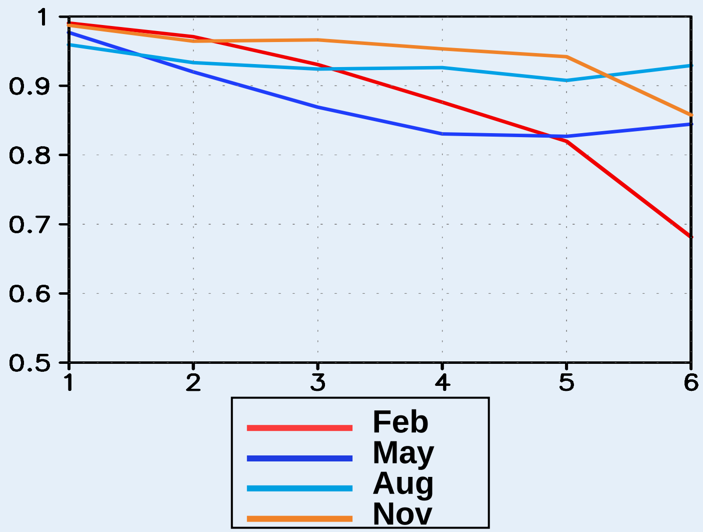
Overall Skill



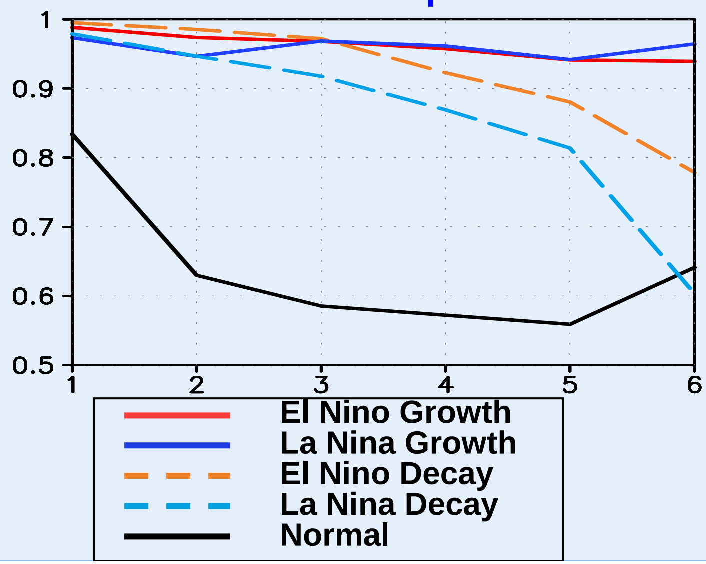


Tier-1 MME Forecast

Seasonal dependence

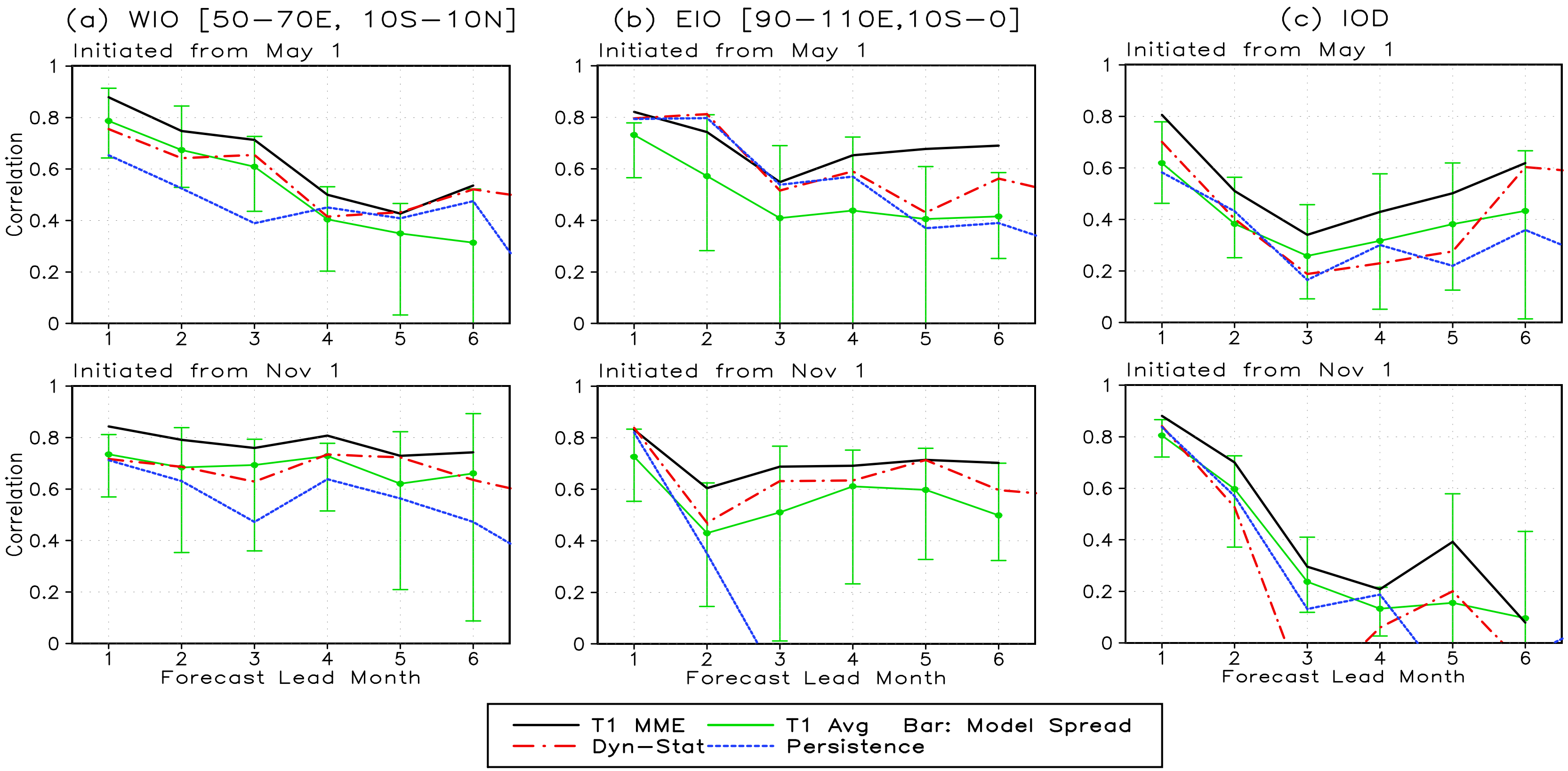


ENSO Phase-dependence



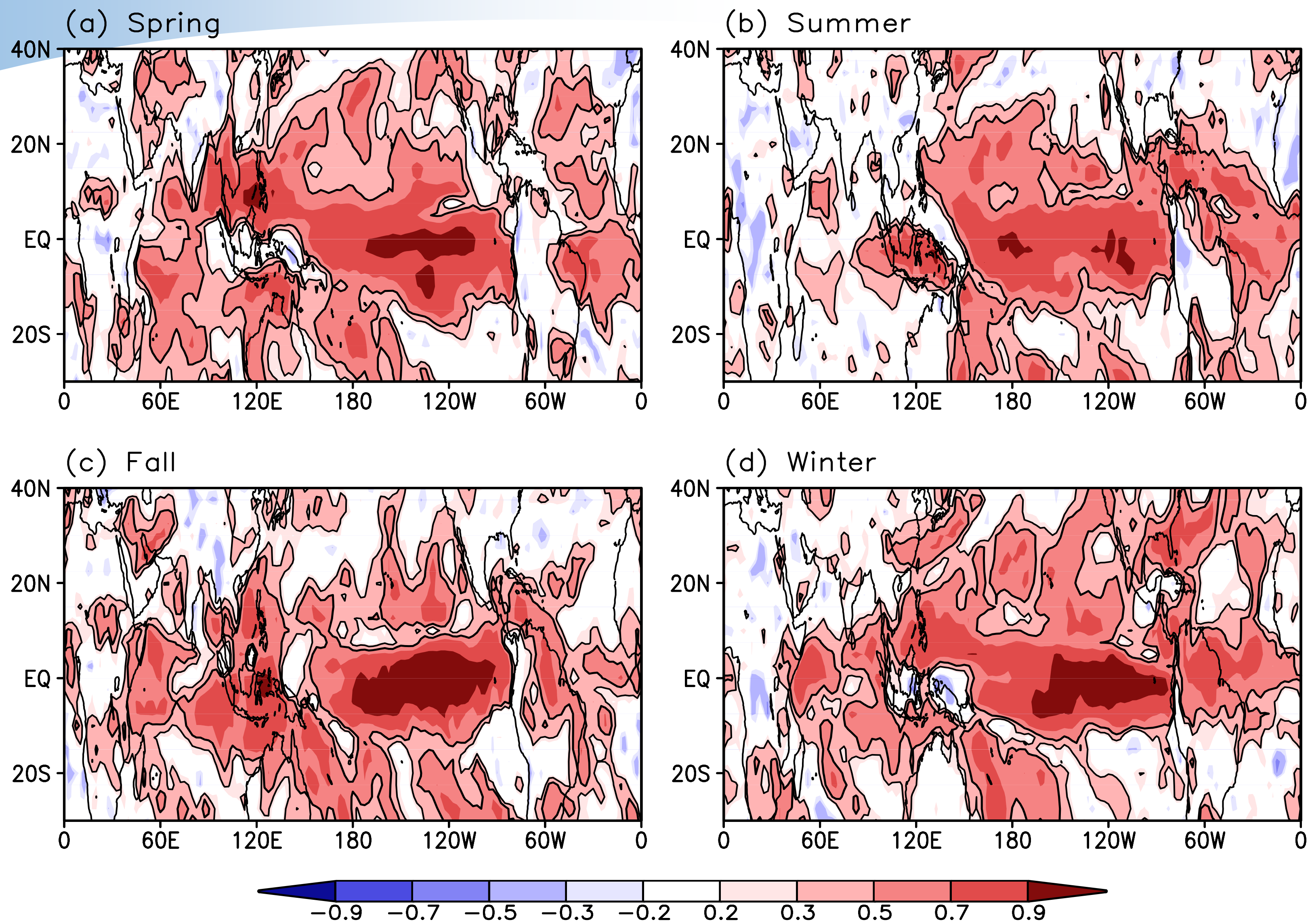
5. Indian Ocean SSTA Hindcast

Correlation Skill for Indian Ocean SSTA

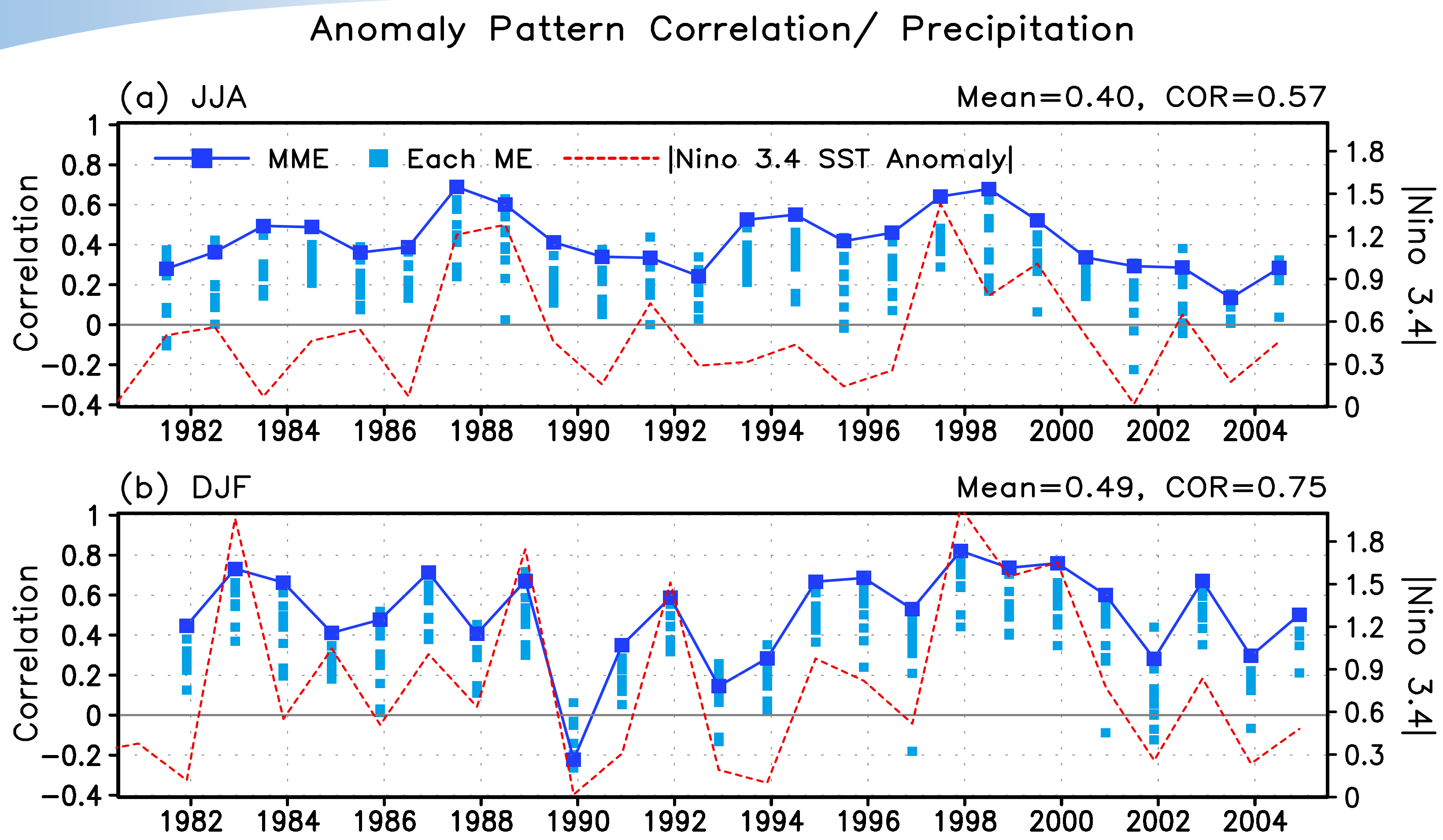


The TCC score over the equatorial EIO reaches about 0.68.
The TCC score for IOD index drops below 0.40 at a three-month lead for both the May and November initiations due to prediction barriers across January and July.

6. Precipitation Prediction: TCC 13 Coupled Model MME



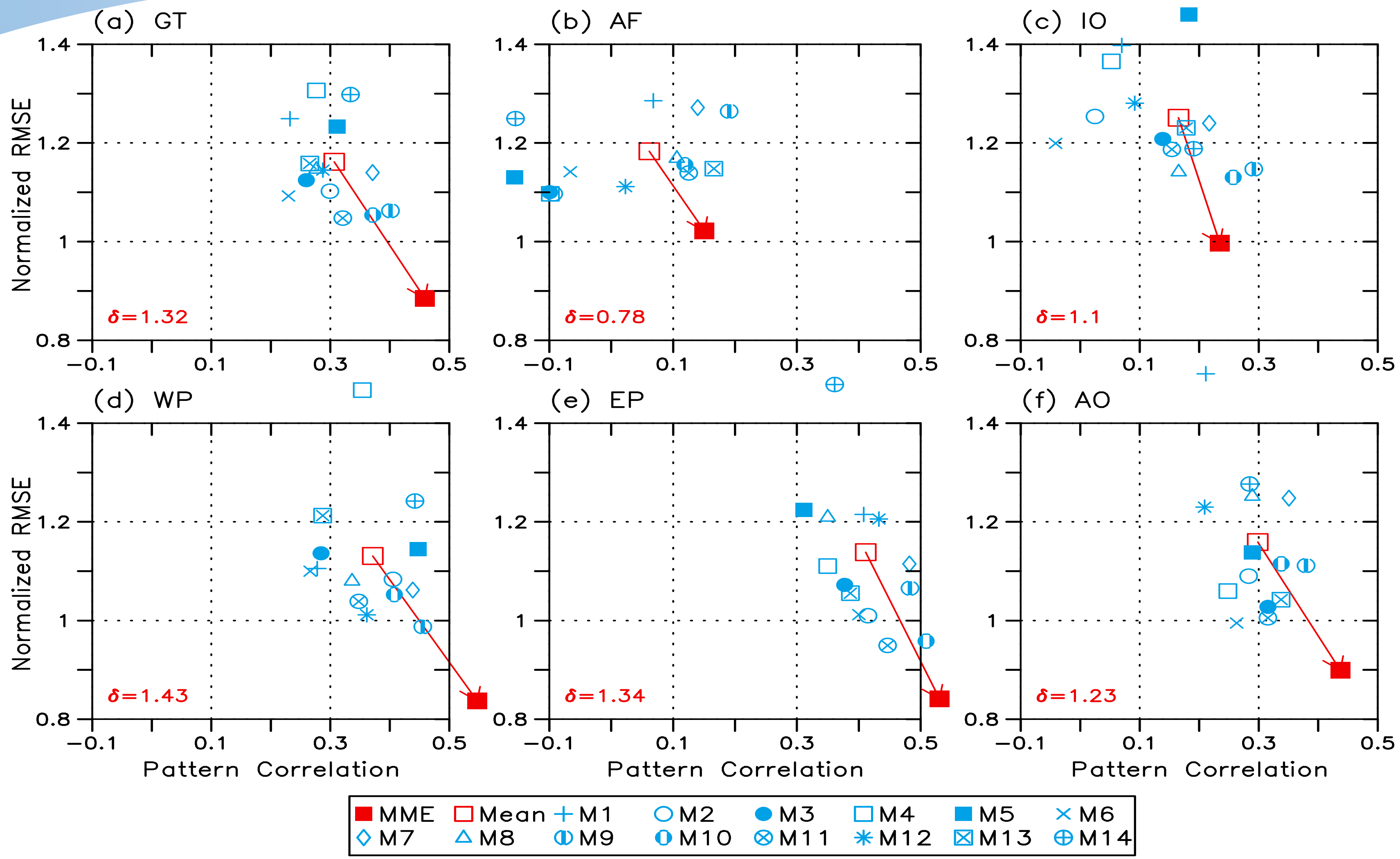
6a Year to year fluctuation



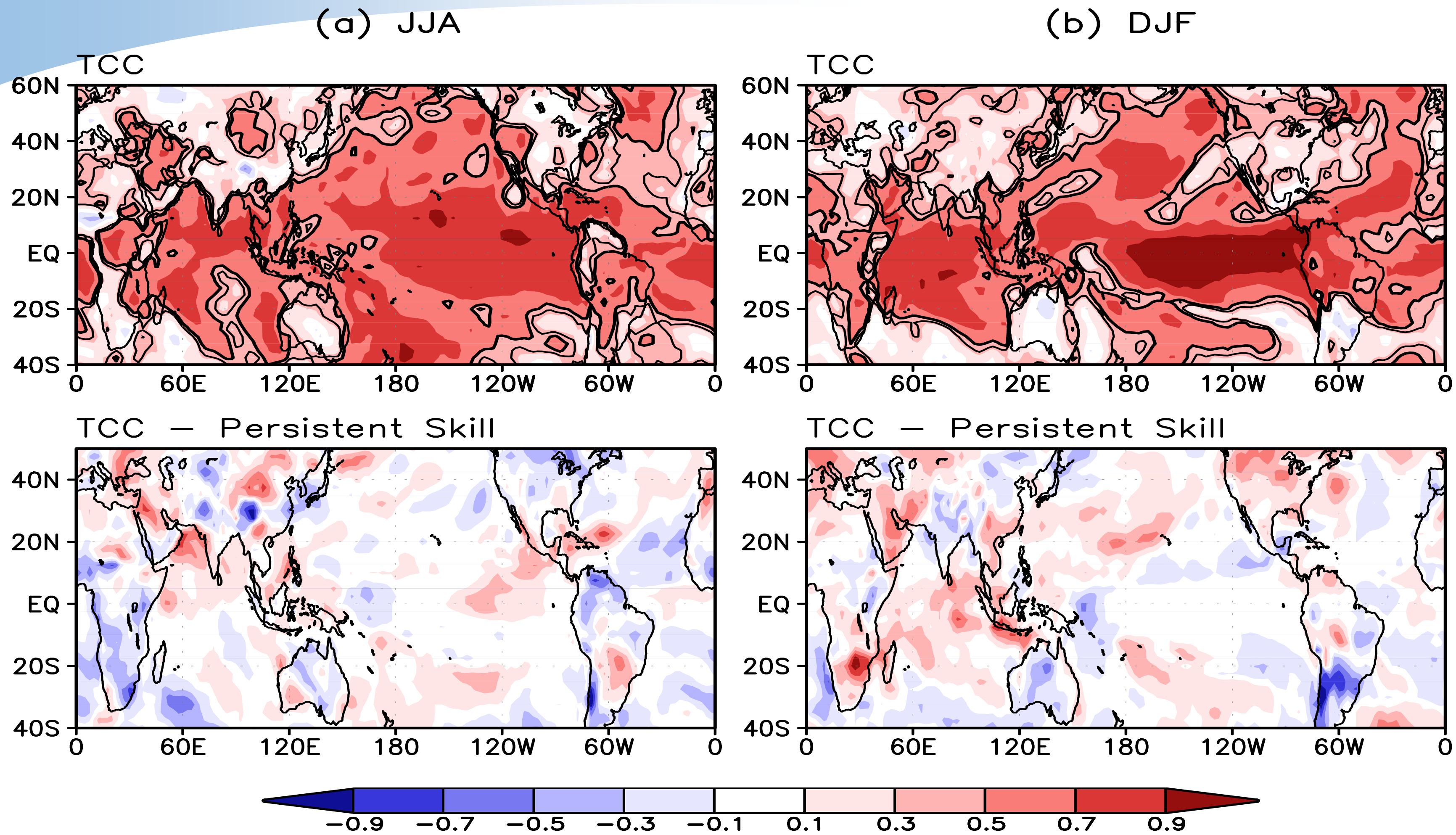
MME prediction skills depend highly on the amplitude of Niño 3.4 SST variation.
Forecasts are better in El Niño years than in La Niña years.
Prediction is better in ENSO-decaying JJA than in ENSO-developing JJA.
Virtually no skill in ENSO-neutral years.

CliPAS

6b Longitudinal dependence

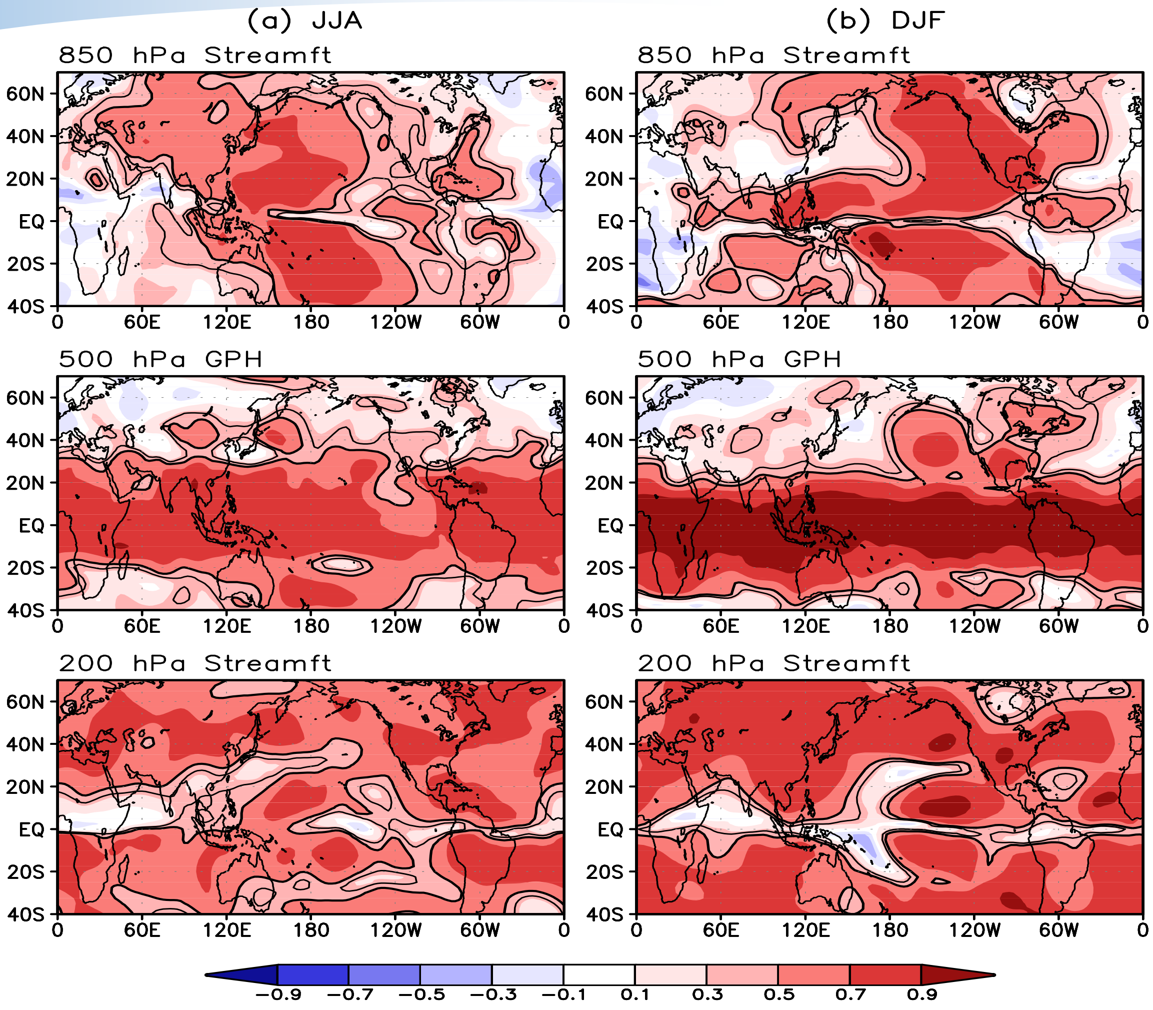


7. MME TCC for Temperature (1981-2003)



JJA skill (0.53) is better than DJF skill (0.50). MME prediction of air temperature is considerably superior to the persistence skill in the warm pool oceans, but not necessarily over the land.

8. Skill for circulation fields are high



prediction of circulation fields better than temperature and precipitation.
200 hPa streamfunction shows very good correlation skill almost everywhere.
The high-skill predictuion of 850 hPa streamfunction shifts eastward from JJA to DJF

Conclusion

1. Relationship between two types of forecast measures
2. Effectiveness of MME approach
3. Equatorial SST: Principal modes
4. ENSO forecast: Season- and Phase-dependent
5. Indian Ocean SST forecast: winter and summer prediction barrier
6. Precipitation: season-, longitude-, and ENSO- dependent
7. Temperature: gains over persistence
8. High circulation prediction

Conclusion

- MME is an extremely valuable approach for reducing errors and quantifying forecast uncertainty due to model formulation.

Thank You !

Any Question and Comment?

Prospectus

How do we move forward with seasonal prediction? Two aspects need to be considered.

- Given the current levels of the climate models, how do we get the best forecast through MME?
- From a long-run, what are the priorities we should take in improving our climate models' physics?

Given the current levels of the climate models, how do we get the best forecast through MME?

- **Improvement of MME approach** for better down scaling
- Determine **predictability of ISO** and make statistical and dynamical forecast ISO and **monthly prediction**.
- Statistical-dynamical approach for climate prediction of extreme events.
- Urgent need is to determine the **role of land-atmosphere interaction** in monsoon predictability.

Directions

- **Improvement of MME approach** for better down scaling
- Determine **predictability of ISO** and make statistical and dynamical forecast ISO and **monthly prediction**.
- Statistical-dynamical approach for climate prediction of extreme events.
- Urgent need is to determine the **role of land-atmosphere interaction** in monsoon predictability.
- Continuously improving **slow coupled physics** is a key for long-lead seasonal forecast.
- Improve **initialization** of **one-tier system,** including **coupled data assimilation and reanalysis**.
- Development of **High resolution global models** for prediction of TC and other extreme events.
- Improvement of models' physics representation and **correcting systematic mean errors**.

CliPAS Publication

- Published:

  Overall assessment of CliPAS MME: Advance and prospectus (Wang et al. 2008);

  Predictability of ENSO (Jin et al. 2008),

  Predictability of the A-AM (Wang et al. 2008),

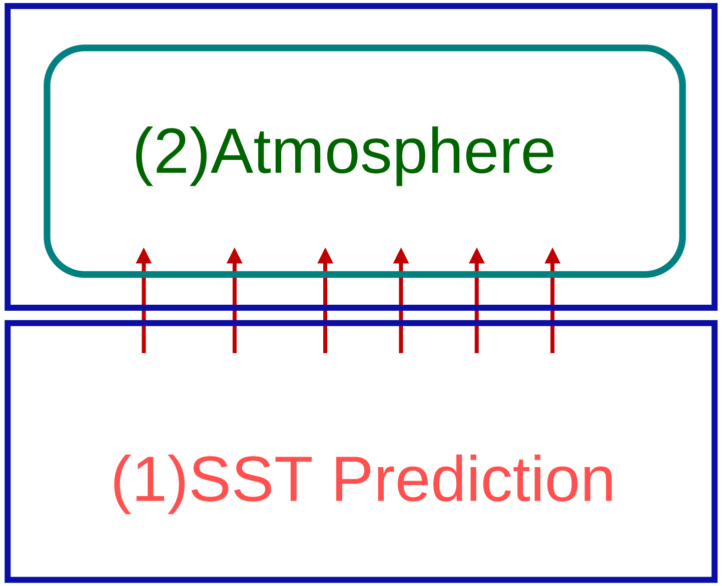
  Predictability of ISV (Kim et al. 2008, Fu and Wang 2007),

  Performance of coupled models on annual cycles and the relation to seasonal prediction skills (Lee et al. 2008), and

  Optimal MME method for seasonal climate prediction (Kug et al 2008).
- A number of manuscripts to be submitted this year

Physical basis

(1) Two-Tier System



Forced problem:
Predictability comes from anomalous lower boundary forcing

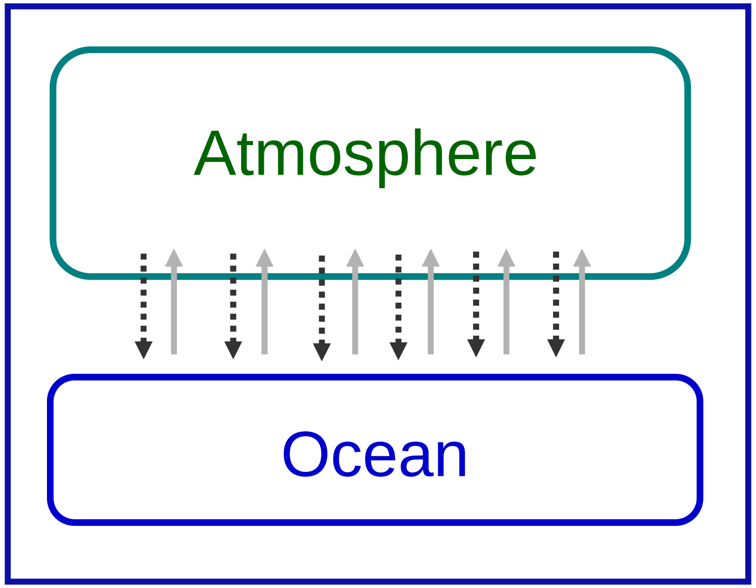
Charney and Shukla (1977, 1981), Lorenz (1982)

Two-tier system:
AGCM forced by predicted SST

Bengtsson et al. (1993), Barnet et al.(1994), Levezey et al. (1996)

Treating monsoon as a slave to prescribed SST results in the models' failure in AMIP-type of simulation (Wang et al. 2004) and **the tier-2 prediction of summer monsoon** (Wang et al. 2005; Wu and Kirman 2005,Kumar et al. 2005, Nanjundiah et al. 2005; Kug et al. 2007), because the Asian-Australian monsoon is essentially a coupled atmosphere-ocean system (Webster et al. 1998, Meehl et al. 2003, Wang et al. 2003)

(2) One-Tier System



Initial value problem:
Predictability comes from Initial memory and slow coupled dynamics.
Palmer (1993), Palmer and Shukla (2000),

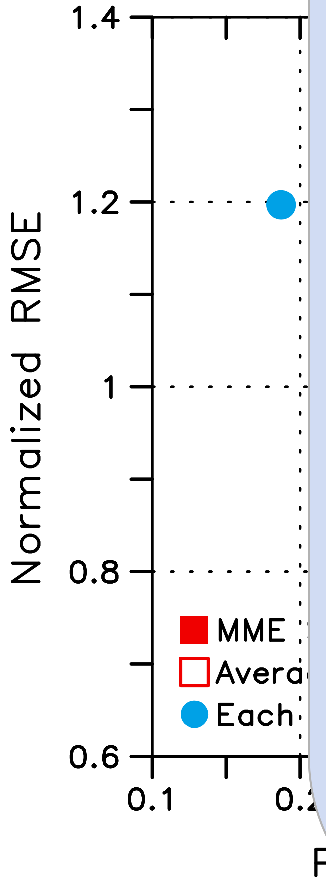
ENSO forecast: Cane and Zebiak (1985)

One-Tier system:
Coupled A-OGCM
Ji et al. (1996), Stockdale et al. (1998)

Systematic biases in coupled mean states and coupled modes

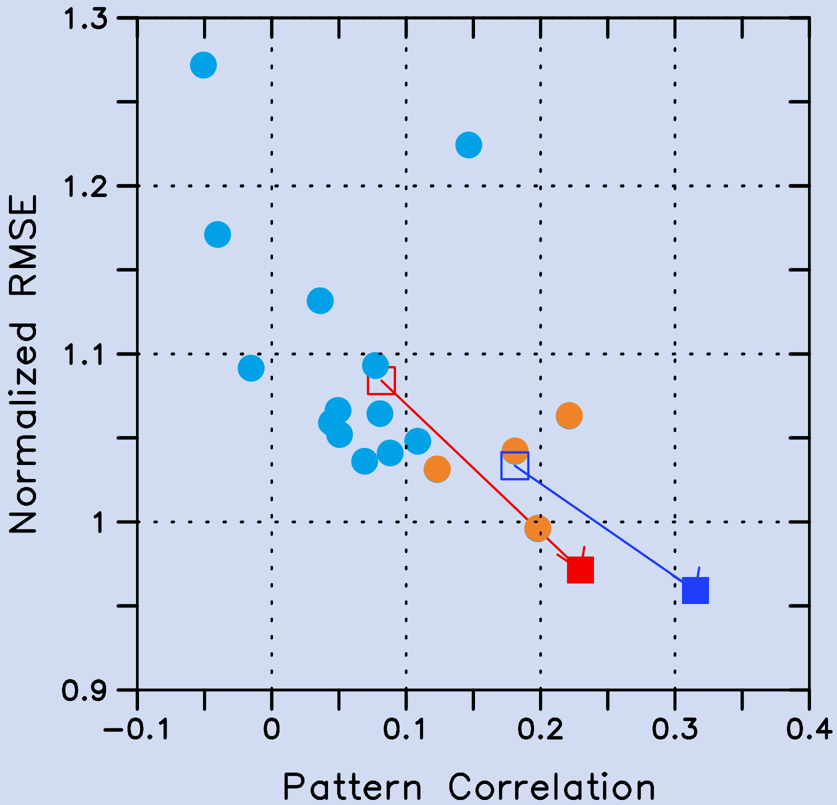
MME prediction: Optimal Selection of Models

Forecast S



Optimal Selection of a Subgroup of Models

Example: East Asian Domain [105-145E, 20-45N]
The best MME skill is obtained using 4 models.



ndo-Pacific
N]

17 climate
n CliPAS

Evaluation of Deterministic forecast

(1) Simple composite

✓ Equal weighting method $P = \frac{1}{M}\sum_i F_i$

✓ Pavan and Doblas-Reyes 2000; Peng et al. 2002; Palmer et al. 2004; Kang et al. 2002; Wang et al. 2004, 2008

(2) Multiple regression and SVD method

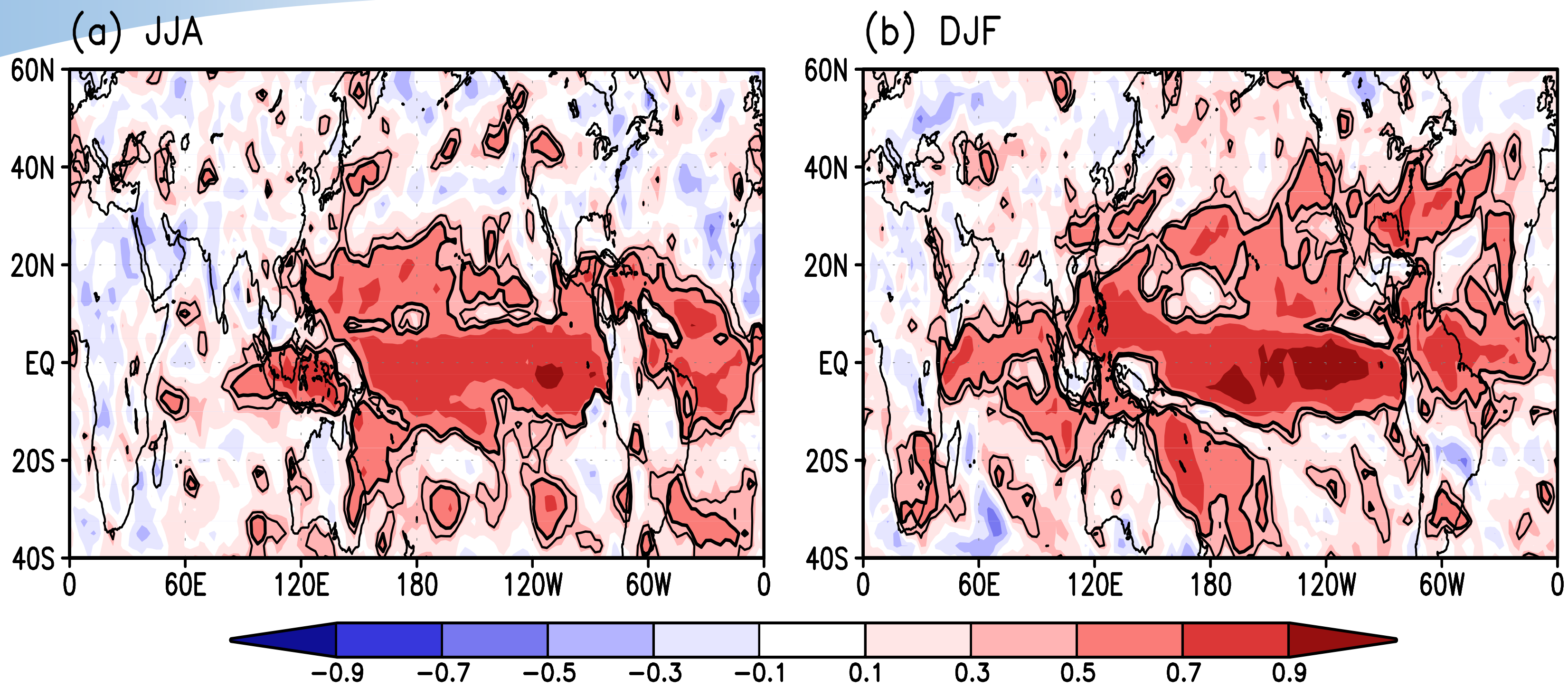
✓ Superensemble method $P = \sum_i a_i F_i$

✓ Krishnamurti et al. 1999, 2000; Kharin and Zwiers 2002, Yun et al. (2003. SVD method)

✓ Yun et al. 2005. Chakraborty and Krishnamurti 2006

(3) SPPM method (more sophisticated statistical post-processes

APCC/CliPAS MME TCC for Precipitation (1981-2003)



Pecipitation skill in DJF (0.57) is significantly higher than that in JJA (0.46) over the global tropics.
The high DJF skill is in NH between 0 and 40°N, and especially in the northern subtropics between 20°N and 40°N from 40°E to 140°E in the A-AM sector and from 60°W and 90°W in the American sector.