The Abdus Salam
International Centre for Theoretical Physics

United Nations
Educational, Scientific and
Cultural Organization

IAEA
International Atomic Energy Agency

1956-15

Targeted Training Activity: Seasonal Predictability in Tropical Regions to be followed by Workshop on Multi-scale Predictions of the Asian and African Summer Monsoon

4 - 15 August 2008

MJO/ISV predictions: dynamical vs. statistical.

Kang In Sik
Seoul National University
School of Earth and Environmental Sciences
Division of Atmospheric Sciences
San 56-1 Shillim-dong, Kwanak-ku, Seoul 151-742
REPUBLIC OF KOREA

Combined and calibrated predictions of intraseasonal variation with dynamical and statistical methods

Hye-Mi Kim and In-Sik Kang

Climate and Environment System Research Center
Seoul National University, Korea

Targeted Training Activity, Aug 2008

What is the predictability of the ISV at present ?

What is the predictability of the ISV at present ?

I. ISV predictions with various statistical models

II. ISV prediction with a current dynamical model

III. Combine and calibrate the ISV predictions

IV. Access to upper limit of ISV prediction

What should we predict?

Previous studies

Different predictands

Statistical ISV prediction

Studies	Statistical Models	Predictand
Waliser et al. (1999)	SVD	Filtered OLR,U200
Lo and Hendon (2000)	EOF and regression	OLR, stream function
Mo (2001)	SSA and regression	Filtered OLR
Goswami and Xavier (2003)	EOF and regression	Rainfall
Jones et al. (2004)	EOF and regression	Filtered OLR, U200, U850
Webster and Hoyos (2004)	Wavelet and regression	Rainfall, River Discharge
Jiang et al. (2008)	Regression	RMM index, OLR, U200, U850

Dynamical ISV prediction

Studies	Dynamical Models	Predictand
Chen and Alpert (1990)	NMC/NCEP DERF (DERF- Dynamical Extended Range Forecast)	30-90d filtered OLR,U200
Lau and Chang (1992)		OLR, stream function
Jones et al. (2000)		Filtered OLR, U200
Seo et al. (2005)		OLR, U200, U850
Vitart et al. 07	ECMWF-MFS	RMM index

What should we predict?

Previous studies

Statistical ISV prediction

EOF, regression, wavelet, SSA, …

Forecast skill : 15 - 25 days

Dynamical ISV prediction

DERF-based model

Forecast skill : 7-10 days

Different predictands

Fair and rigorous reassessment is needed in real-time prediction framework

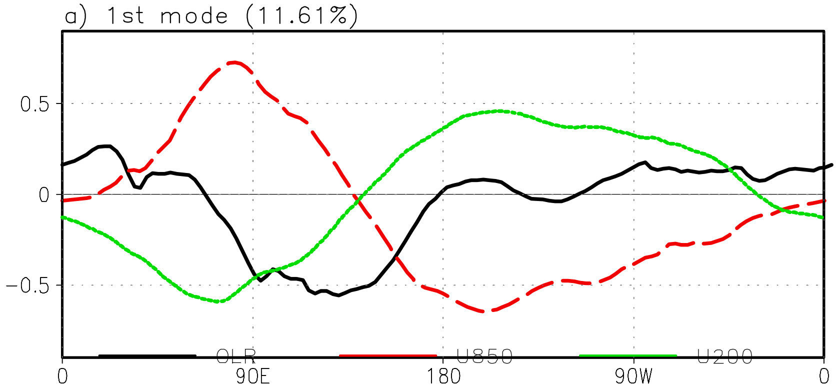
What should we predict?

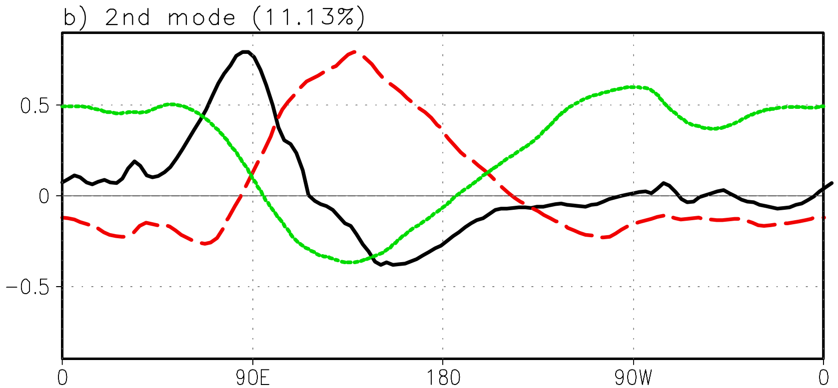
Real-time Multivariate MJO index (RMM):

The PCs of combined EOFs (Equatorially averaged OLR, U850, U200)

(Wheeler and Hendon 04)

EV of Combined EOF





1. Annual cycle removed;

2. Interannual variability (ENSO) removed:

- Regression pattern of each variable against NINO3.4

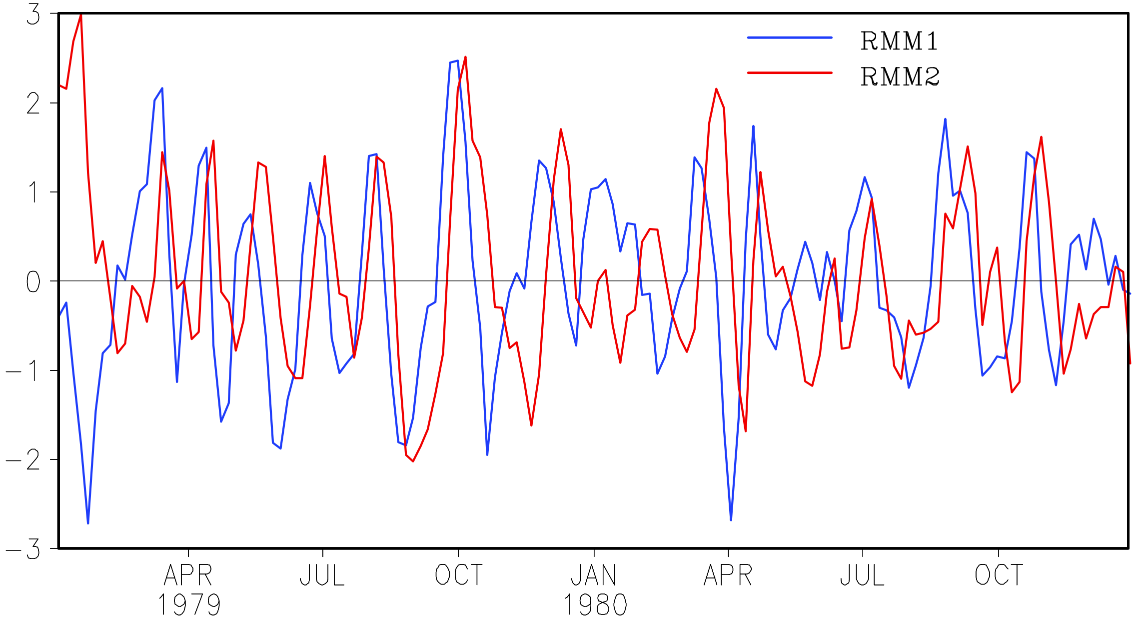
- Mean of previous 120 days

What should we predict?

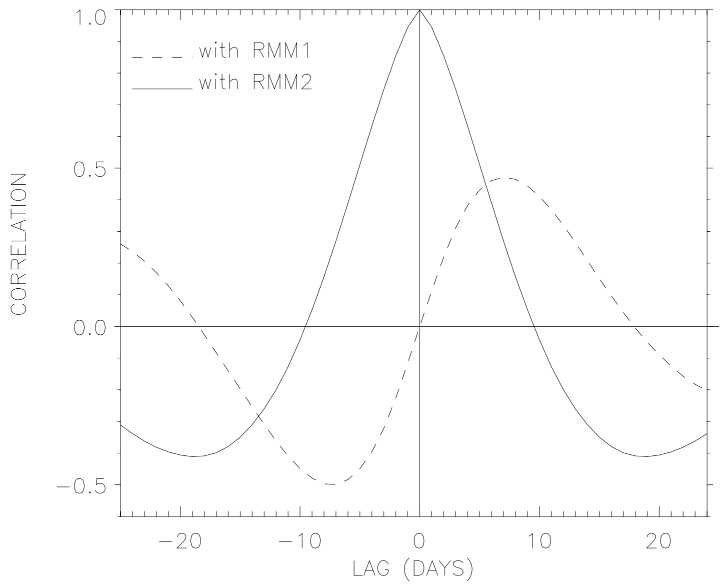
Real-time Multivariate MJO index (RMM):

The PCs of combined EOFs → RMM1 and 2

RMM-1 and RMM-2



Lag correlation to RMM1



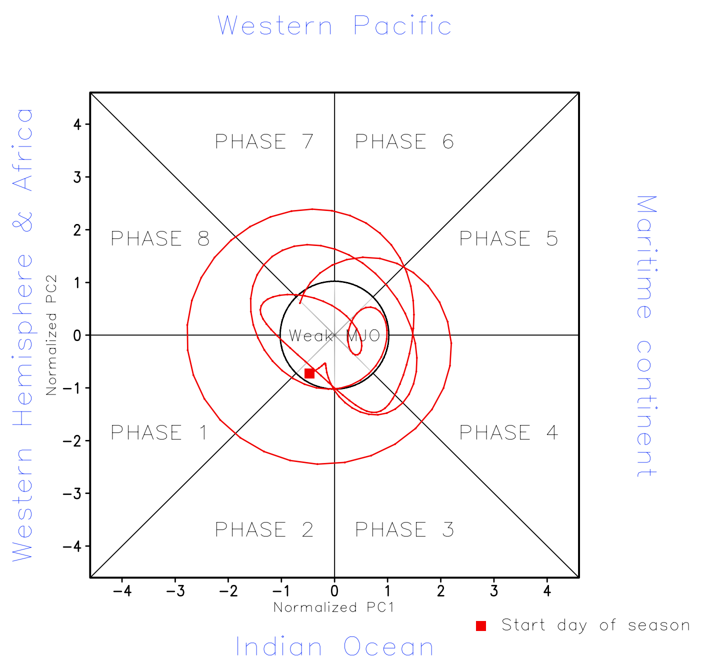
These two indices will be the target for prediction

What should we predict?

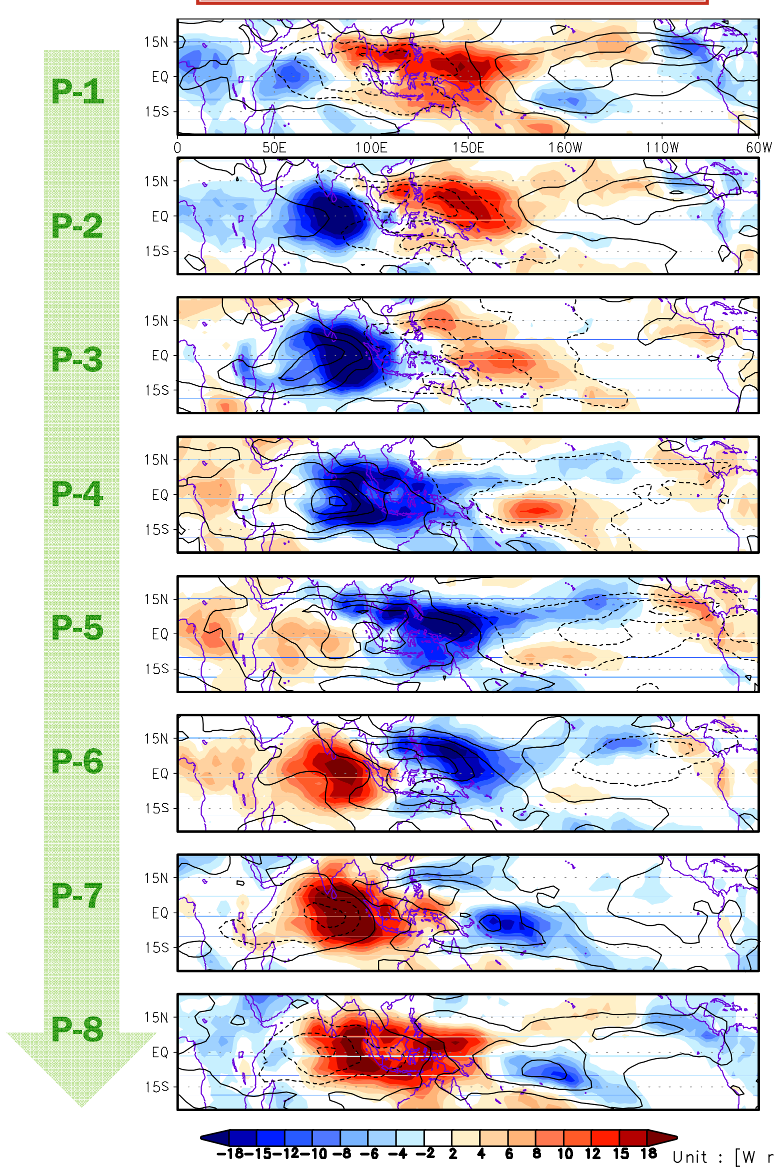
Advantages of RMM index

1. Avoid the typical Filtering problem in real-time use
2. Convenient for application (monitoring and prediction):
   Reduction of parameters
3. Represent the MJO in individual phase

Phase diagram (RMM1, RMM2): 1979 Jan-Dec



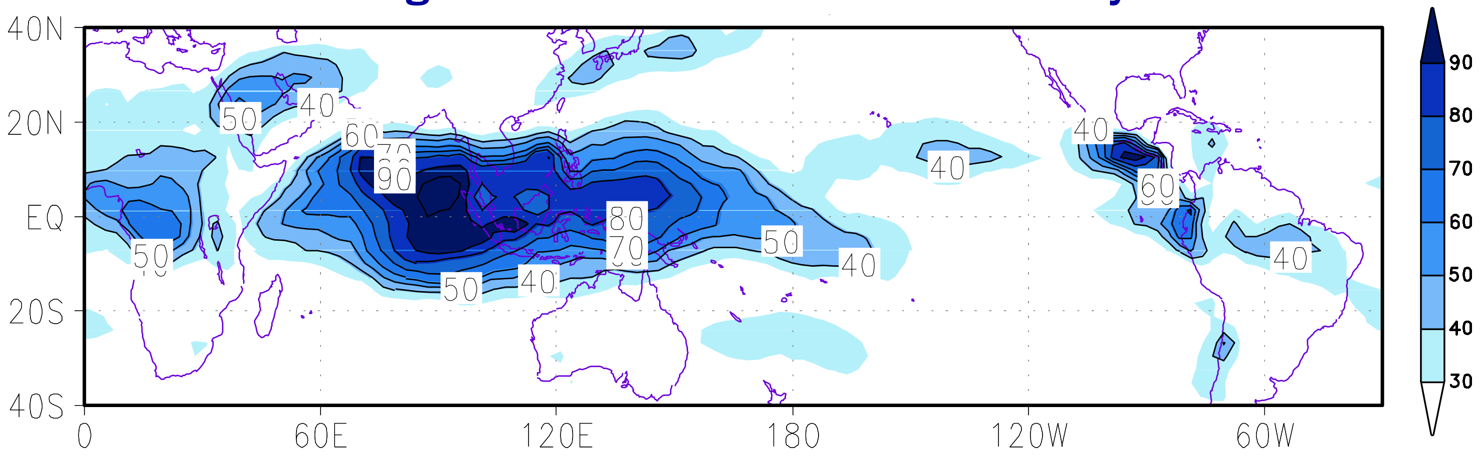
Composite: OLR & U850



What should we predict?

MJO Variability

Ratio of RMM-regressed OLR variance to the 20-70 day filtered variance



→ **Two modes explain much of the tropical MJO variability**
→ **Recently, it is used for real-time monitoring/prediction of MJO (http://www.cdc.noaa.gov)**

Decision of common predictand for various prediction models
→ PC1 and PC2 of combined EOF, the RMM index

Statistical prediction

- Multi regression model
- Wavelet based model
- SSA based model

Statistical model

Predictand: RMM index

Multi-regression — Wavelet — SSA

Prediction of RMMs (regression)

$$X(t_0+\tau)=\sum_{p=1}^{m}\sum_{j=1}^{\lambda}B_{pj}(\tau)X_p(t_0-j+1)$$

$j = j^{th}$ day earlier from t_0

$\tau = $ lead time

$\lambda = $ lag

$m = PCs$

$B_{pj} = $ lag – regression coeff

Wavelet analysis

↓

Prediction of bands (regression)

↓

Reconstruction

(Torrence and Compo, 1998)

$$W_n(s)=\sum_{n'=0}^{N-1}x_{n'}\left(\frac{\delta t}{s}\right)^{1/2}\psi_o\left[\frac{(n'-n)\delta t}{s}\right]$$

$$R(t_0+\tau)=\sum_{p=1}^{m}\sum_{j=1}^{\lambda}B_{pj}(\tau)R_p(t_0-j+1)$$

$$x_n=\frac{\delta j\,\delta t^{1/2}}{C_\delta\psi_0(0)}\sum_{j=0}^{J}\frac{\Re\{W_n(s_j)\}}{s_j^{1/2}}$$

SSA

↓

Prediction of PCs (regression)

↓

Reconstruction

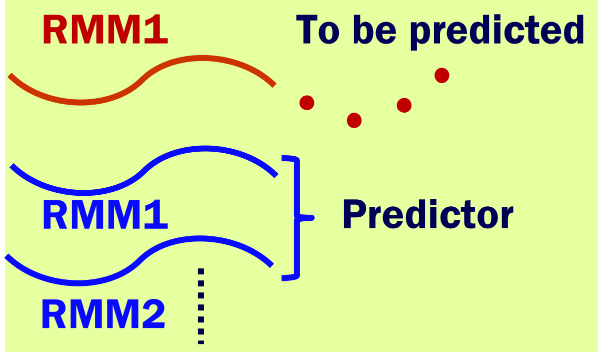
$$PC_k(t+\tau)=\sum_{p=1}^{m}\sum_{j=1}^{\lambda}B_{pj}(\tau)PC(t+\tau-j)$$

$$RC_k(t+\tau)=\frac{1}{M}\sum_{s=1}^{M}PC_k(t-s+1)EV_k(s)$$

Statistical model

Multi-regression

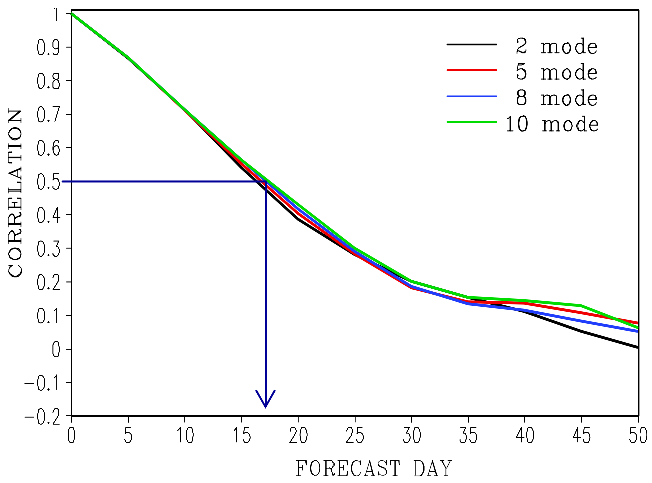
Prediction of RMMs (regression)



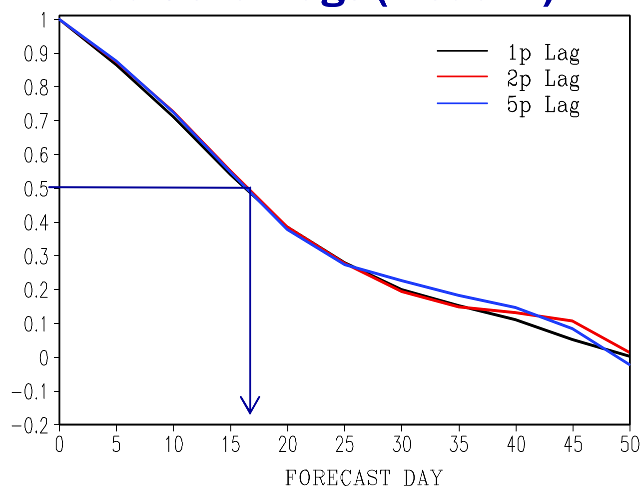
Forecast skill of RMM1

Correlation 0.5 at (day)
16~18

More modes (lag=1)



Additional Lags (mode=2)

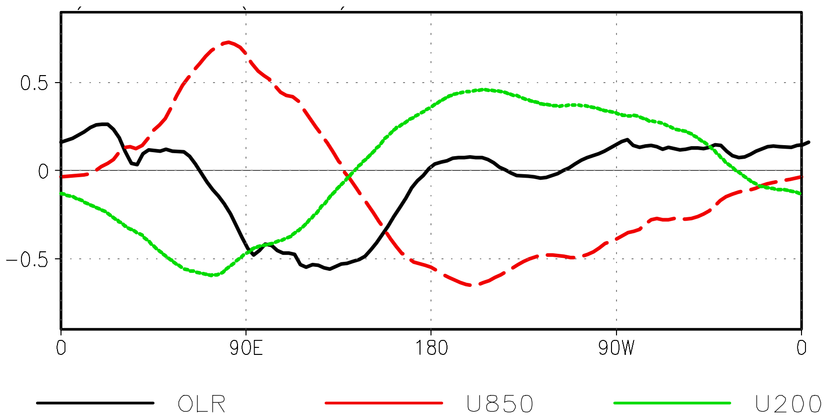


Statistical model

Multi-regression

Combined EOF

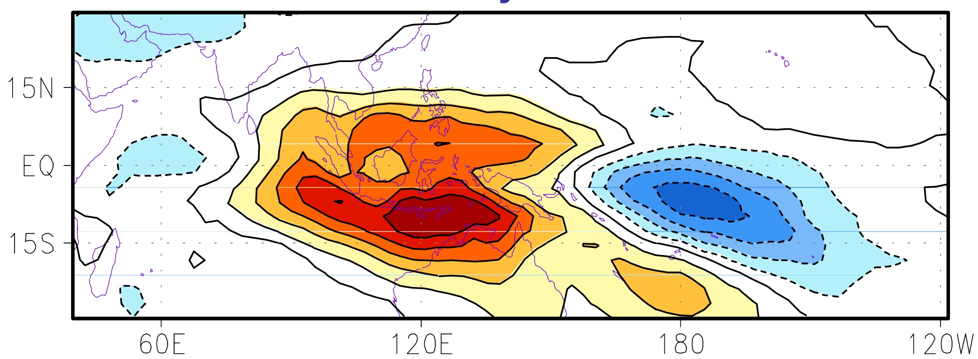
1st EOF of latitude averaged field



Spatial EOF

(Lo and Hendon 00, Goswami and Xavier 03, Jones et al. 04)

1st EOF: OLR anomaly



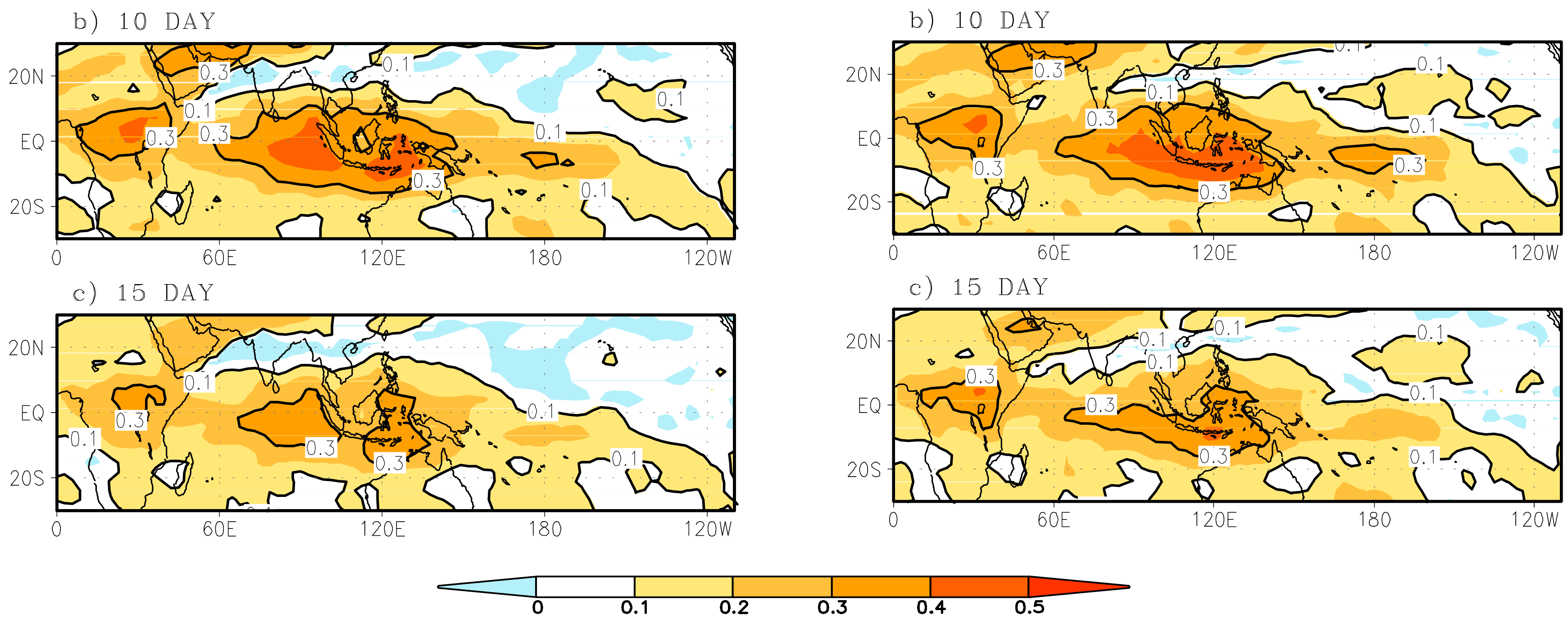
* Five Predictand = two EOFs of OLR and three of SF200

Statistical model

Multi-regression

Combined EOF **Spatial EOF**

Predictability of unfiltered-OLR anomaly



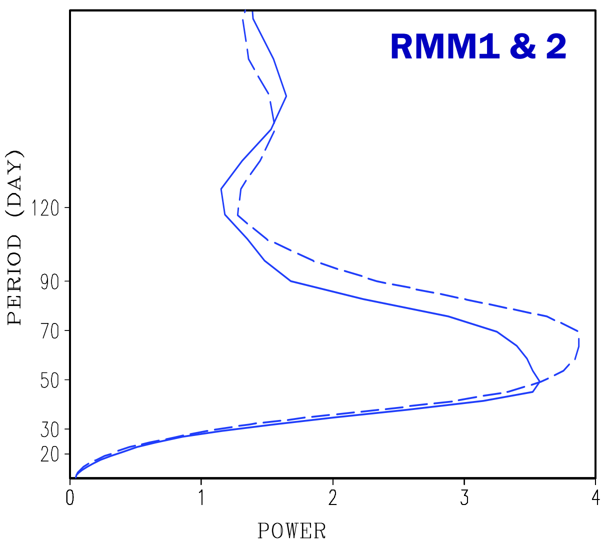
Statistical model

Wavelet

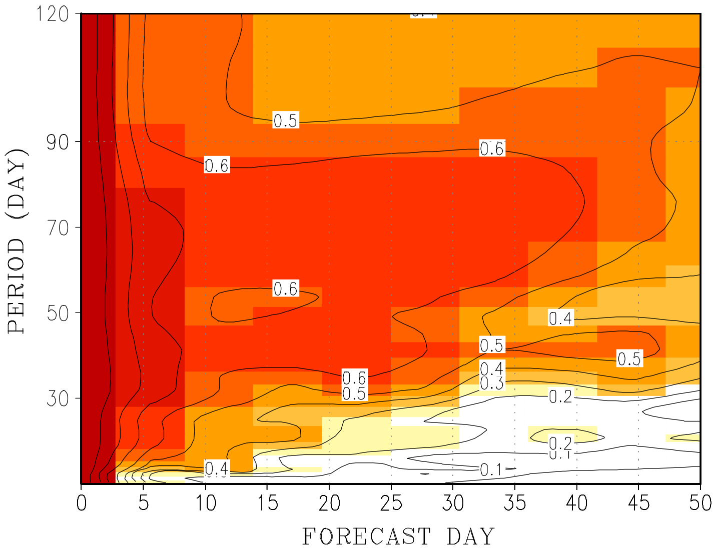
Wavelet analysis: Divide a continuous-time signal into different frequency bands

Wavelet band separation → **Prediction of bands (regression)** → **Reconstruction**

Average of wavelet spectra



Forecast skill of wavelet bands



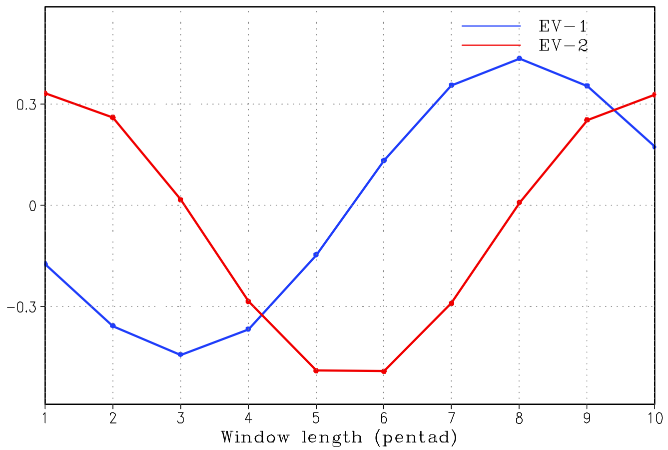
Statistical model

SSA

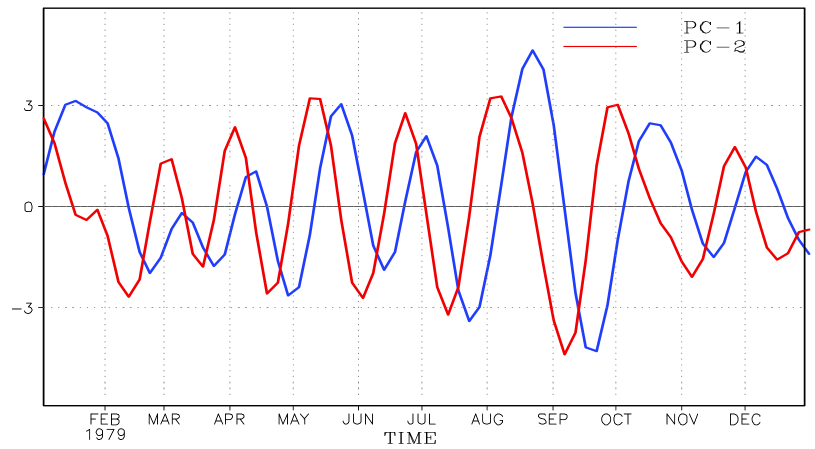
SSA: Extract the dominant mode to isolate quasi-oscillations from noisy time series

SSA → **Prediction of PCs (regression)** → **Reconstruction**

Eigenvector: SSA-RMM1



PC timeseries

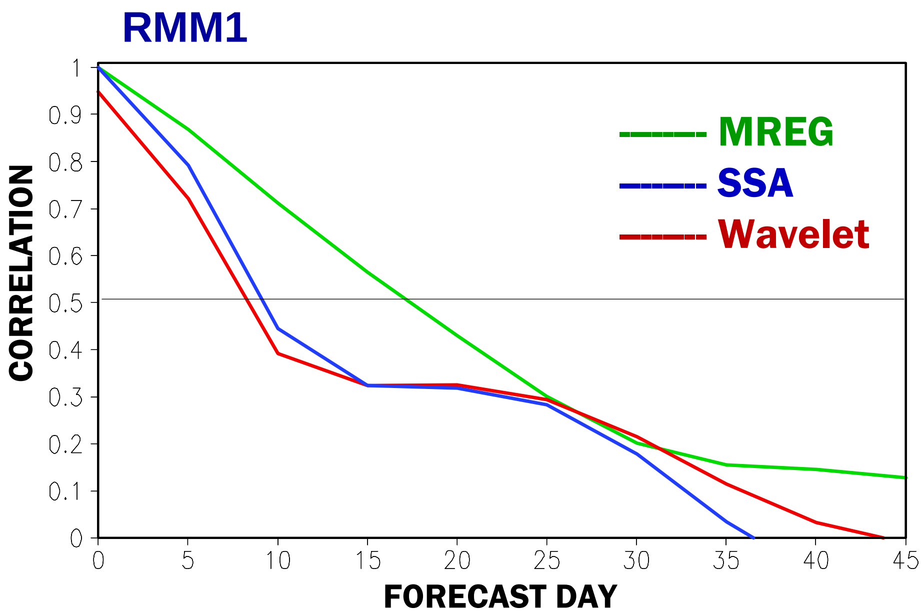


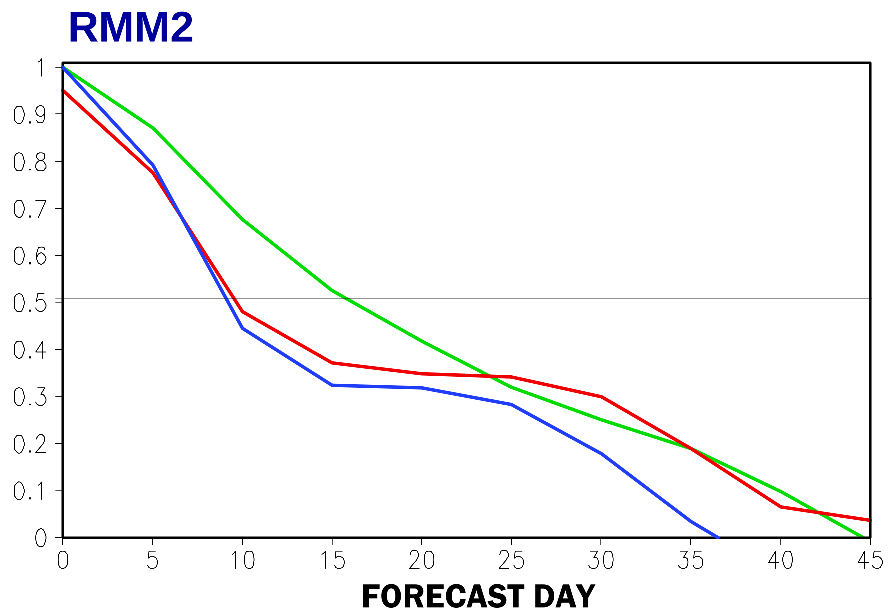
EOF1+2 > 55%
Period: 45-50 day

Statistical model

Multi-regression — Wavelet — SSA

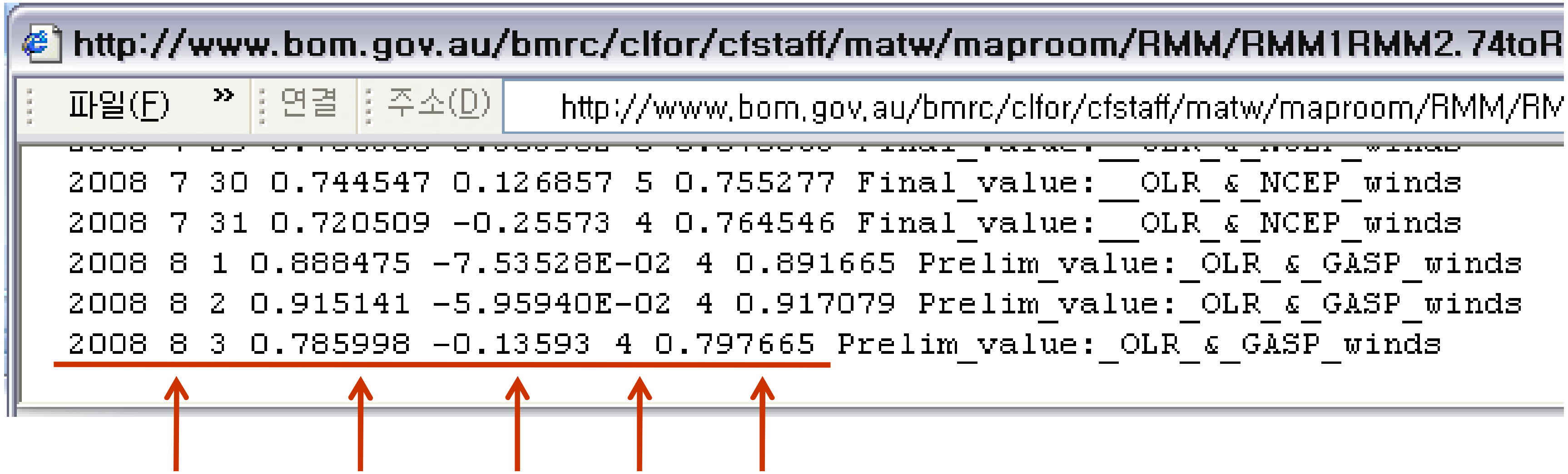
Correlation 0.5 at (day)		
	RMM1	RMM2
MREG	16-17	15-16
Wavelet	7-8	9-10
SSA	8-9	9-10





How to apply the statistical prediction in real-time ?

1) Download the observed RMMs from BMRC in near real-time


http://www.bom.gov.au/bmrc/clfor/cfstaff/matw/maproom/RMM/RMM1RMM2.74toR

파일(F) » 연결 주소(D) http://www.bom.gov.au/bmrc/clfor/cfstaff/matw/maproom/RMM/RM

```
2008 7 30 0.744547 0.126857 5 0.755277 Final_value:__OLR_&_NCEP_winds
2008 7 31 0.720509 -0.25573 4 0.764546 Final_value:__OLR_&_NCEP_winds
2008 8 1 0.888475 -7.53528E-02 4 0.891665 Prelim_value:_OLR_&_GASP_winds
2008 8 2 0.915141 -5.95940E-02 4 0.917079 Prelim_value:_OLR_&_GASP_winds
2008 8 3 0.785998 -0.13593 4 0.797665 Prelim_value:_OLR_&_GASP_winds
```

Date /RMM1/RMM2/Phase/Amplitude

“ The index is usually available in near real time about 12 hours after the end of each Greenwich day (i.e. at about 1200 UTC) “

http://www.bom.gov.au/bmrc/clfor/cfstaff/matw/maproom/RMM/RMM1RMM2.74toRealtime.txt

How to apply the statistical prediction in real-time ?

2) Apply the multi linear regression prediction model to RMMs

$$X_{1,2}(t_0+\tau)=\sum_{p=1}^{m}\sum_{j=1}^{\lambda}B_{pj}(\tau)X_p(t_0-j+1)$$

$X : RMMs$

$\lambda : 5\ \ pentads$

$m : 2\ \ \mathrm{mod}\,es$

3) Downscaling to specific regions

$$\Psi(t_0+\tau)=\beta_1X_1(t_0+\tau)+\beta_2X_2(t_0+\tau)$$

*** Regression coefficients can be obtained from historical data**

How to apply the statistical prediction in real-time ?

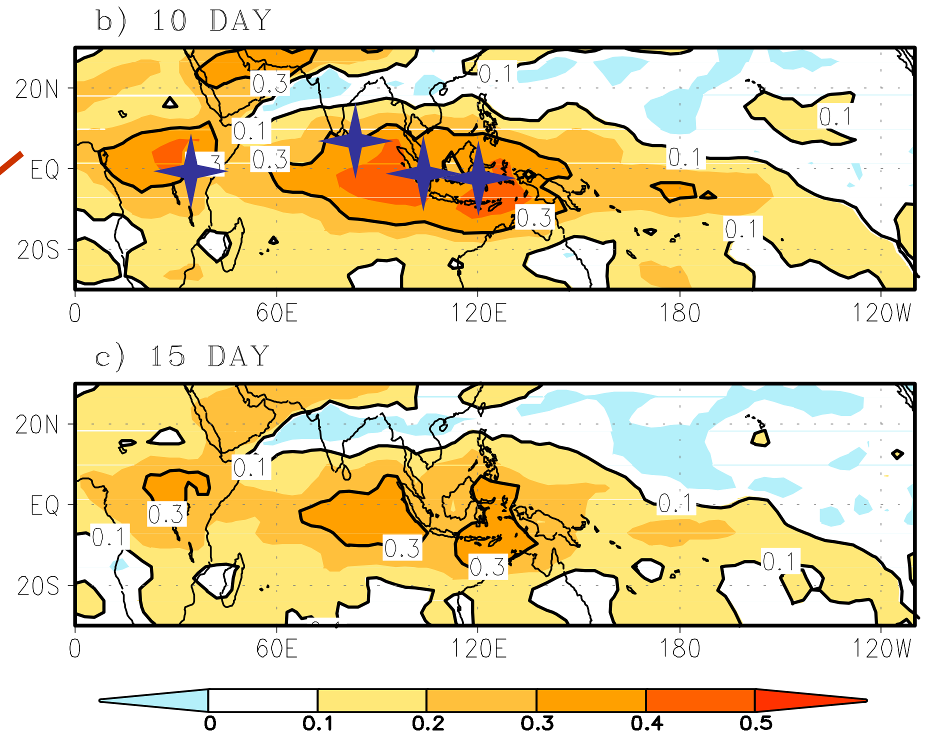
Example for downscaling

Downscaling to grids

$$\Psi(t_0+\tau)=\beta_1 X_1(t_0+\tau)+\beta_2 X_2(t_0+\tau)$$

Kenya (30E, EQ)
Sri-Lanka (80E, 5N)
Singapore(105E, EQ)
Indonesia(120E, EQ)

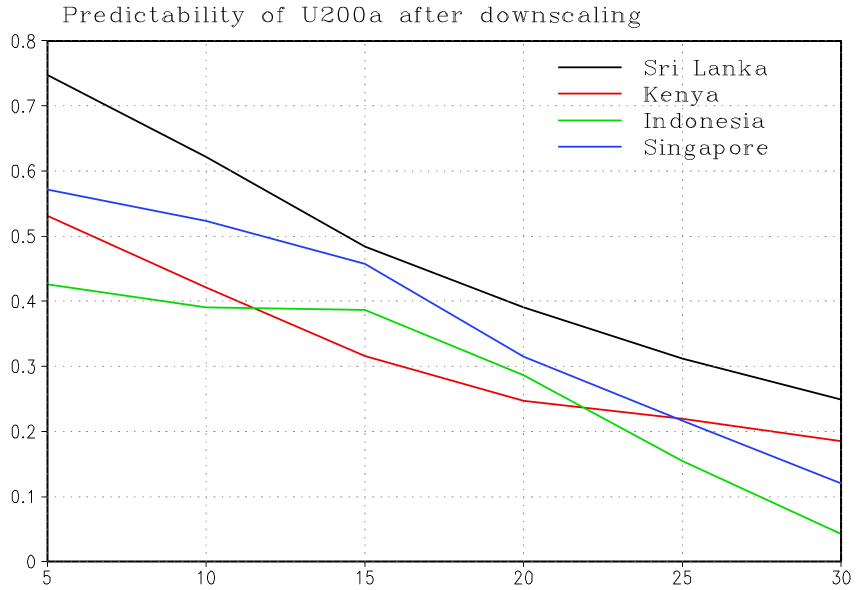
Predictability of downscaling results: unfiltered-OLRa



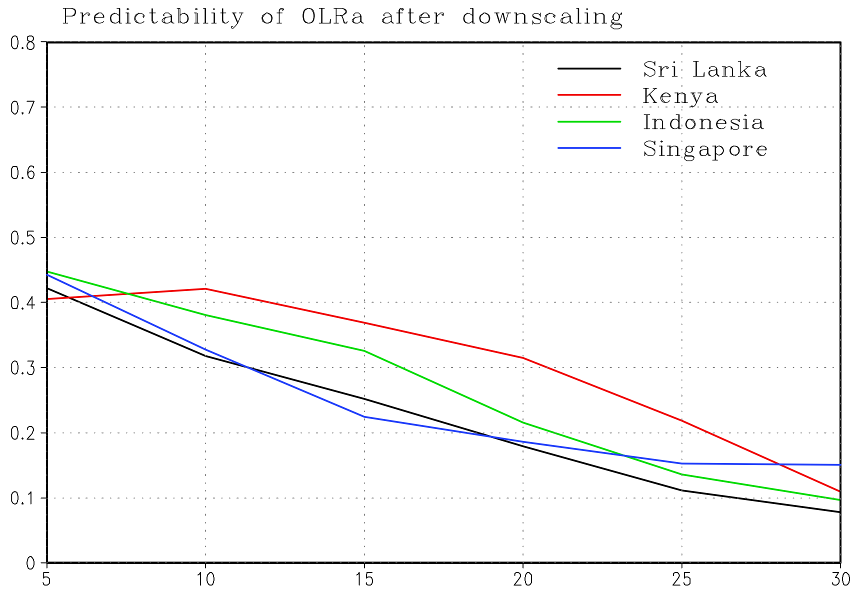
How to apply the statistical prediction in real-time ?

Example for downscaling

Unfiltered U200 anomaly



Unfiltered OLR anomaly



Dynamical prediction

- Simulation Performance
- Optimal Experimental Design
- Dynamical Predictability

Dynamical model

Dynamical model description

SNU CGCM

Model	Resolution	Note
SNU AGCM	T42, 21 levels	Bonan (1996) land surface Relaxed Arakawa-Shubert cumulus convection (Moorti and Suarez 1992)
MOM2.2 OGCM	1/3° lat. x 1° lon. over tropics(10S-10N), Vertical 32 levels	Ocean mixed layer model (Noh and Kim, 1999)

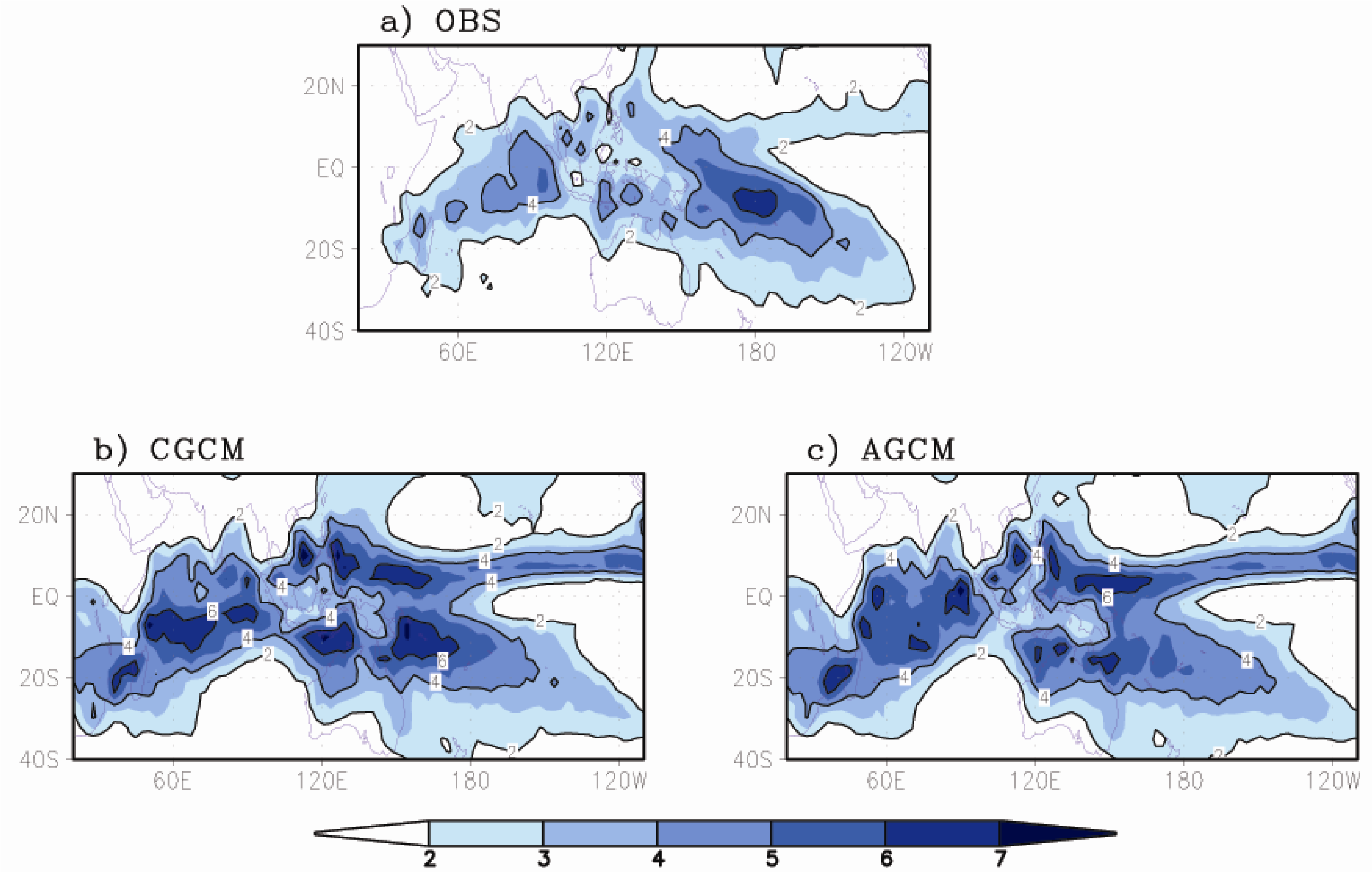
Coupling Strategy

- 1-day interval exchange
- Ocean : SST
- Atmosphere : Heat, Salt, Momentum Flux
- No Flux Correction is applied

Dynamical model

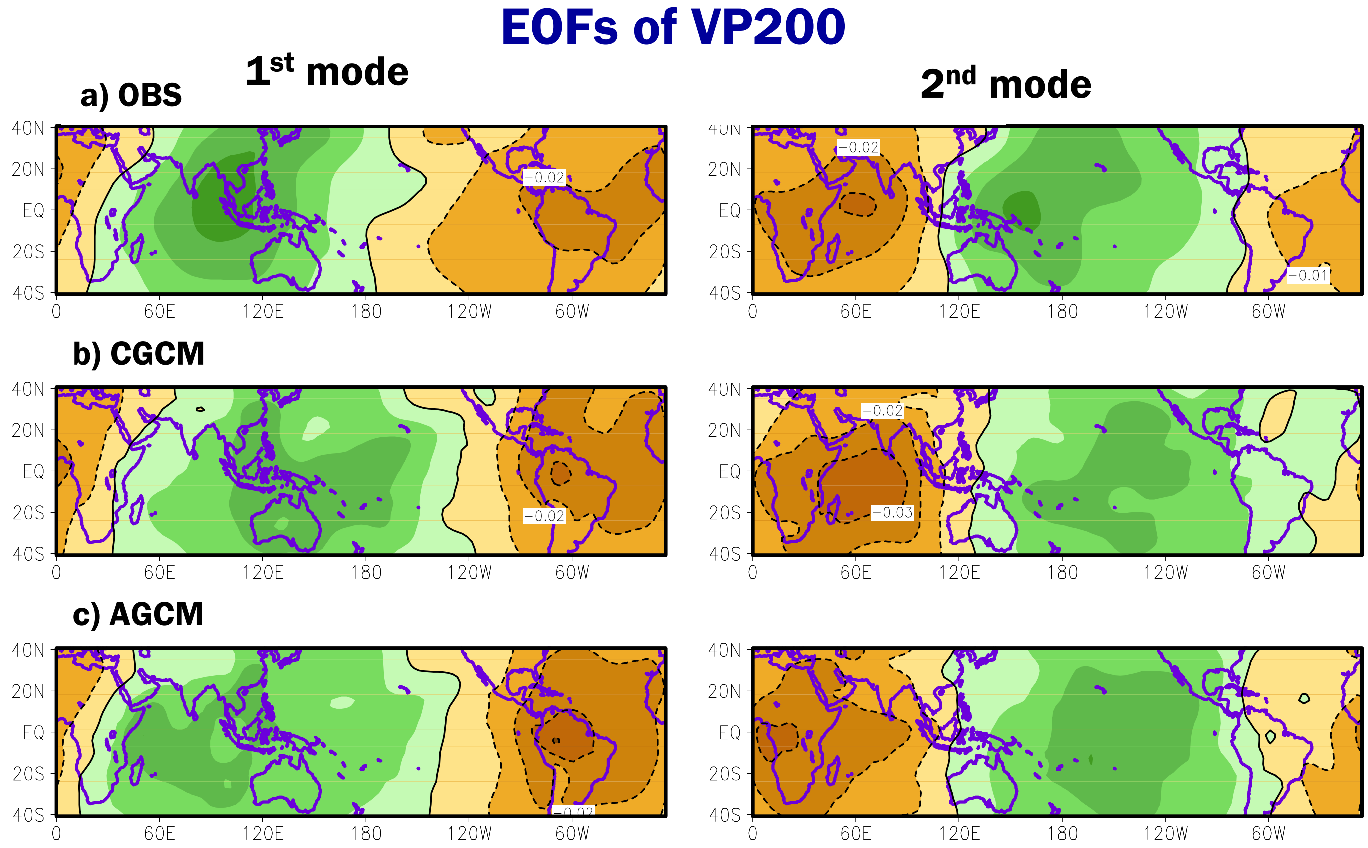
MJO simulation: Variability

Standard deviation of 20-70 filtered PRCP (1-30 day FCST)



Dynamical model

MJO simulation: Propagation



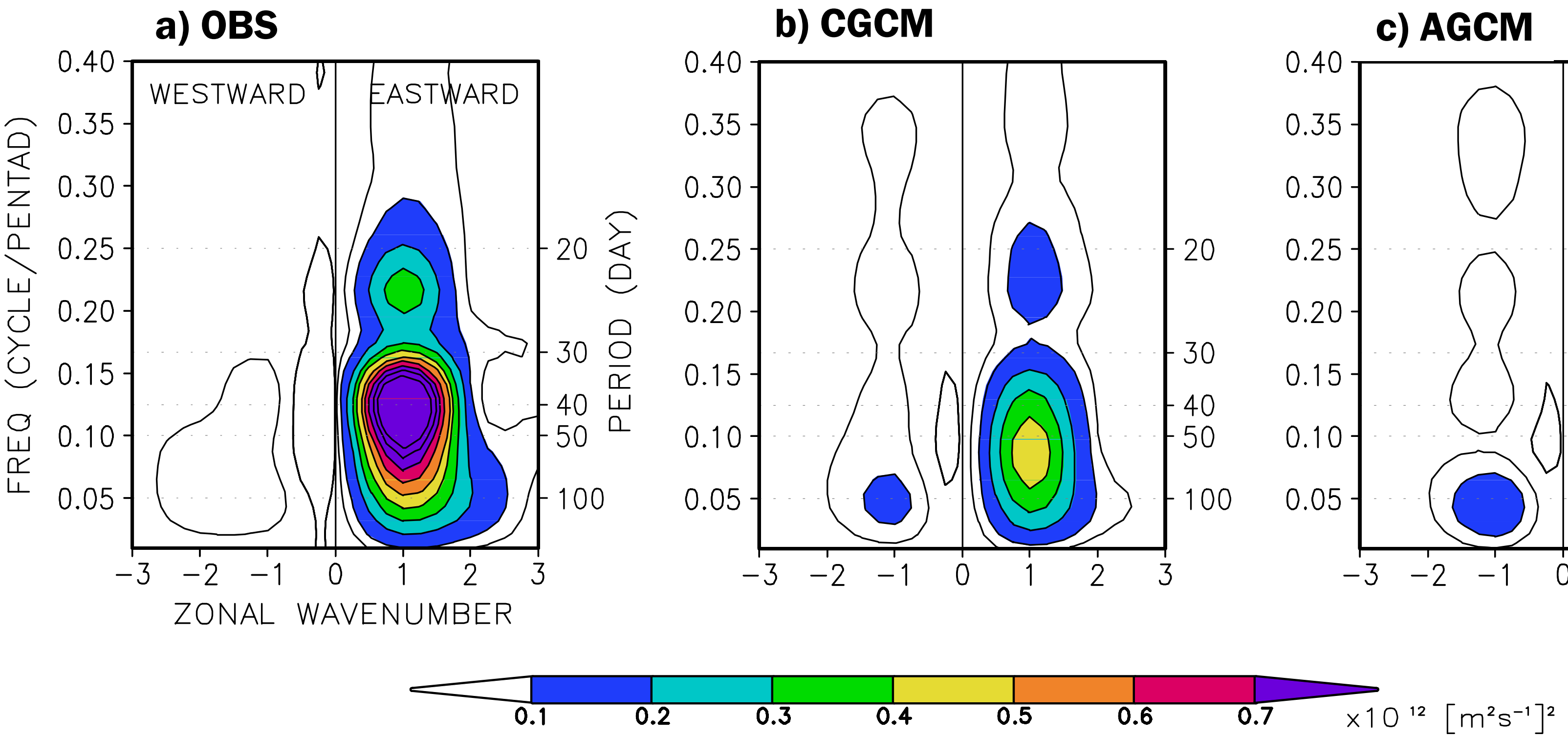
The observed two leading EOFs

- Eastward propagation mode
- Highly correlated between PC1 and PC2
- Two modes Explains more than half of the total variance

Dynamical model

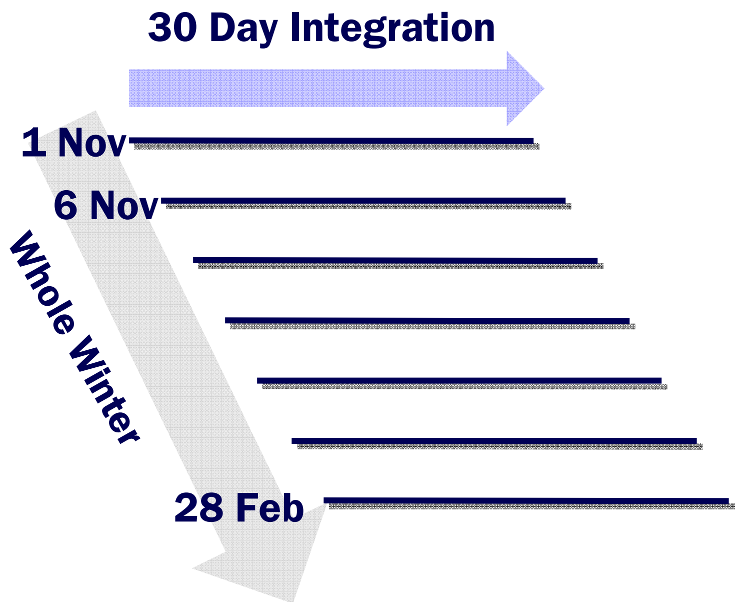
MJO simulation: Propagation

Space-time power spectrum (VP200 10S-10N, 1-30 day FCST)



Dynamical model: Experimental design

Serial integration through all phases of MJO life cycle



Serial run > Seasonal prediction

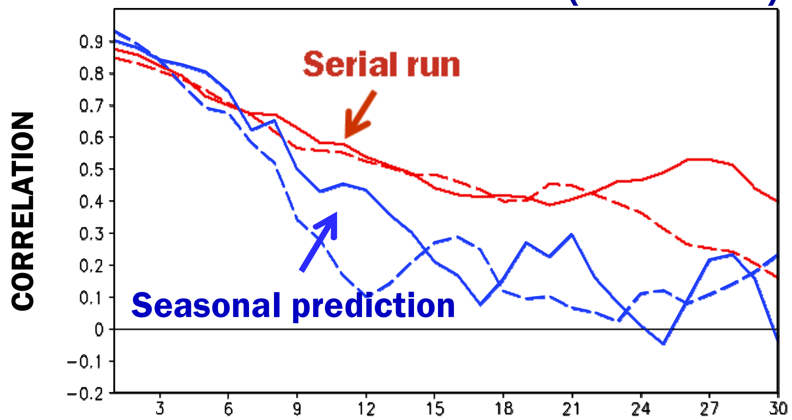
- Plenty of prediction samples
- Include whole initial phases

Does seasonal prediction work for MJO prediction?

Serial run with SNU GCM

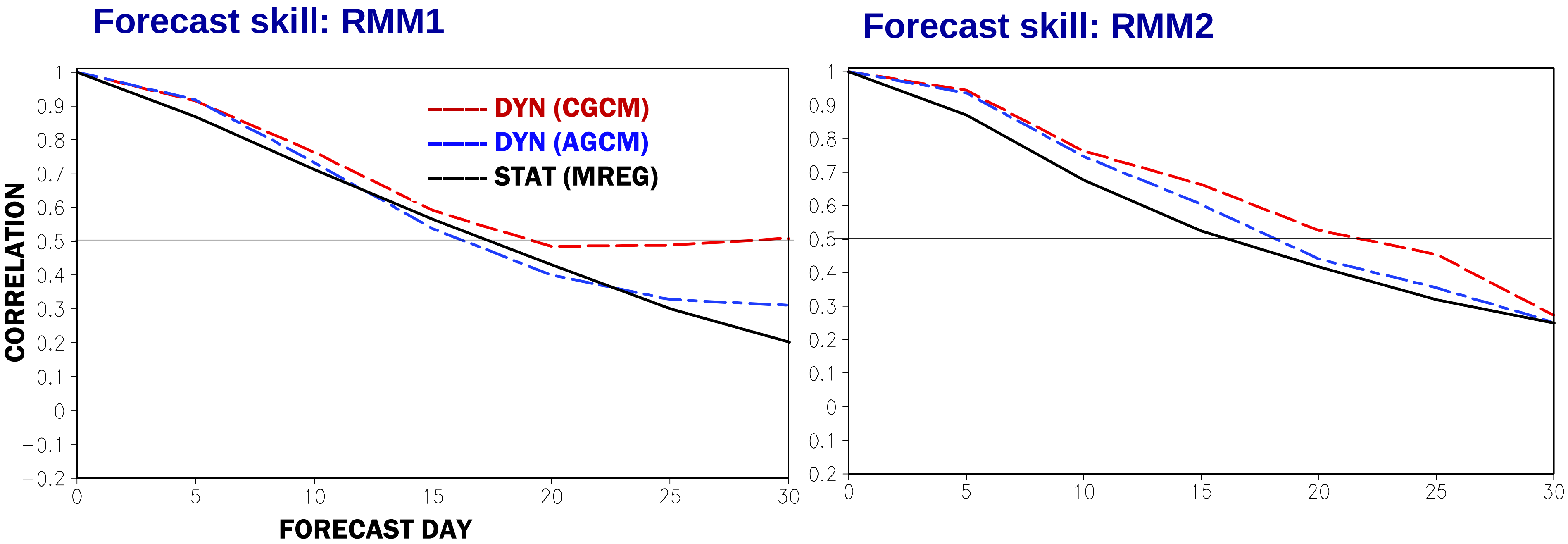
EXP	Period	Total 30-day forecasts	Using 1-CPU
AGCM Long-term	27-year (79-05)	621	4 month
CGCM	8-year (98-05)	184	2 month

Forecast skill : RMM1 and 2 (SNU CGCM)



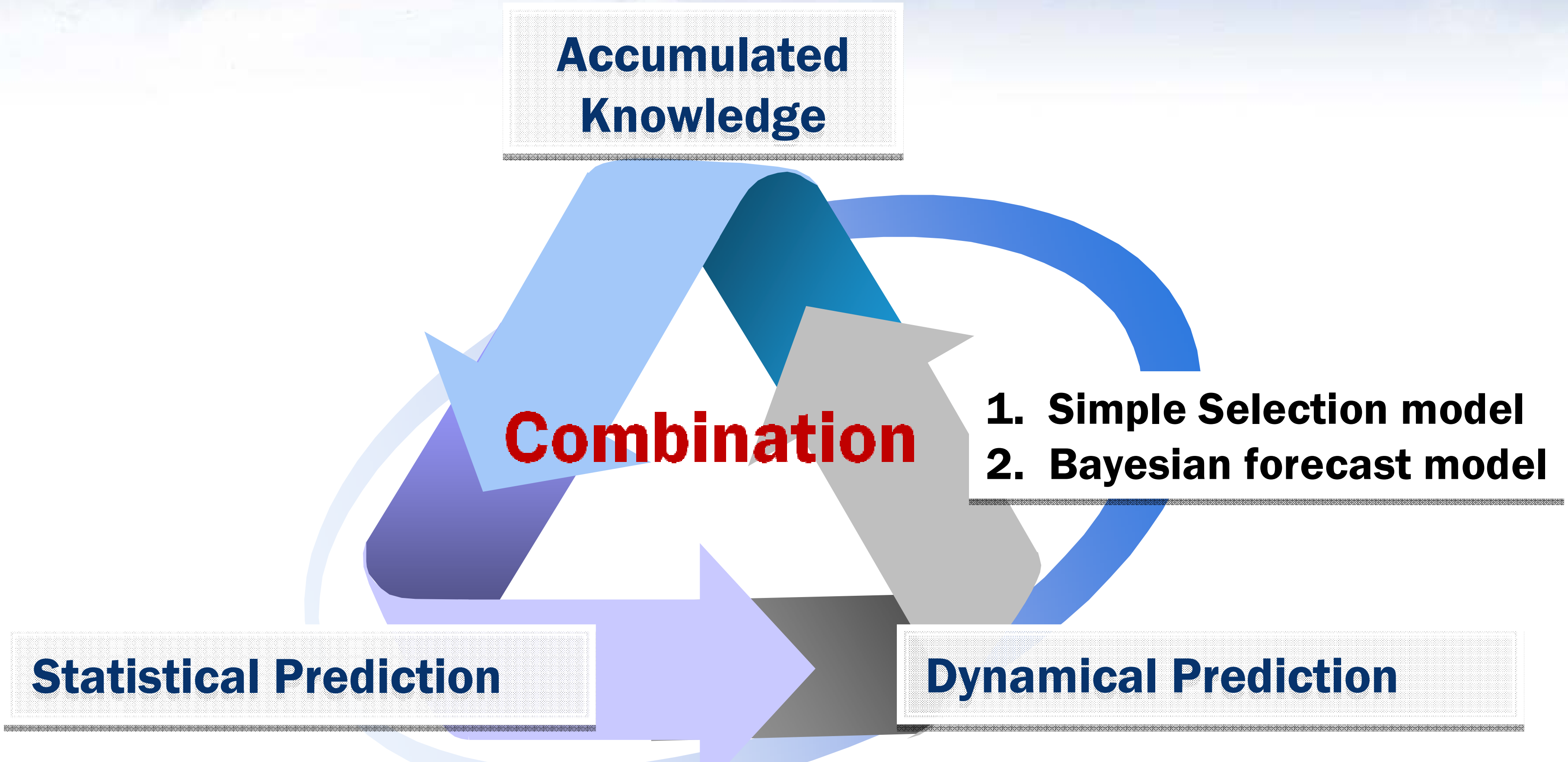
Statistical & Dynamical

Statistical vs. Dynamical prediction



Correlation 0.5 at (day)		
	RMM1	RMM2
DYN (CGCM)	18-19	22-23
DYN (AGCM)	15-16	17-18
STAT (MREG)	16-17	15-16

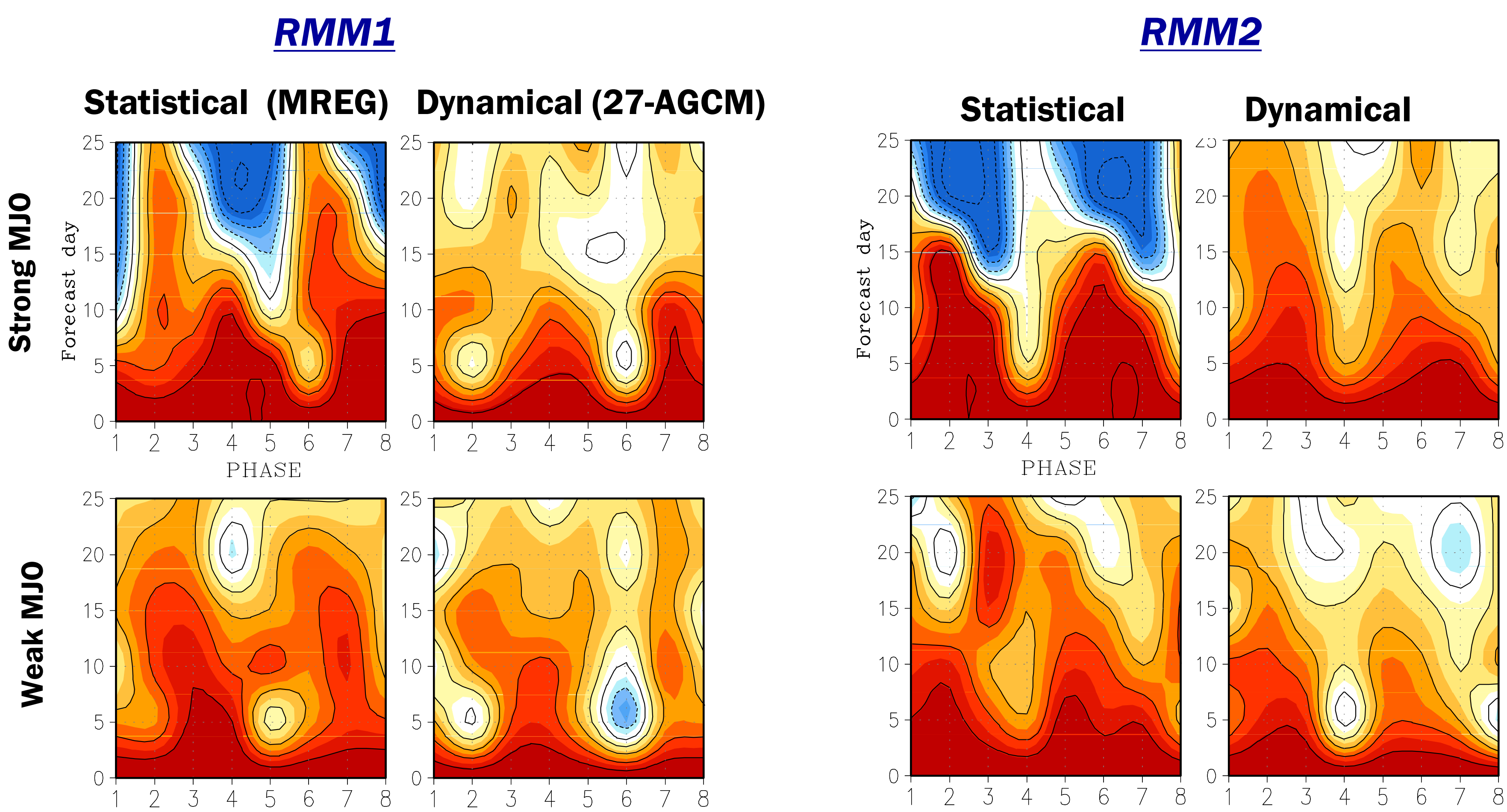
Combination and Calibration



- Comparable predictability
- Independent predictions

Combination: Selection model

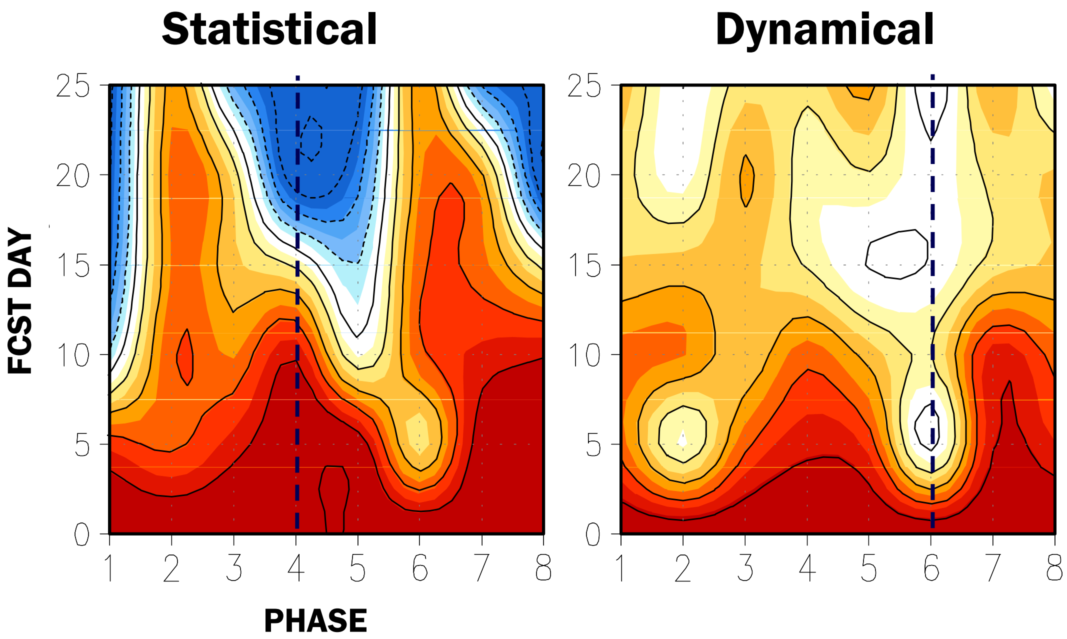
Sensitivity to initial phase and amplitude: Prediction skill of RMMs



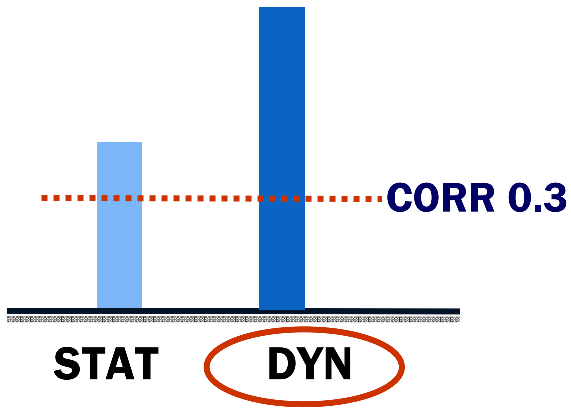
Combination: Selection model

Forecast skill of RMM1

Strong MJO



Selection process

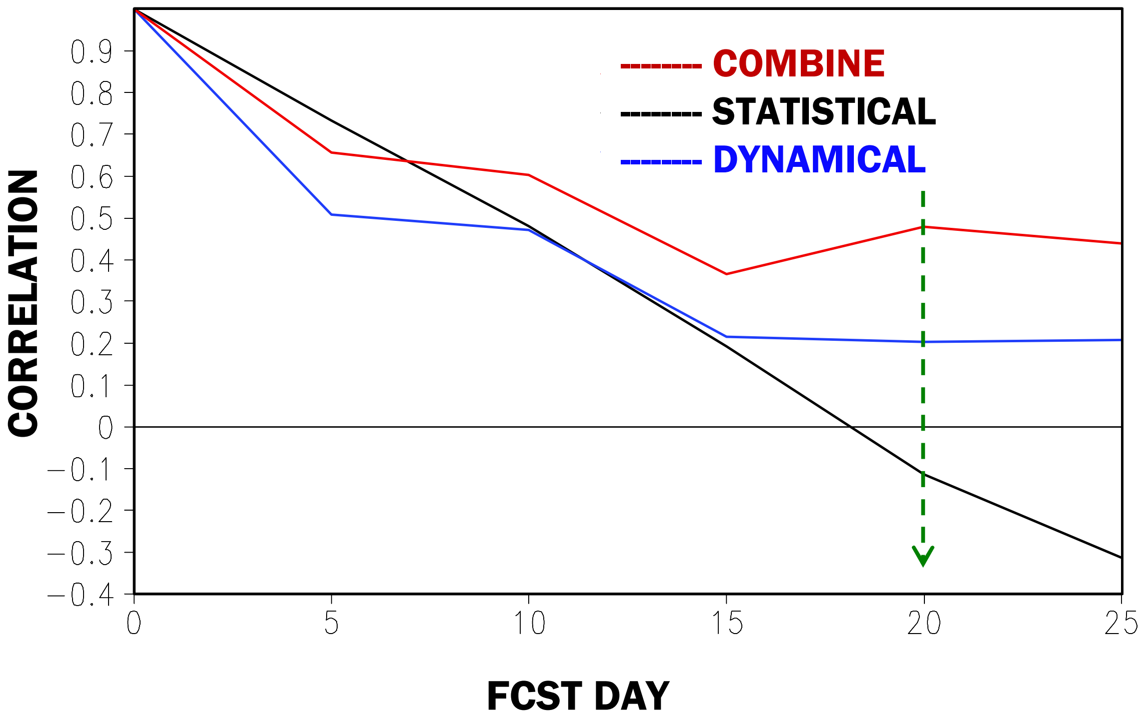


- More than 0.3: Better prediction
- Lesser than 0.3: Persistence

Combination: Selection model

Forecast skill of RMM1

Predictability of RMM1 (Strong MJO)



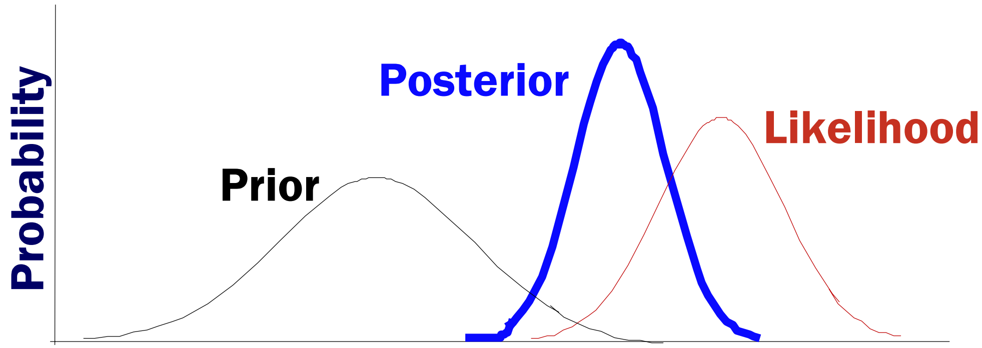
Correlation at 20-day	
COMB	0.5
STAT	- 0.1
DYN	0.2

Combination: Bayesian forecast

Bayes' theorem

To construct a reliable data with combination of existing knowledge

$$\overbrace{p(S_f \mid D_f)}^{\text{Posterior}} = \frac{\overbrace{p(D_f \mid S_f)}^{\text{Likelihood}}\ \overbrace{p(S_f)}^{\text{Prior}}}{p(D_f)}$$



→ **Prior PDF is updated by likelihood function to get the less uncertain posterior PDF**

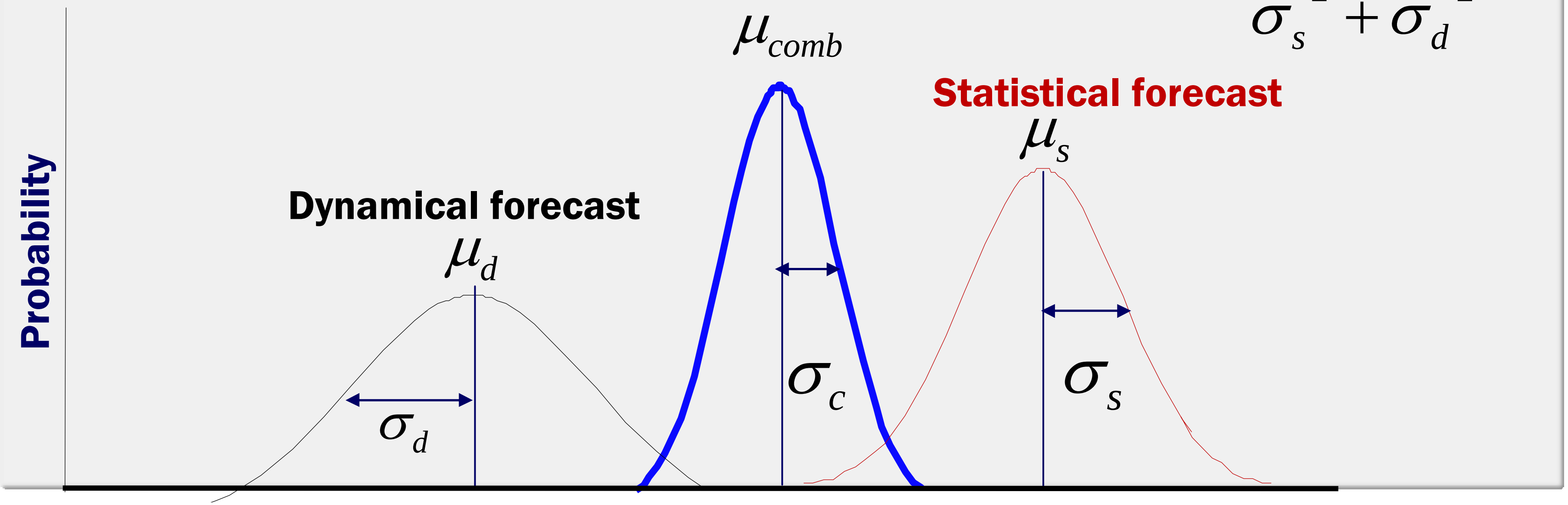
- Choice of the Prior: Statistical forecast (MREG)
- Modeling of the likelihood function:
  Linear regression of past dynamical prediction and on past observation
- Determination of the posterior

Combination: Bayesian forecast

Minimize the forecast error

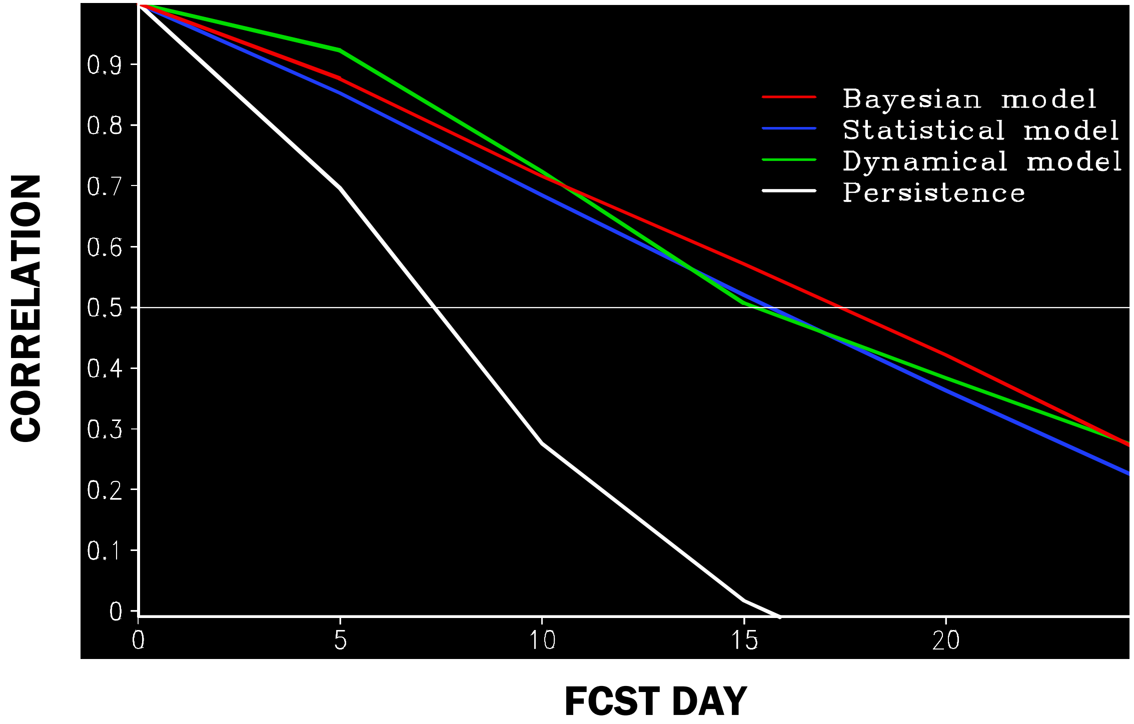
$$\Psi_{comb} = (1-K)\cdot\Psi_{stat} + K\cdot\Psi_{dyn} \qquad , K = \frac{\sigma_s^{\,2}}{\sigma_d^{\,2} + \sigma_s^{\,2}}$$

Combined forecast→ $\mu_{comb} = \dfrac{\sigma_d^{\,2}\mu_s + \sigma_s^{\,2}\mu_d}{\sigma_s^{\,2} + \sigma_d^{\,2}}$



Combination: Bayesian forecast

Forecast skill of RMM1

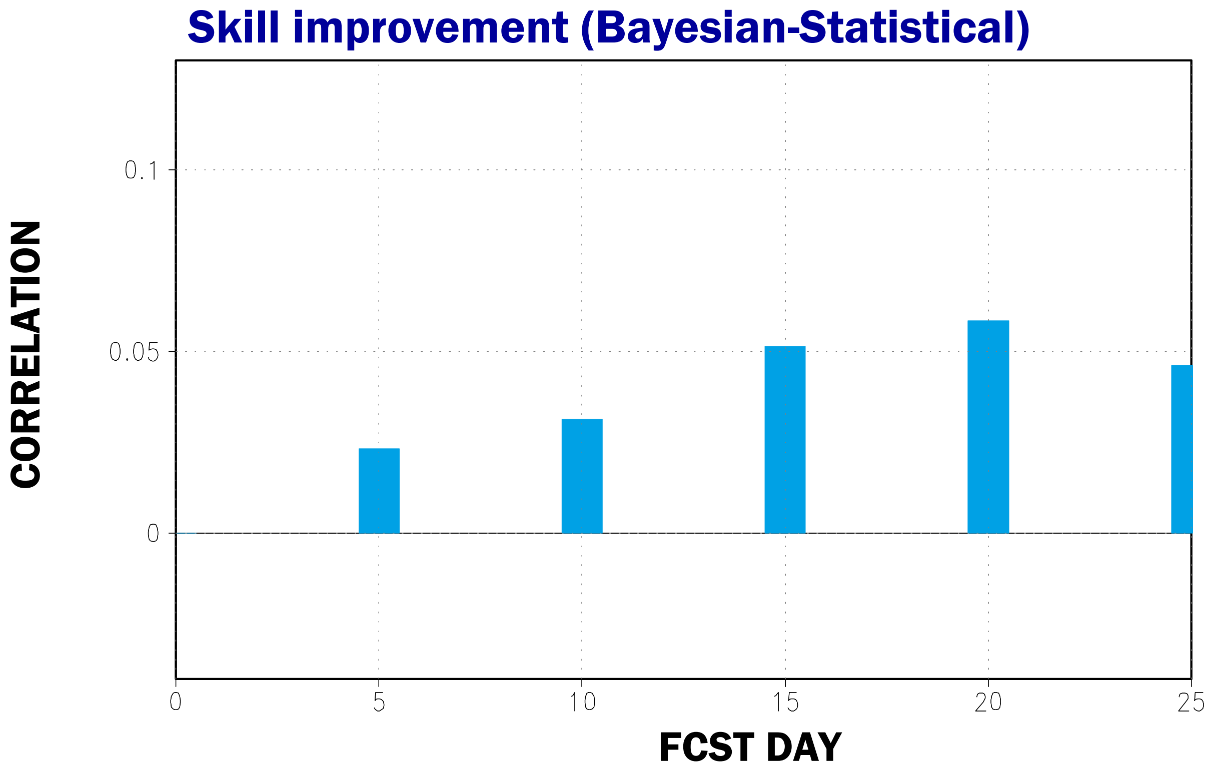


Correlation 0.5 at (day)	
Combined	17-18
Statistical	16-17
Dynamical	15-16
Persistence	7~8

Improvement of forecast skill through combination by Bayesian forecast model

Combination: Bayesian forecast

Forecast skill of RMM1



Bayesian method is superior to both of dynamical and statistical prediction, just by minimizing the forecast error

Possibilities for improvement

- Better initialization
- Multi-model ensemble
- Model improvement
  - High resolution modeling
  - Physical parameterization

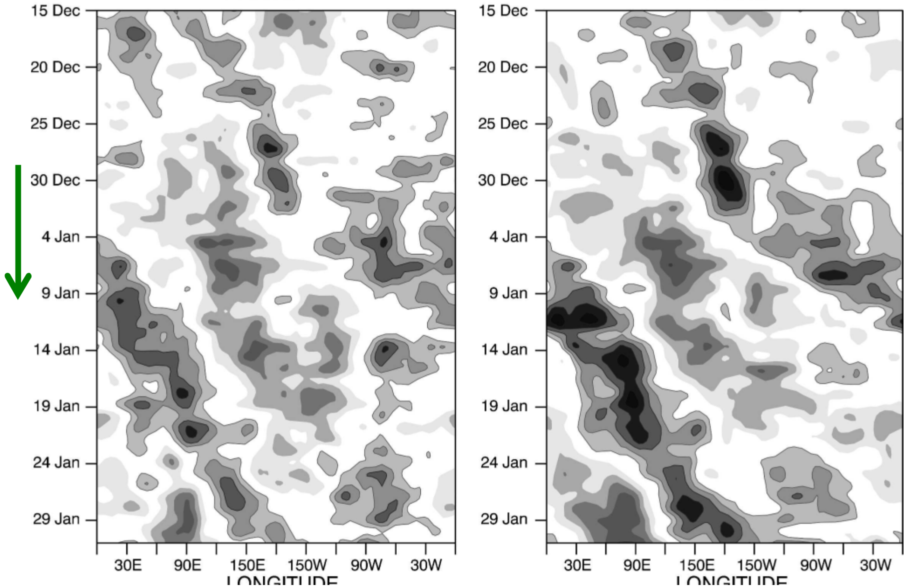
Possibilities for improvement

Better initialization

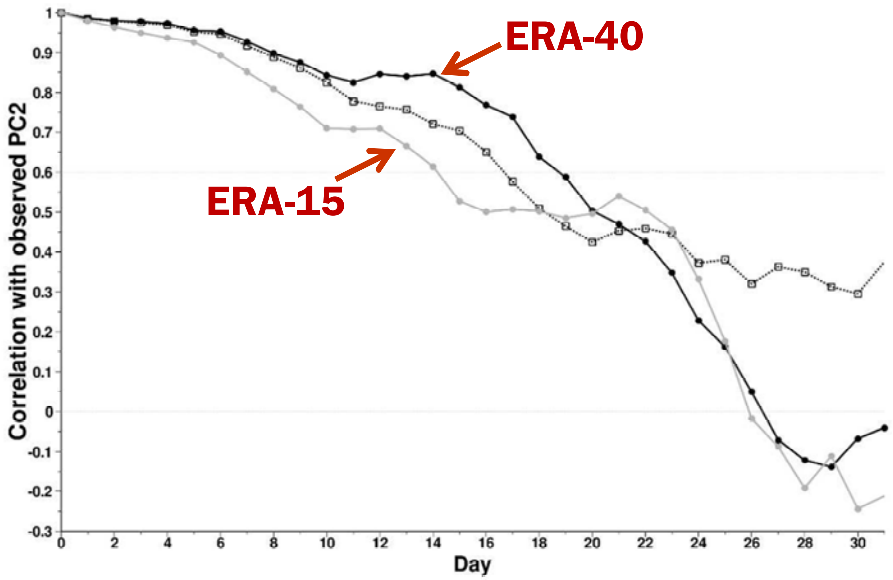
Sensitivity to the quality of the Atmospheric initial conditions

Vitart et al. (2007)

ERA-15 **ERA-40**



RMM-2 Forecast skill (1992/93)



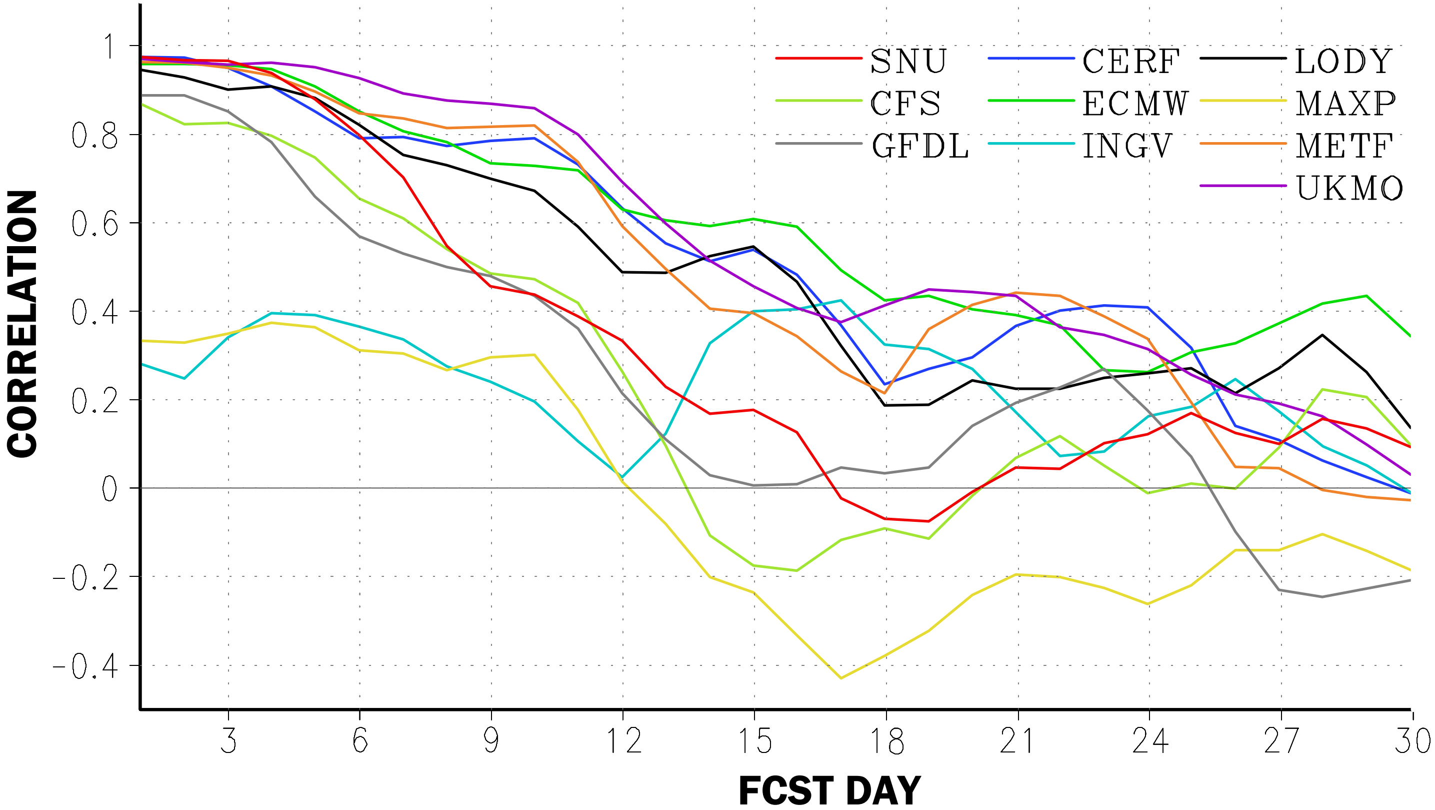
→ **Stronger MJO intensity in ERA-40**

→ **Better in ERA-40 than ERA-15**

Possibilities for improvement

Better initialization

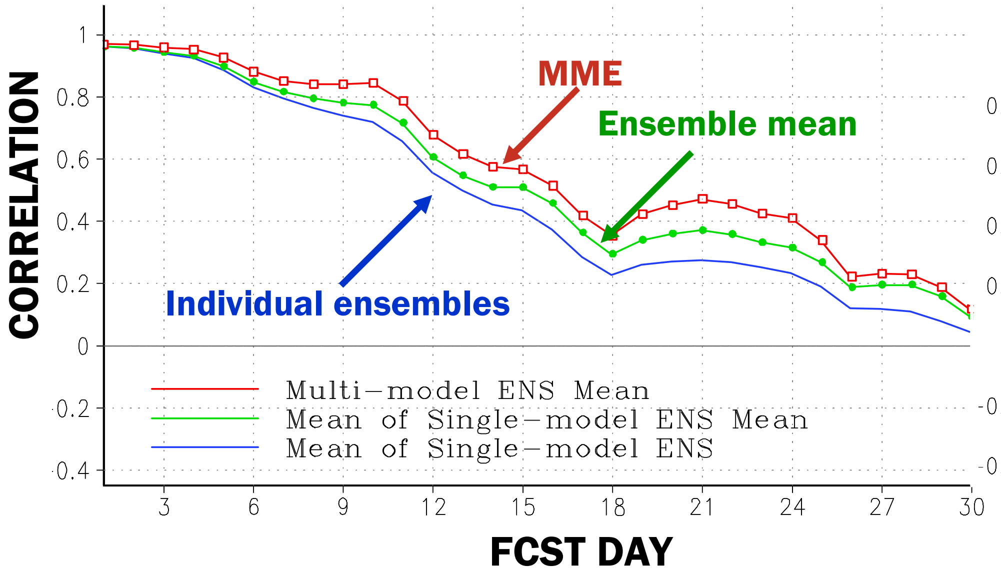
Forecast skill: RMM1



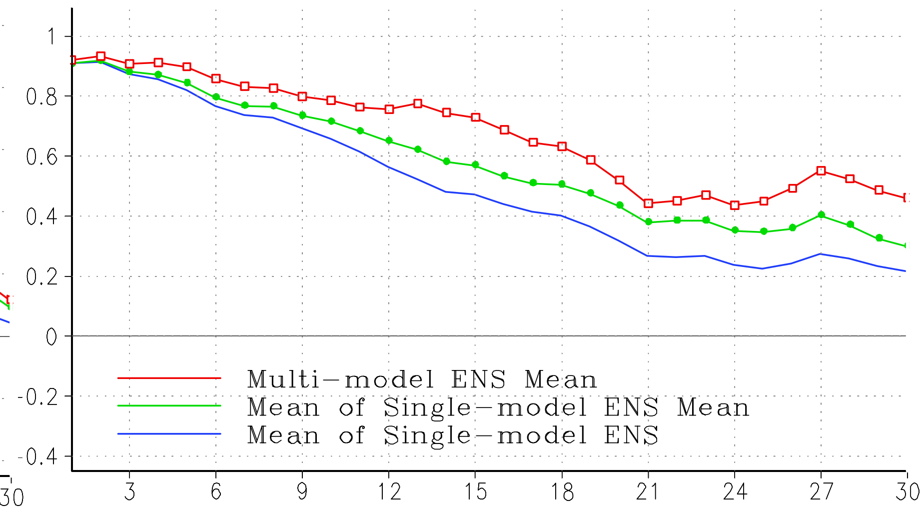
Possibilities for improvement

Multi-Model Ensemble (MME)

Forecast skill: RMM1



Forecast skill: RMM2



$$MME = \frac{1}{M}\sum_{i=1}^{M} F_i$$

$F = forecasts$

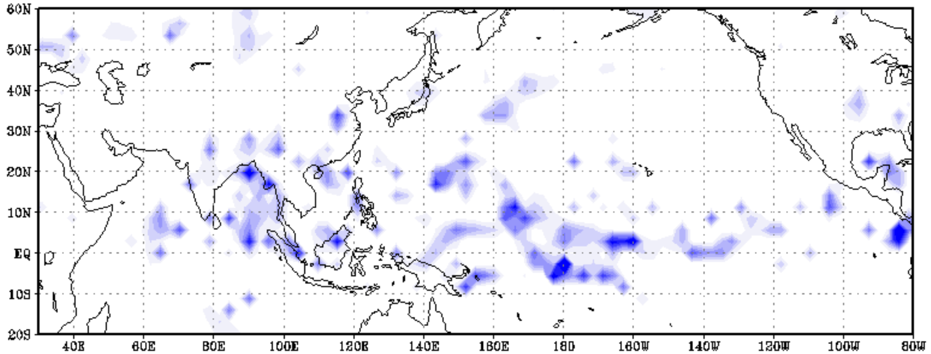
$M = Model\ number\ (M = 10)$

Possibilities for improvement

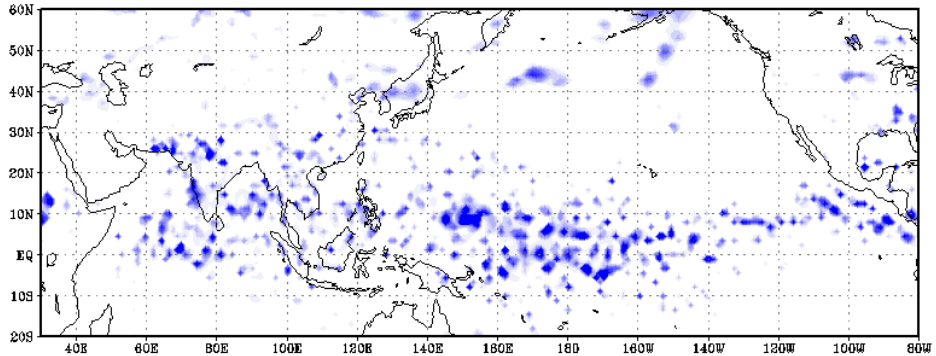
Model improvement: High-resolution (FV AGCM, 10-year)

3-hourly precipitation

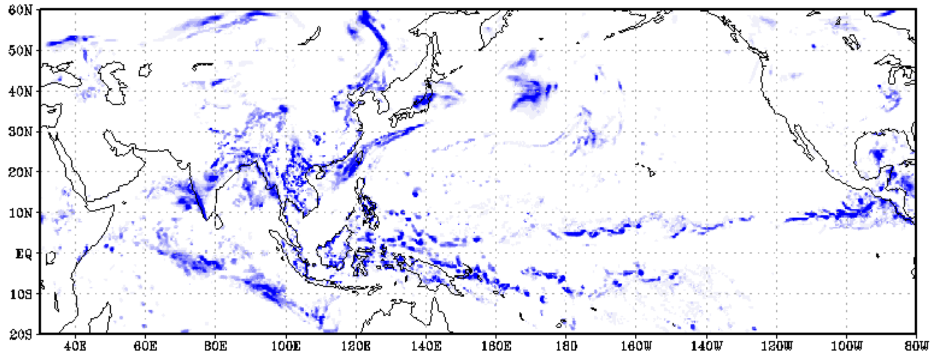
300km resolution



100km resolution



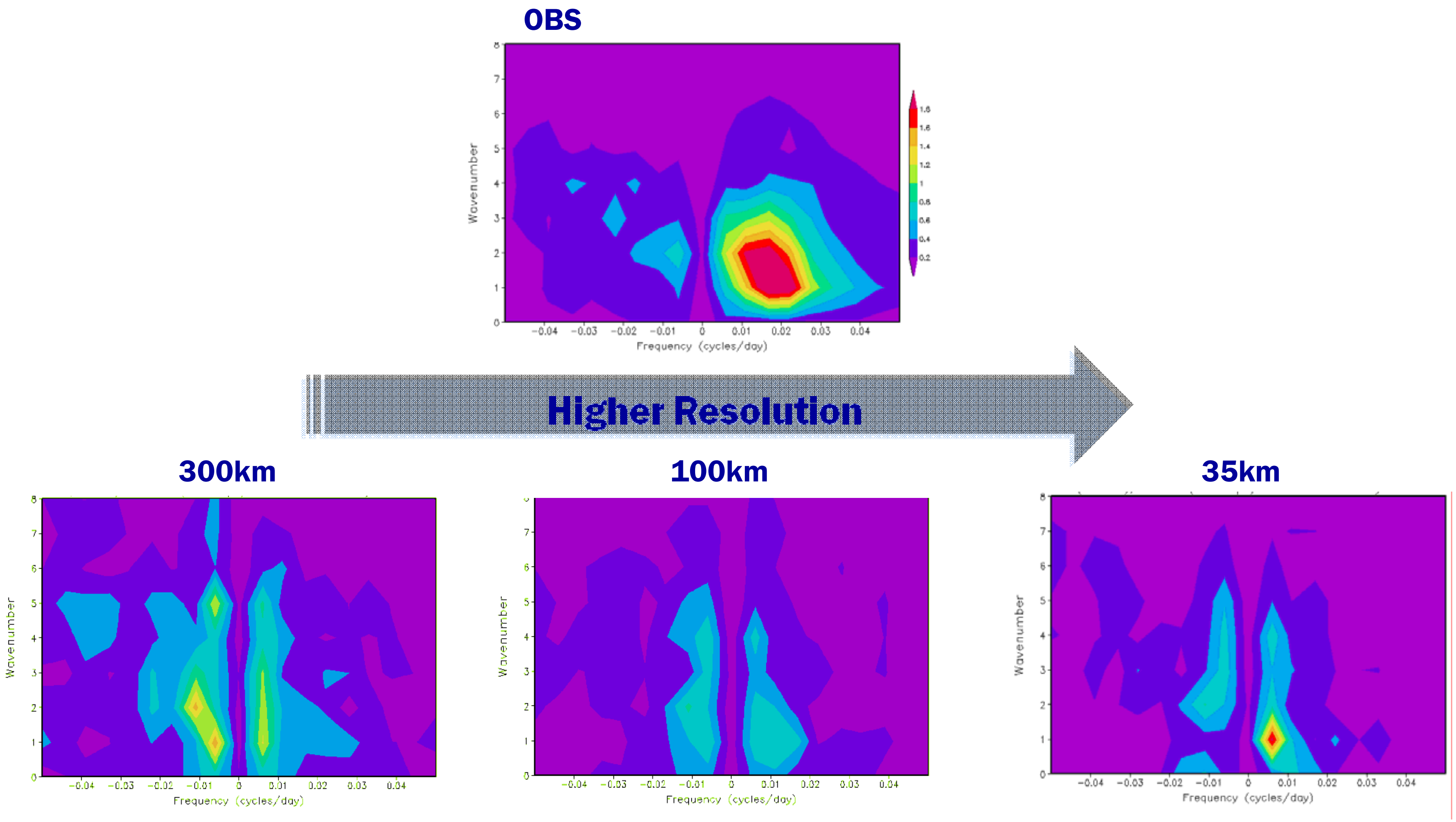
35km resolution



Possibilities for improvement

Model improvement: High-resolution

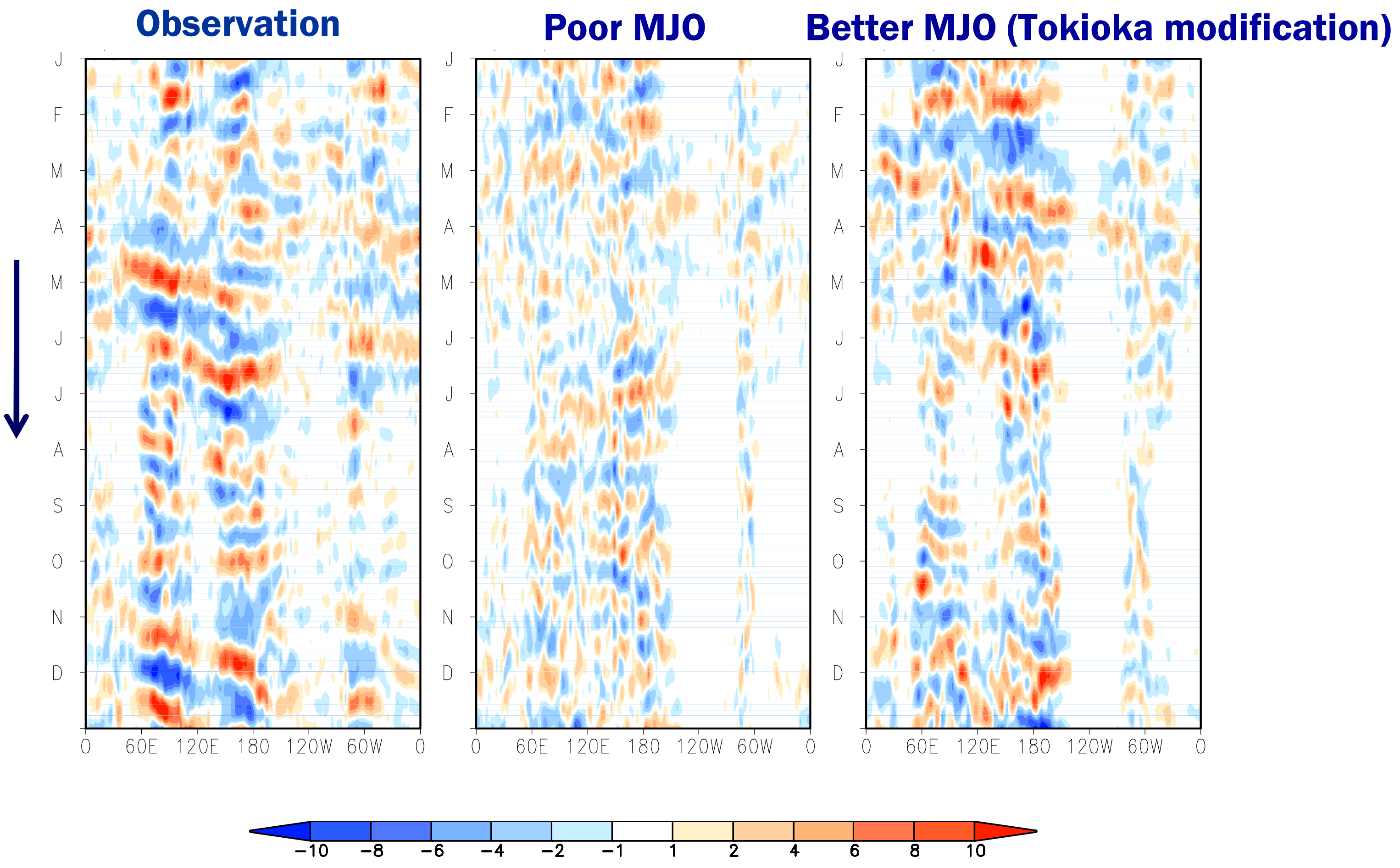
Space-time power spectrum (Winter OLR)



Possibilities for improvement

Model improvement : Physical parameterization

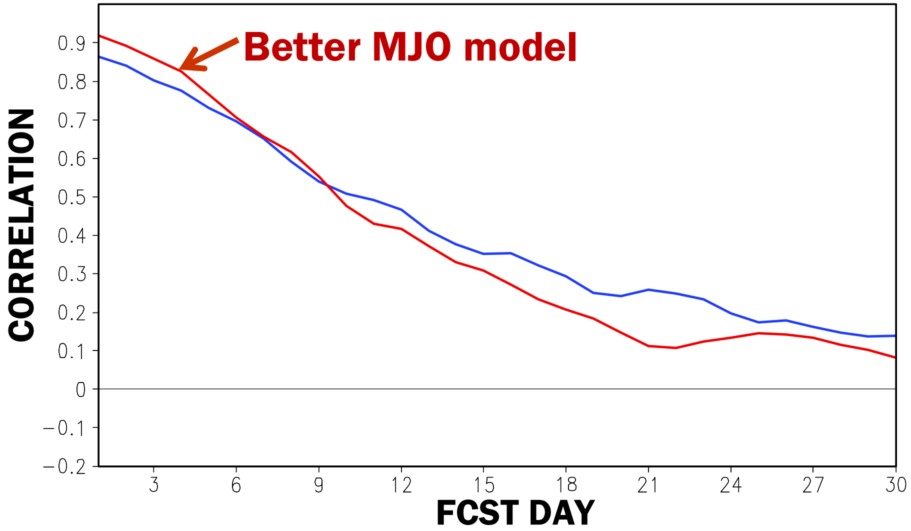
Filtered (20-100 day) Precipitation (5ºS-5ºN)



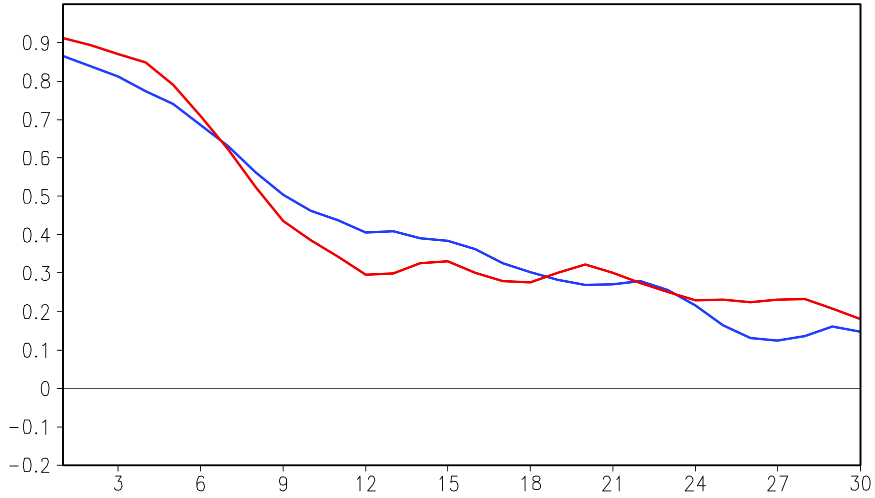
Model improvement : Physical parameterization

13-year Serial forecast experiment (AGCM, 1983-2005)

Forecast skill: RMM1



Forecast skill: RMM2



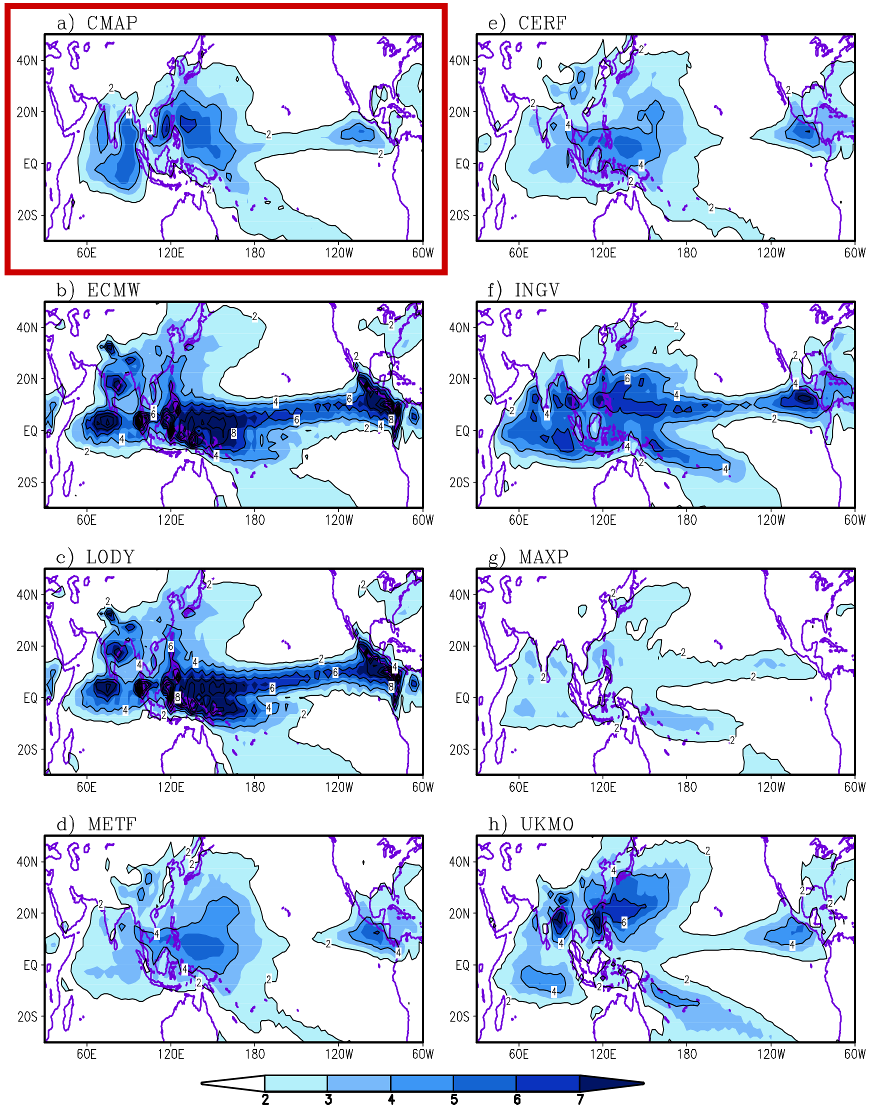
The ISV (MJO) prediction has possibility for improvement through better initialization, multi-model ensemble, and model improvement

Thank you

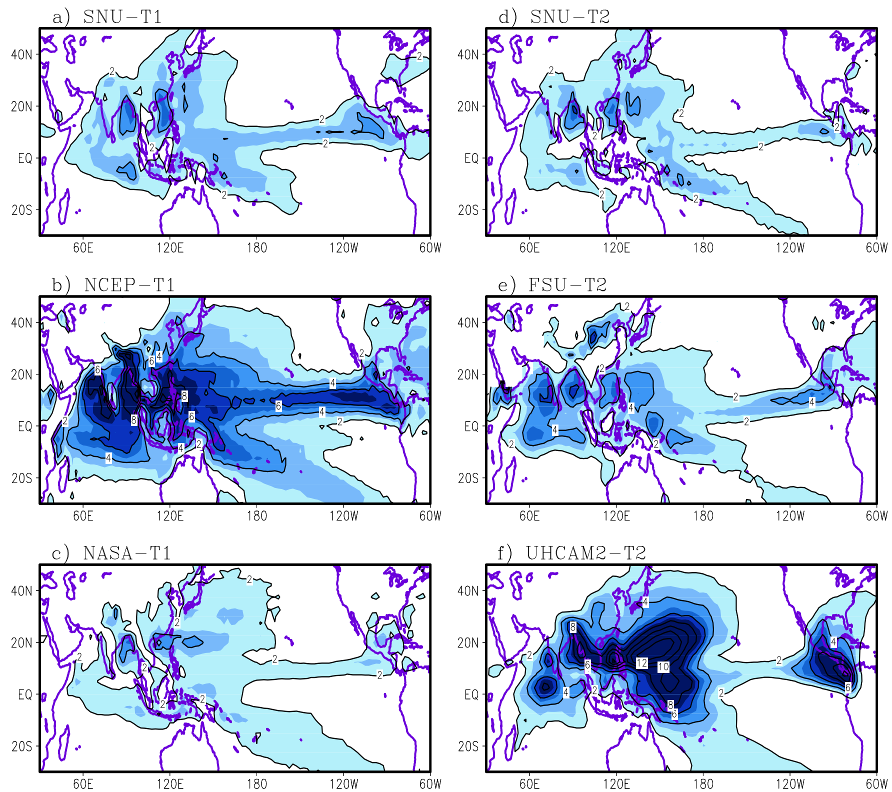
Statistical correction of ISV activity

ISO activity (MJJA) : STD of 20-90 days filtered PRCP

DEMETER



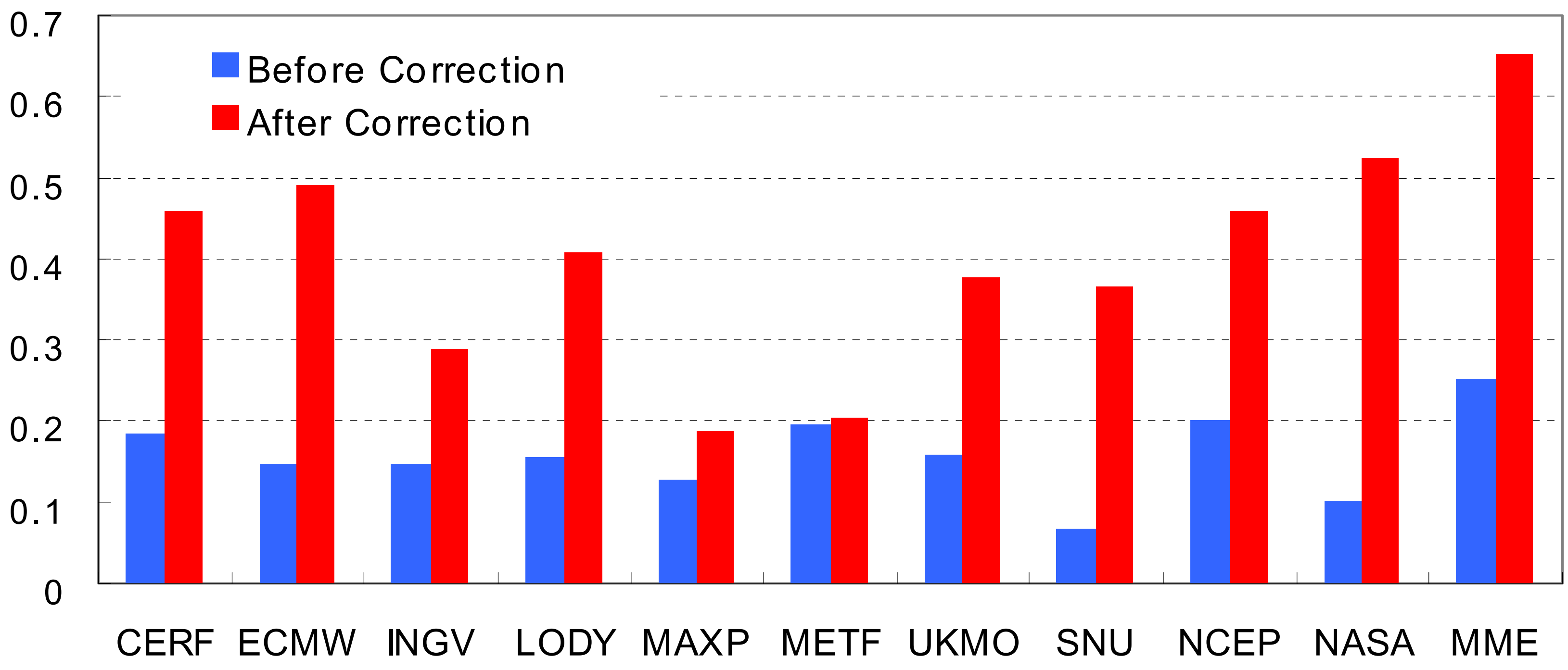
APCC/CliPAS



Kim et al. (2008) Climate Dynamics

Predictability of ISO activity

Pattern Correlation of ISO activity (60-180E.10S-30N)



The predictability of ISO activity is enhanced in all models after correction

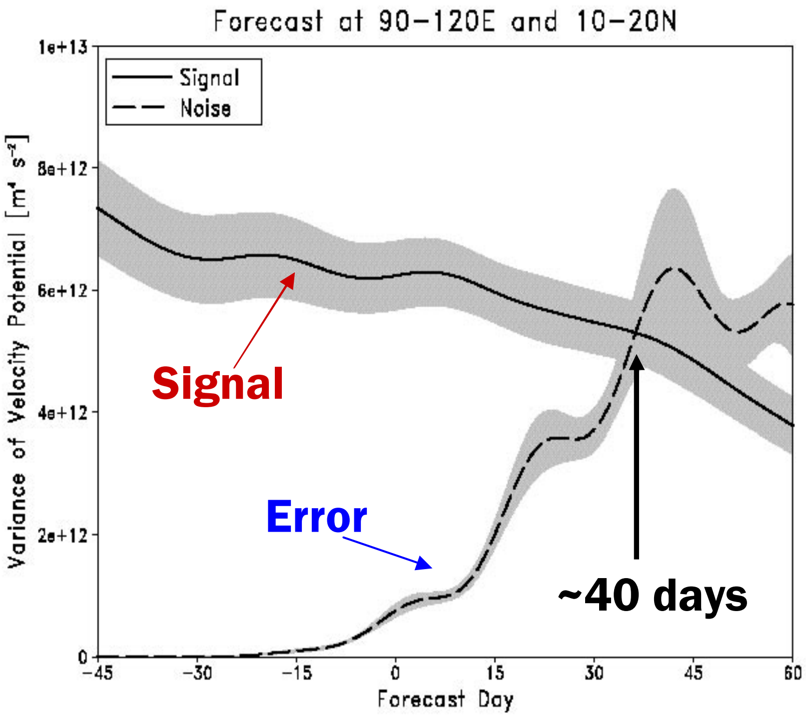
Potential predictability of ISO

Limitations in prediction with dynamical model:

Model systematic bias
Initial condition error

Perfect model experiment

200hPa Velocity Potential



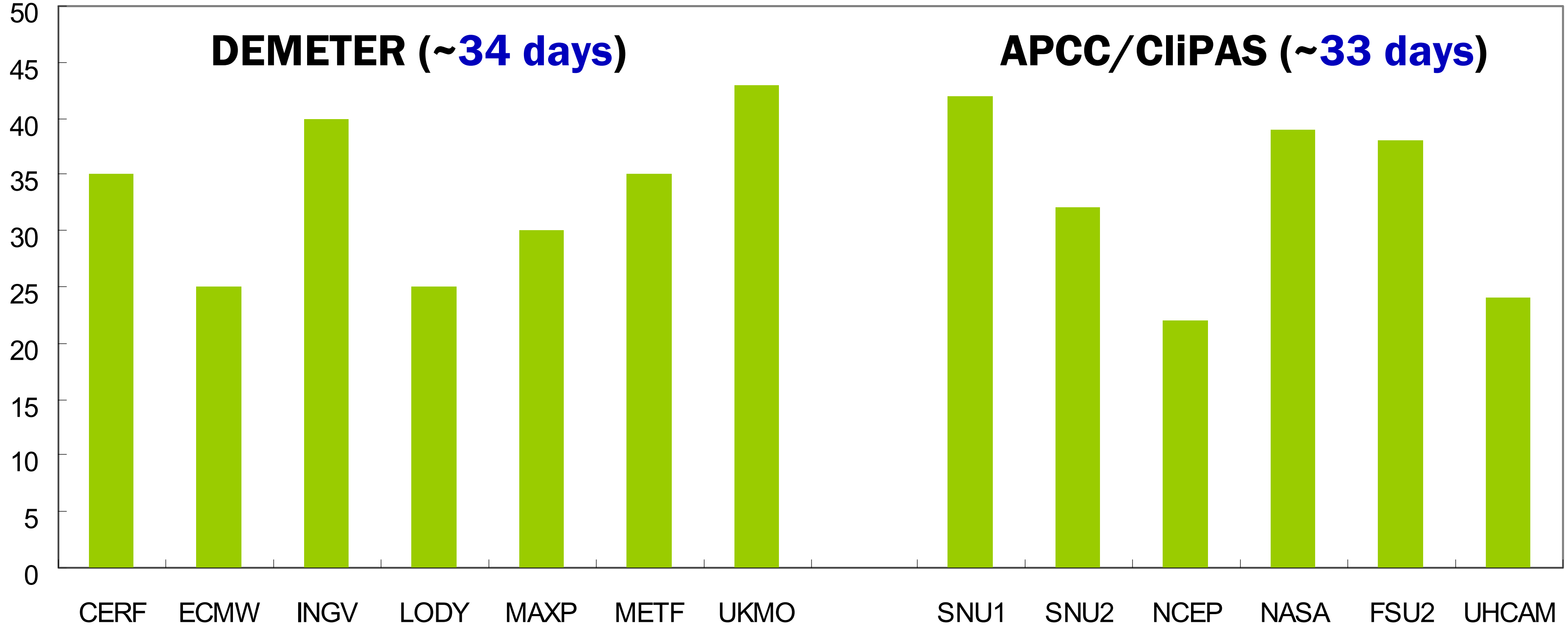
* Liess et al 2005

Potential predictability of ISO

Predictability : Signal to Error Ratio
Signal: Mean variance in ISO period
Error: Mean variance between ENS

Potential predictability of ISO

Potential predictability of ISO (when error overwhelms signal)



*** (40E-200E, 20S-40N)**