Assessment of MJO Predictability with Various Statistical and Dynamical Models

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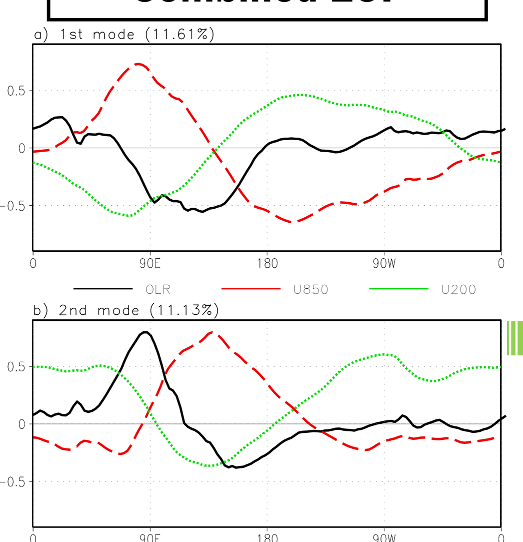
ABSTRACT

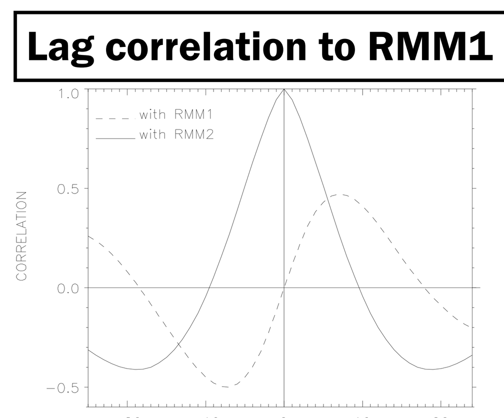
The predictability of intraseasonal variation in the tropics is assessed in the present study by using various statistical and dynamical models with rigorous and fair measurements. For a fair comparison, the real-time multivariate Madden-Julian Oscillation (RMM) index is used as a predictand for all models. The statistical models include the models based on a multi linear regression, a wavelet analysis, and a singular spectrum analysis (SSA). The prediction limits (correlation skill of 0.5) of statistical models for RMM12 index are at day 15-16 for the multi regression model, whereas, they are at day 9-11 for the wavelet and SSA based models, respectively. To assess the dynamical predictability, long-term serial prediction experiments with a prediction interval of every 5 days are carried out with both SNU AGCM and CGCM for 20 years for the summer period (MJJASO). The prediction limits occur at day around 22 days for both AGCM and CGCM. These results demonstrate that the skills of dynamical models used in this study are better than those of the three statistical predictions. The dynamical and statistical predictions are combined using a multi-model ensemble method. The combination provides a superior skill to any of the statistical and dynamical predictions with a prediction limit of 22-24 days.

PREDICTAND: RMM index

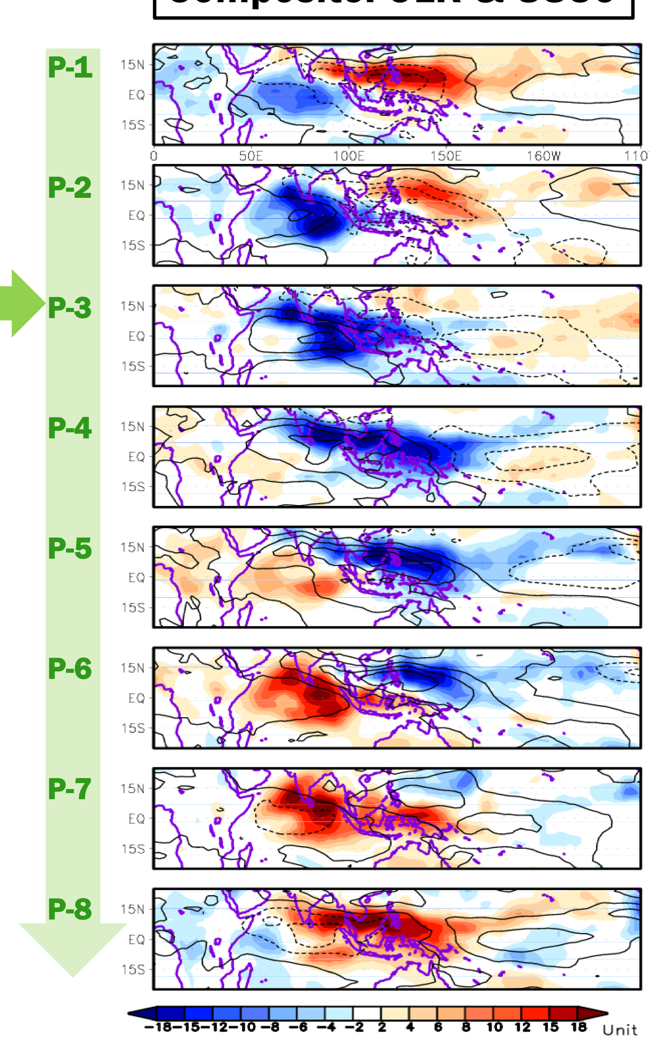
Combined EOF



Lag correlation to RMM1



Composite: OLR & U850



1. Annual cycle removed:
2. Interannual variability removed: Mean of previous 120 days

STATISTICAL PREDICTION

Kang and Kim (2010)

Multi-regression

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

τ = lead time

λ = lag

m = PCs

B_{pj} = lag − regression coeff

Wavelet

Wavelet analysis (Torrence and Compo, 1998)

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

Prediction of bands (regression)

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

Reconstruction

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

SSA

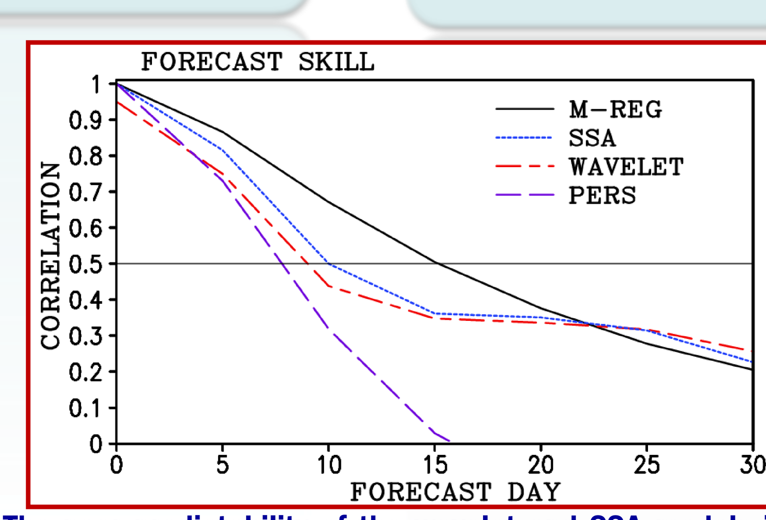
SSA

Prediction of PCs (regression)

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

Reconstruction

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



❖The poor predictability of the wavelet and SSA models is related to the tapering problems for a half length of the time window before the initial coendition.

Correlation 0.5 at (day)	
M-REG	15-16
Wavelet	9-10
SSA	10-11
Persistent	7-8

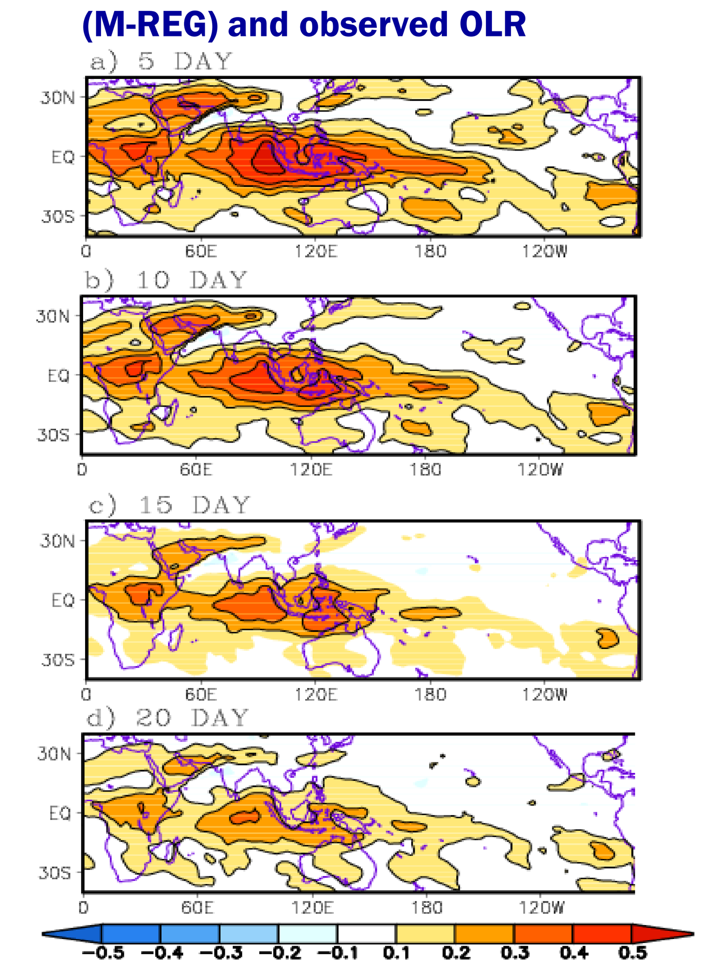
Bivariate Correlation

$$COR(\tau)=\frac{\sum_{t=1}^{N}[a_1(t)b_1(t,\tau)+a_2(t)b_2(t,\tau)]}{\sqrt{\sum_{i=1}^{N}[a_1^2(t)+a_2^2(t)]}\sqrt{\sum_{i=1}^{N}[b_1^2(t,\tau)+b_2^2(t,\tau)]}}$$

$a_1(t), a_2(t)$: Observed RMM1,2 at day t

$b_1(t), b_2(t)$: Forecasted RMM1,2 at day t

Correlation : Predicted R-OLR (M-REG) and observed OLR



Reconstruction

$$R-OLR(x,y,t_0+\tau)=X_1(x,y)\times RMM1(t_0+\tau)+X_2RMM2(t_0+\tau)$$

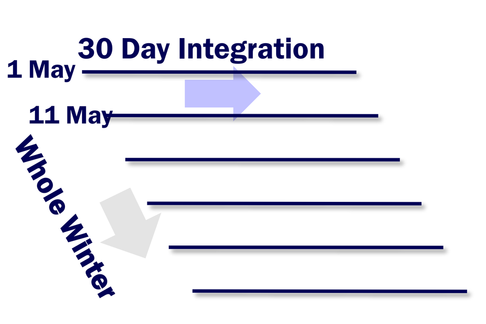
R-OLR: reconstructed OLR anomaly

$X_{1,2}$: regressed OLR anomaly onto $RMM_{1,2}$

DYNAMICAL PREDICTION: SUMMER ISV

1. Dynamical Model and Experimental Design

Serial integration through all phases of MJO (Summer)

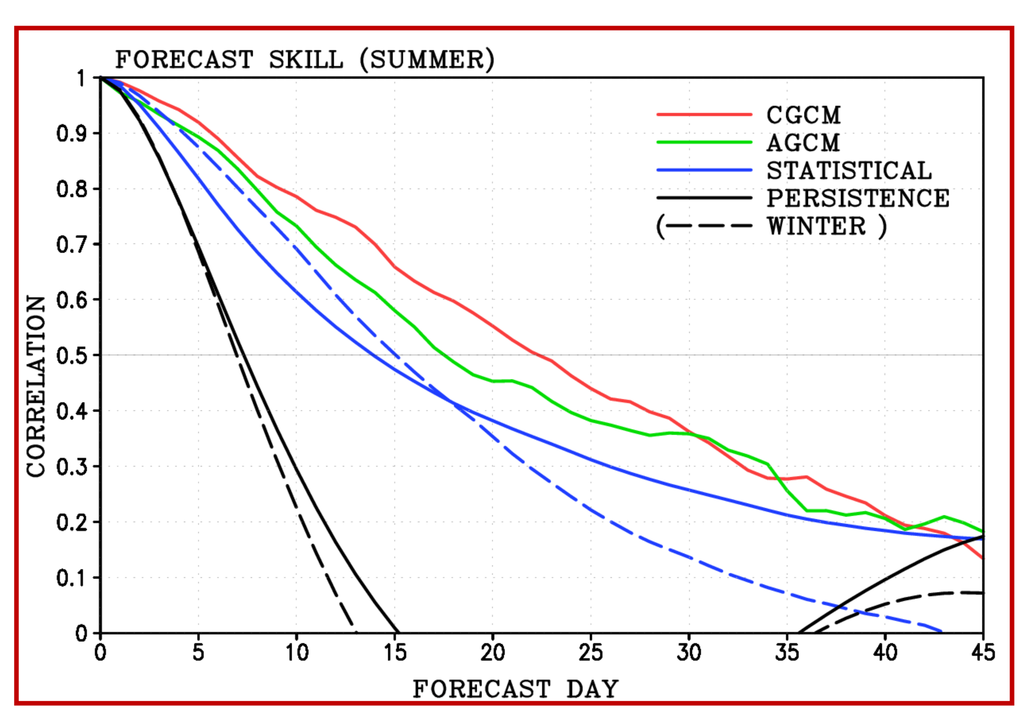


EXP	Period	Total 45-day forecasts	ATM IC
CGCM	20-year (89-08)	360	ERA interim
AGCM (Persistent SST)	18-year (89-06)	324	ERA interim

Dynamical model: SNU GCM

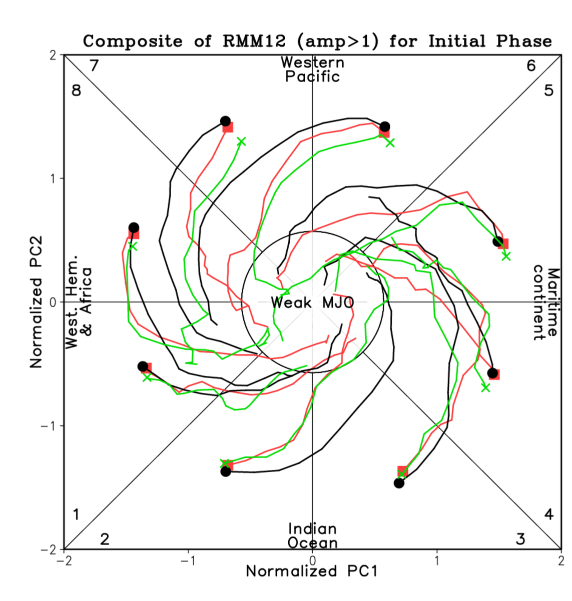
Model	Resolution	Note
SNU AGCM	T42, 21 levels	Cumulus Momentum Transport Diurnal coupling Tokioka constraint (0.1) Auto-conversion rate 3200s
MOM2.2 OGCM	1/3° lat. x 1° lon. over tropics(10S-10N), Vertical 32 levels	Ocean mixed layer model (Noh and Kim, 1999)

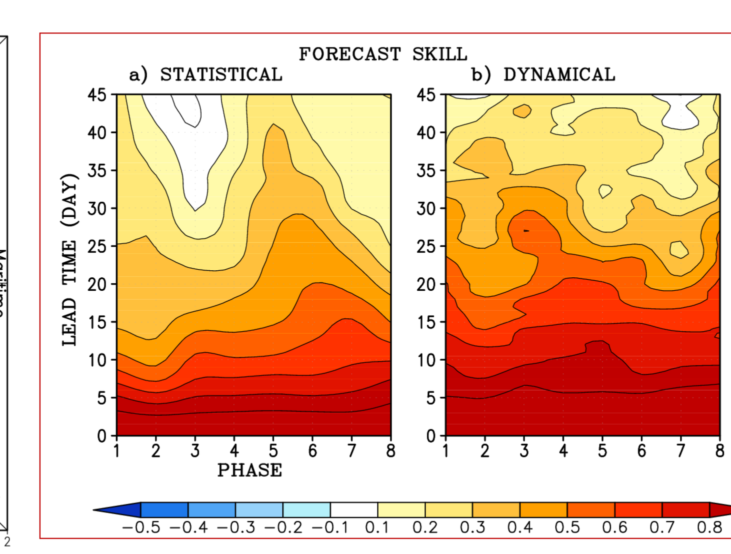
2. Forecast skill



Correlation 0.5 at (day)	
DYN (CGCM)	22-23
DYN (AGCM)	17-18
STAT (MREG)	14-15
PERSISTENCE	7-8

3. Dependency on Initial Phase





❖ The results demonstrate that the skills of dynamical models are better than those of the three statistical predictions, especially when the ocean-atmosphere coupling is included.

❖ The skill of the dynamical model shows little sensitivity to the initial MJO phase out to 15 days, while statistical model (M-REG) shows lower skill in phase 1-2 when MJO convection is developing in the Indian Ocean.

4. MJO simulation: CGCM vs AGCM

Kim et al. (2010)

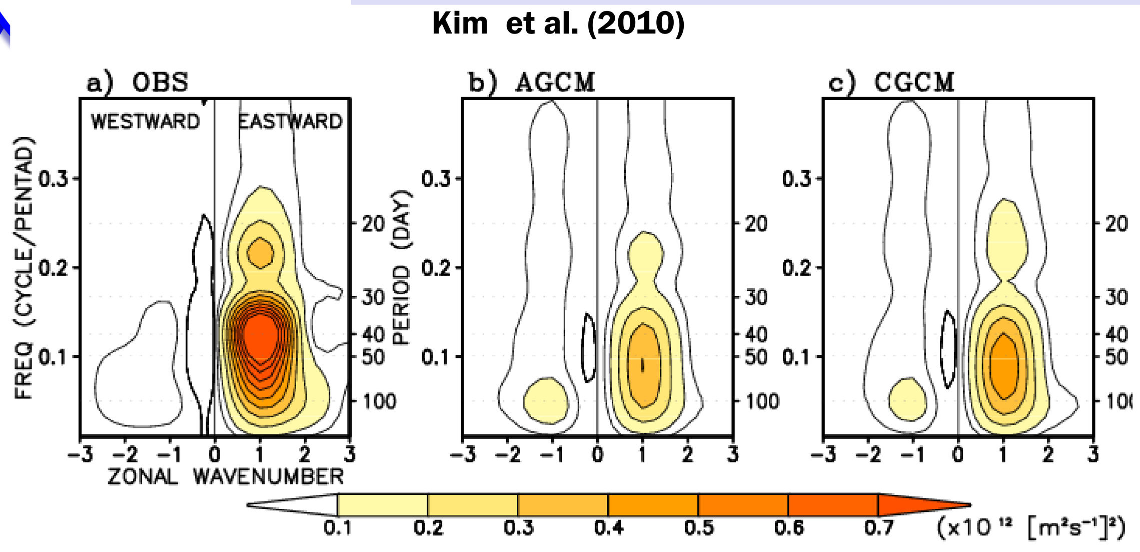


Fig. Wavenumber-frequency power spectra computed from equatorial (10˚S-10˚N) time-longitude for filtered VP200 averaged from 1-day to 30-day forecast

❖ The ocean-atmosphere coupling acts to improve the simulation of the spatio-temporal evolution of the eastward propagating MJO and the phase relationship between convection (OLR) and SST over the equatorial Indian Ocean and the western Pacific.

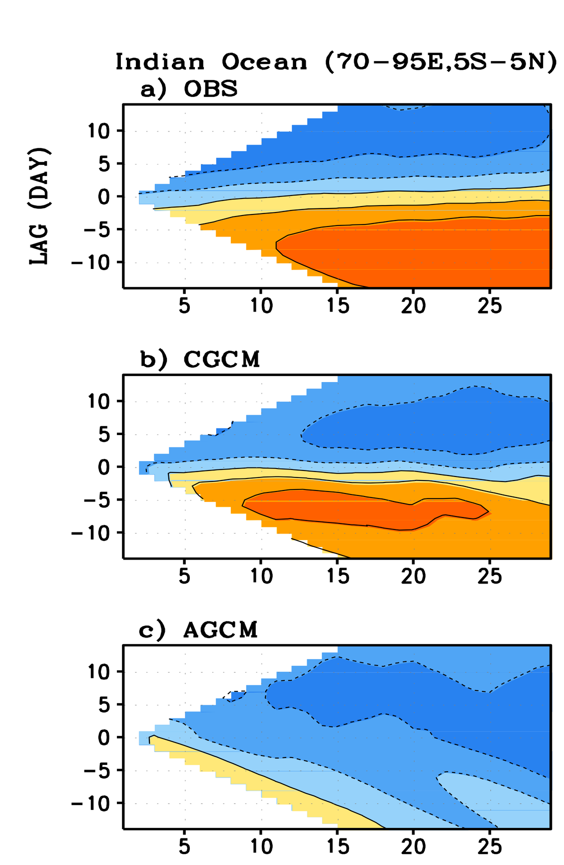


Fig. Lag correlation between filtered OLR and SST anomalies. In OBS and CGCM, positive SST leads enhanced convection.

✓ Kang, I. S. and H. M. Kim, 2010: Assessment of MJO predictability for boreal winter with various statistical and dynamical models. *J. Climate*, 23, 2368-2378.

✓ Kim, H. M., P. J. Webster, C. D. Hoyos, and I. S. Kang, 2010: Ocean-atmosphere coupling and the boreal winter MJO. Climate Dynamics, doi: 10.1007/s00328-009-0612-x

COMBINED PREDICTION

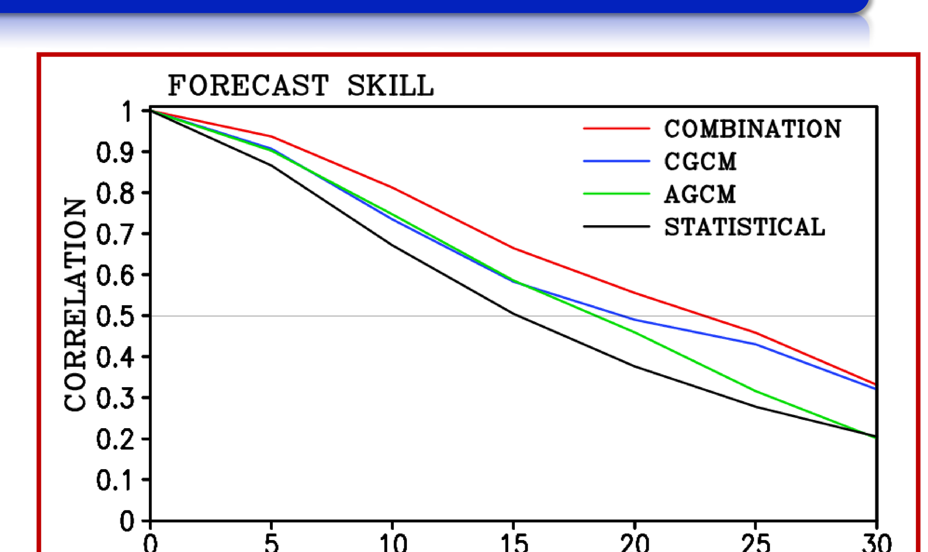
Kang and Kim (2010)

Correlation 0.5 at (day)	
	RMM1
COMBINATION	23-24
DYN (CGCM)	20-21
DYN (AGCM)	18-19
STAT (M-REG)	15-16

Combined prediction (Super Ensemble)

$$\Psi(t)_{comb}=\beta_{t,0}\Psi(t)_{stat}+\beta_{t,1}\Psi(t)_{agcm}+\beta_{t,2}\Psi(t)_{cgcm}$$

β ; regression coefficient obtained by a minimization procedure during the training period for each of forecast lead times.



❖ The combination provides a superior skill to any of the statistical and dynamical predictions with a prediction limit of 23-24 days.