

Issues on Seasonal Prediction

In-Sik Kang

Seoul National University





Issues on Dynamical Seasonal Prediction

1. Model Development

- Dynamics: High resolution
- Physics: Better parameterization

2. Seasonal Prediction System

- Tier2 vs Tier1
- Initialization

3. Multi-Model Ensembling

- Deterministic and Probabilistic forecasts
- Prediction of daily or Pentad variations



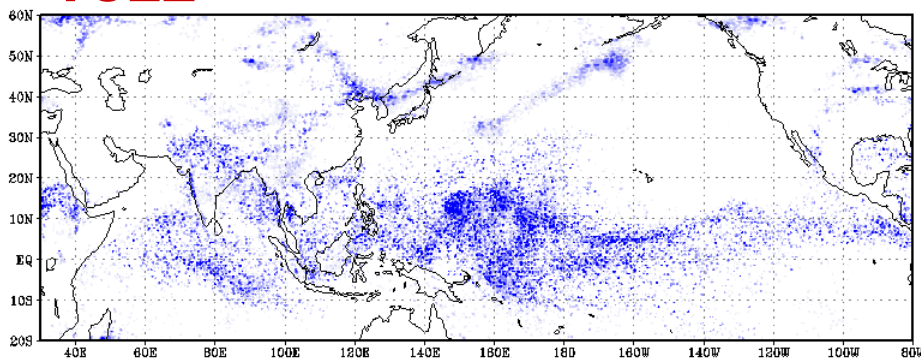
Resolution Issue

Very high-Resolution Global Model (1997.7.20~31)

SNU AGCM

prep 1096hour T512

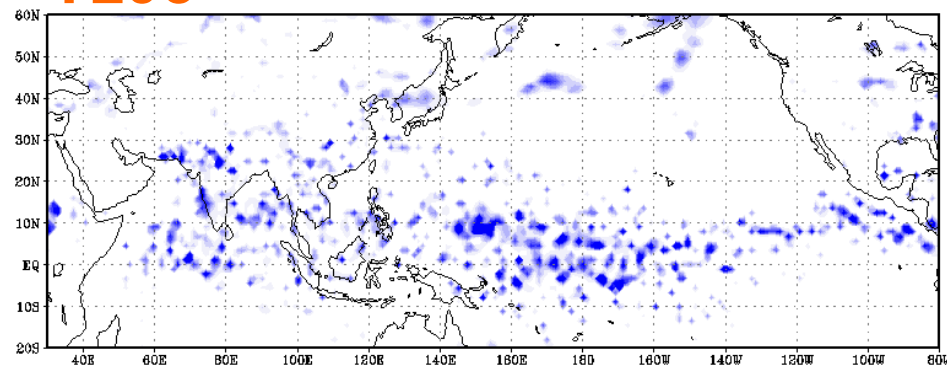
T512



Very expensive!
It takes 4 hours to integrate
1day using 60 CPUs of
CRAYX1E

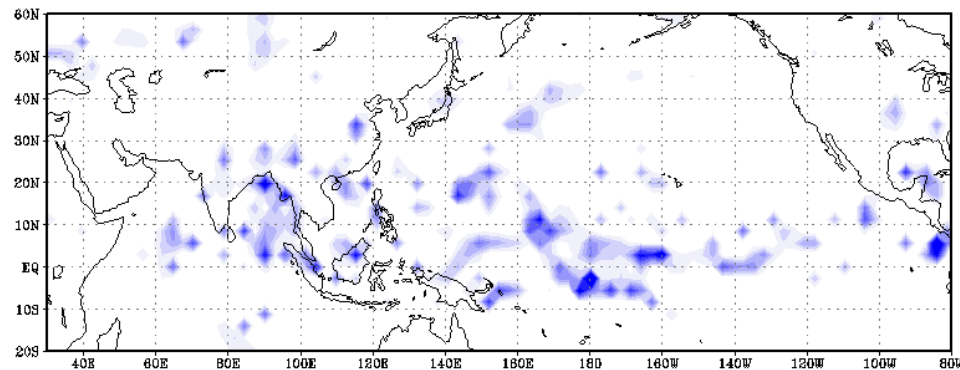
prep 1096hour T106

T106



prep 1096hour T42

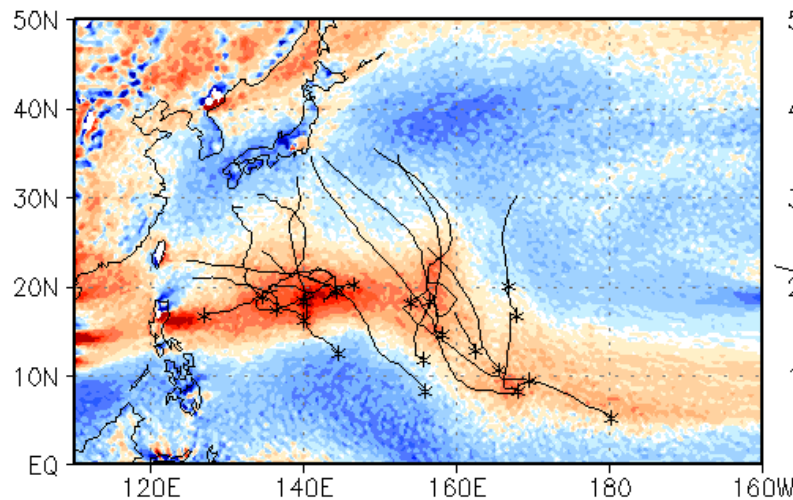
T42



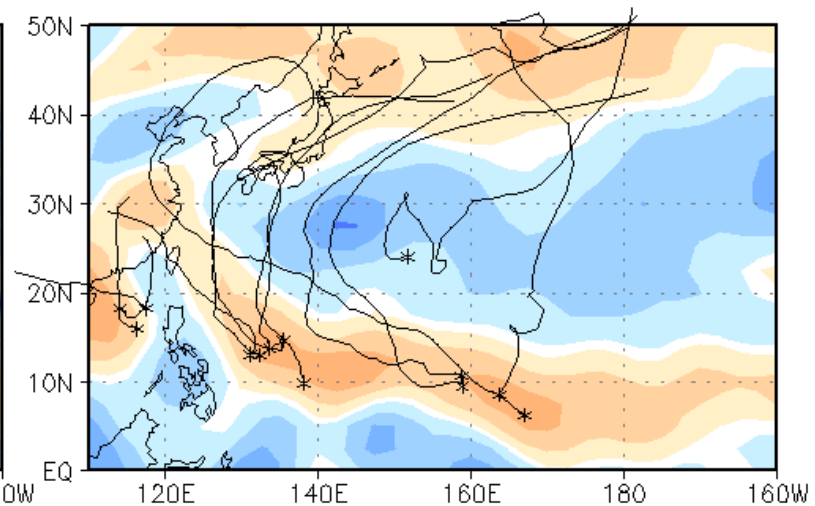


Typhoon (Vorticity)

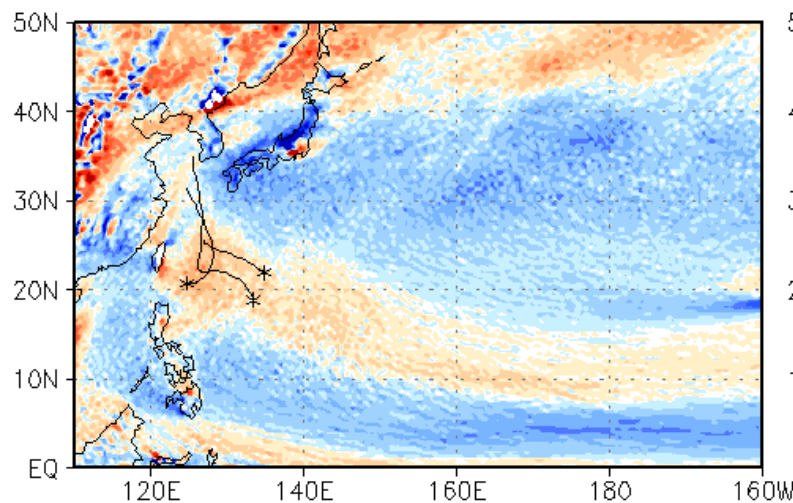
a) 97JJA (T512)



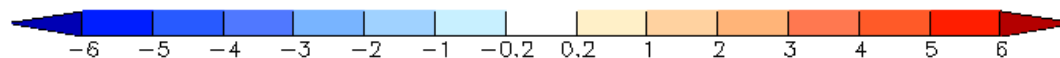
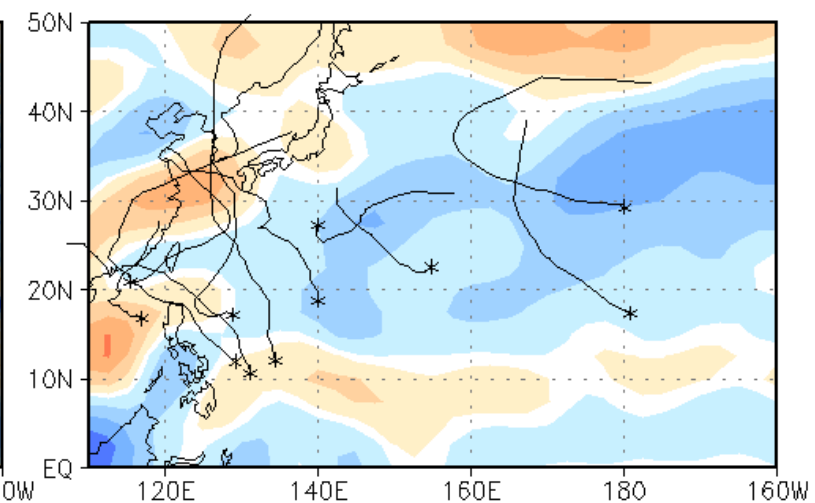
c) 97JJA (NCEP)



b) 99JJA (T512)

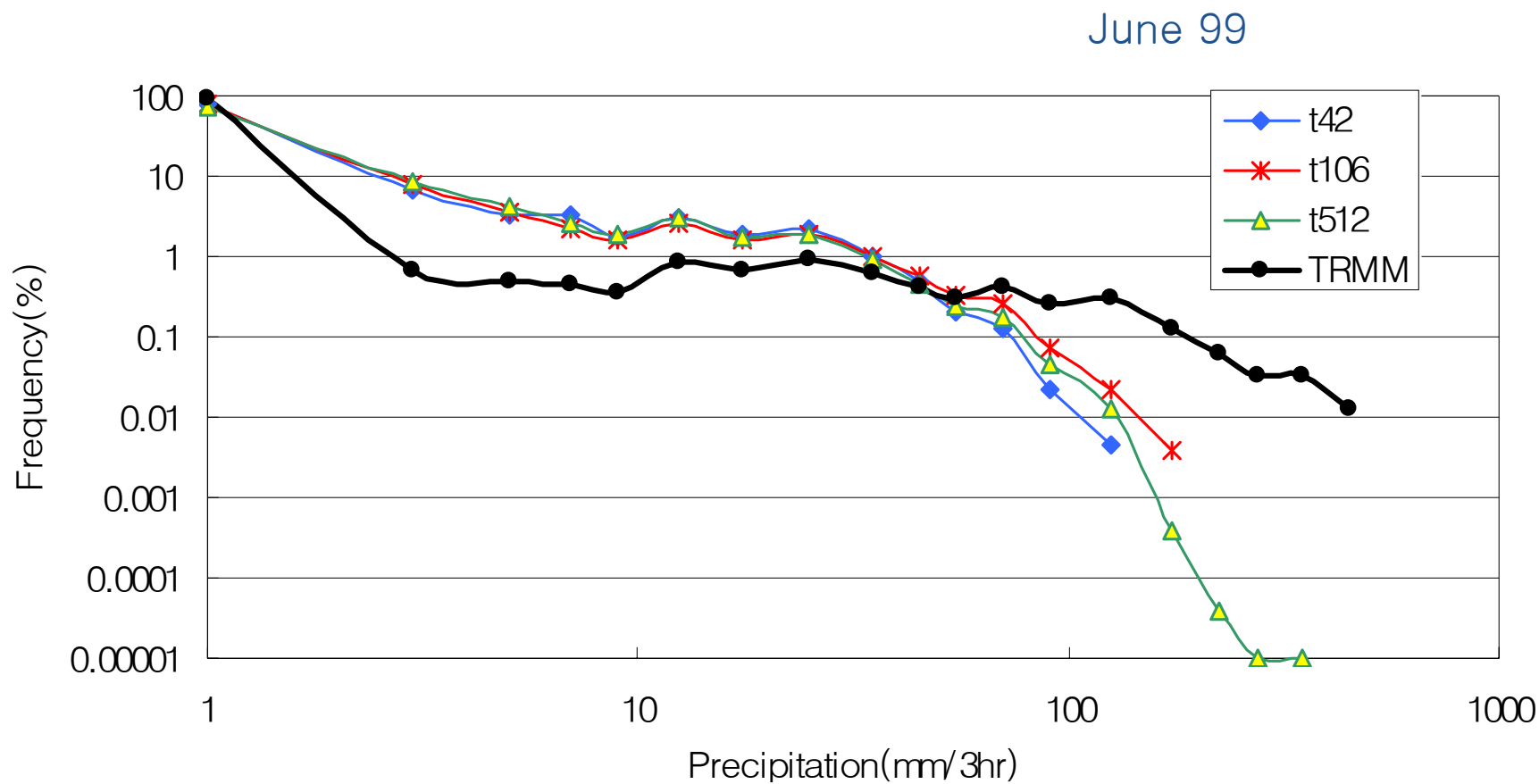


d) 99JJA (NCEP)



High-Resolution Model

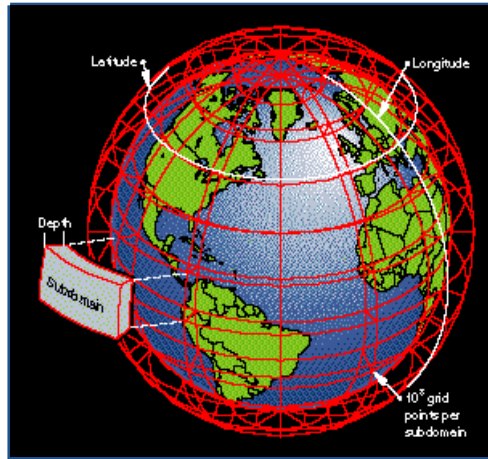
Frequency of event





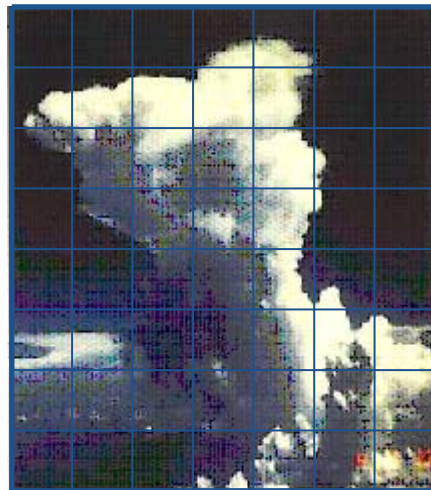
Next Generation Climate Prediction Model

GCM



- 1-grid box
- Parameterization
- Uncertainty of the number and position of the clouds

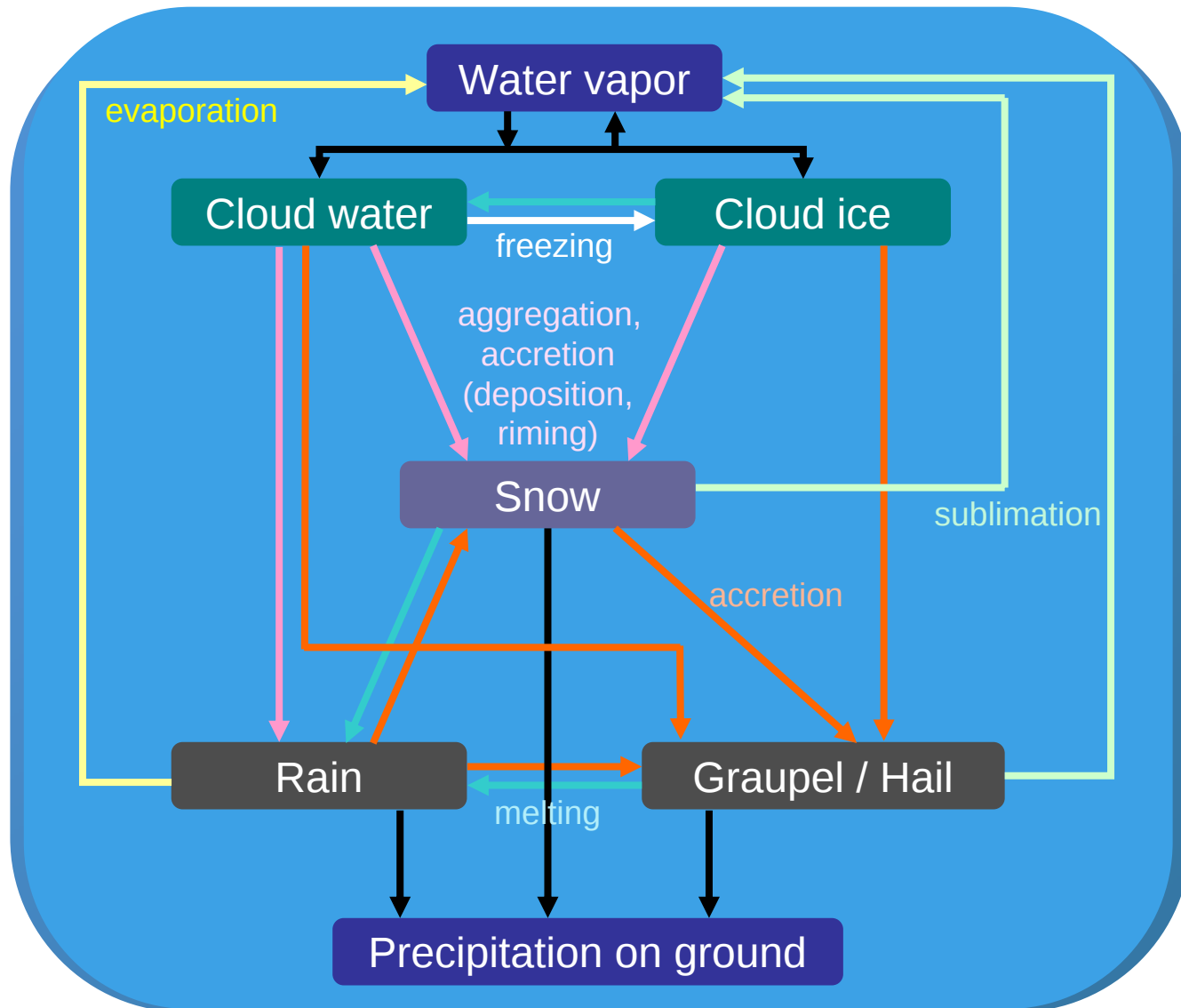
High
resolution
GCM +
Microphysics



- High-resolution grid box
- Cloud resolving more correctly
- improvement of the precipitation prediction in global model



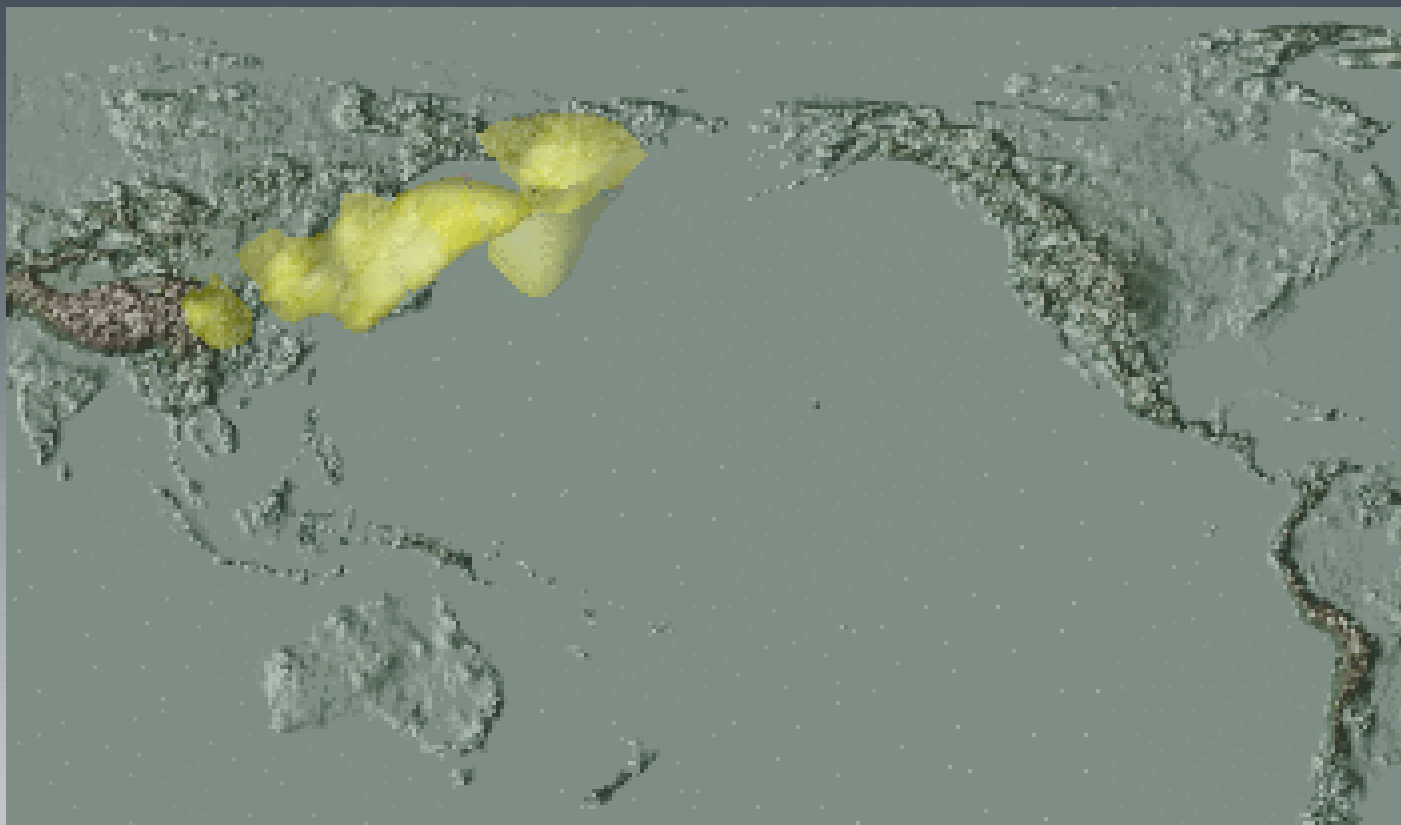
Microphysics





Climate-Environment System Model

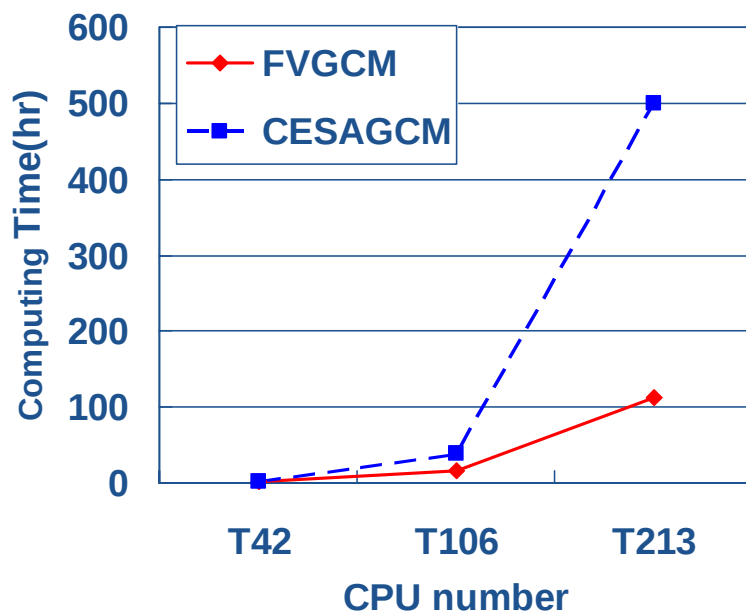
Daily evolution of Dust, Spring 2001



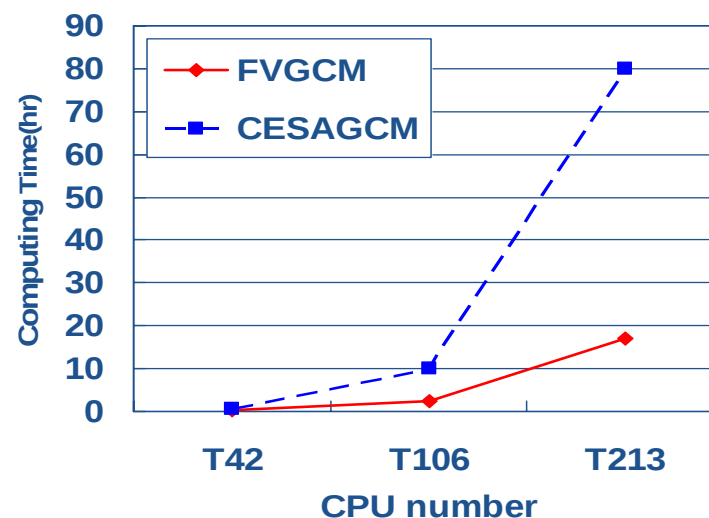


Computational Efficiency

Single CPU(1month)



8 CPU(1month)



- FVGCM is **5 times** as fast as CESAGCM at T213
- Longer time step in FVGCM(30min at T213)
- In supercomputer, It is expected that the total computing time will decrease as twice as linux cluster



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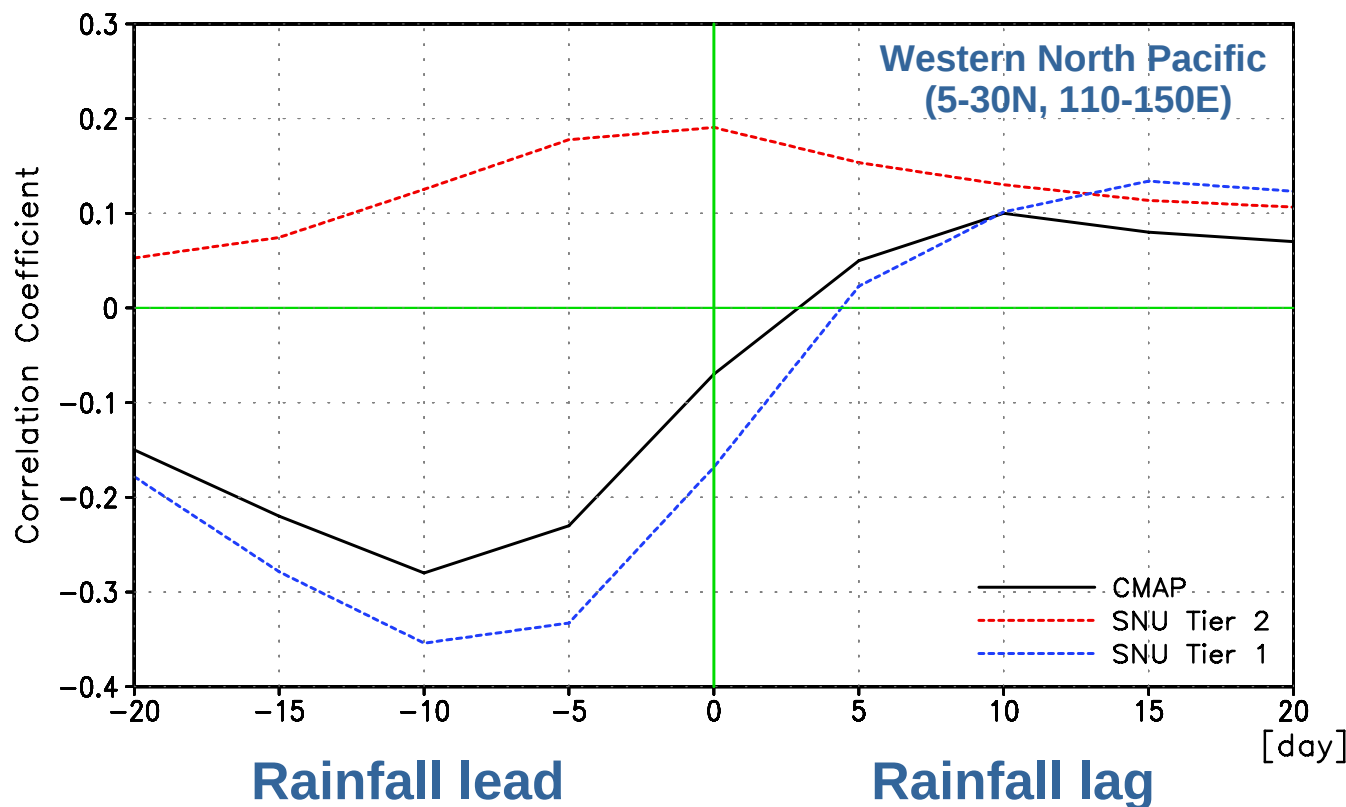
3. Multi-Model Ensembling

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Tier1 vs. Tier2

Lead-Lag Correlation between SST and Precipitation



Atmosphere



Ocean

- MJJAS for 21 years of 1981-2001



Tier1 → Initialization Problem

Prediction Memory

2-tier system (AGCM) :	Predicted SST Land Initial Condition
1-tier system (CGCM) :	Ocean Initial Condition Land Initial Condition

Initial Drift

Imbalances < between Atmosphere and Ocean
between Initial condition and Model Physics

→ Cause serious initial drift

Current Approaches

- Ocean spinning up (SNU, MAXP)
- Coupled SST nudging (SINTEX)
- 3DVAR/4DVAR (DEMETER, COLA, GFDL)
- Ensemble Kalman Filter (GFDL, SNU)



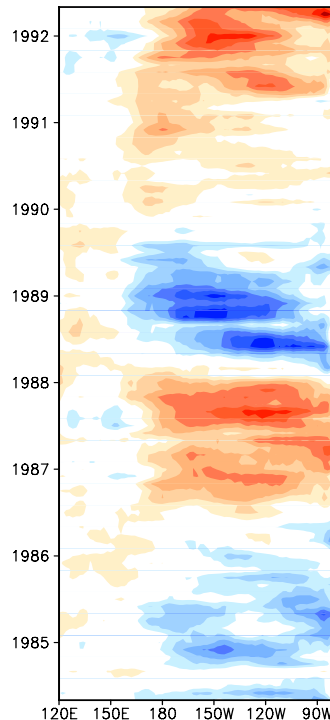
Initialization

Small error, system imbalance

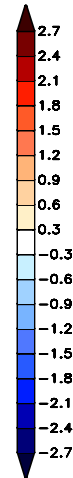
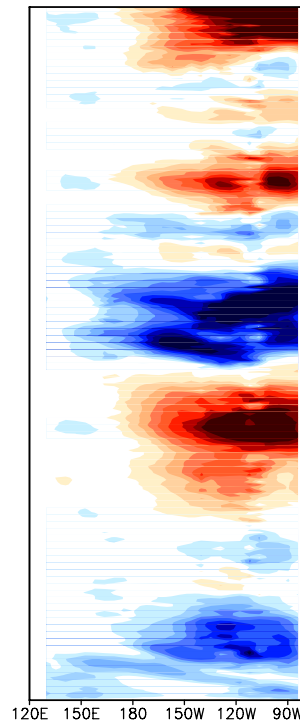


System balance, relative large error

OBS



Ensemble Kalman Filter



**Initial Condition of
Model Simulation
for Climate Prediction**

Benefit :

- Maintain memory longer
(More similar to OBS than Background)
- Reduce Initial Drift
(More balanced than OBS)

8 ensemble members are used.
TAO data (SST & isothermal depth) is used for assimilation.



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Multi-Model Ensemble (MME)

$$X_i = y + e_i + \varepsilon_i$$

Forecast = True + Error + Noise

E_M : Error variance of **Multi-Model Ensemble** $E_M = \frac{1}{M} \left[\bar{V}(e) + \frac{2}{M} \sum_{ij} COV(e_i, e_j) + \bar{V}(\varepsilon) \right]$

E_S : Error variance of **Single Model** $E_S = \bar{V}(e) + \bar{V}(\varepsilon)$

For example : Two Models (M=2)

Error variance of Multi-Model Ensemble $E_M = \frac{1}{2} [\bar{V}(e) + COV(e_1, e_2) + \bar{V}(\varepsilon)]$

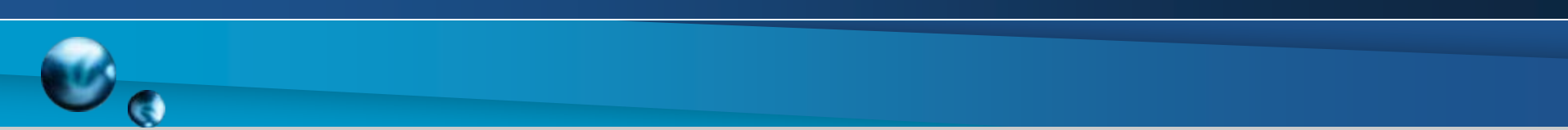
Error variance of Single Model $E_S = \bar{V}(e) + \bar{V}(\varepsilon)$

Mean Square Error $E = E_M - E_S = -\frac{1}{2} \bar{V}(e) + \frac{1}{2} COV(e_1, e_2) - \frac{1}{2} \bar{V}(\varepsilon)$

Reduction of Systematic Error
Reduction of Random Noise

For Improvement $\rightarrow E < 0$

Where **Models are independent** each other $\rightarrow COV(e_i, e_j) = 0$



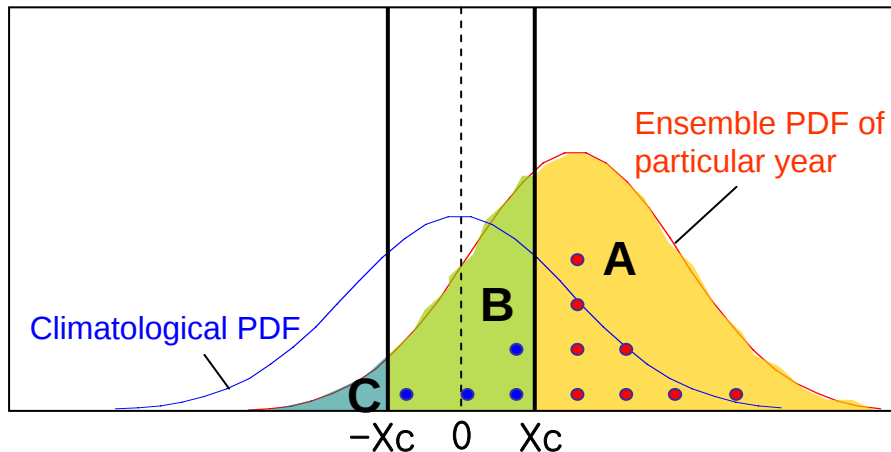
MME schemes

- 1. Deterministic forecast**
- 2. Probabilistic forecast**



Testing probabilistic MME schemes in a simple model

Simple Pooling method



- A** Probability of ABOVE normal
- B** Probability of Near normal
- C** Probability of BELOW normal

Bayesian based MME scheme (IRI)

$$P_i^{new} = a_i P_c + b_i P_i$$

$$P_{MME} = a' P_c + b' \left(\sum_i \frac{a_i}{\sum_k a_k} P_i \right)$$

Another scheme (FSU: SPENS)

$$w_i = \frac{c_i^k}{\sum_{i=1}^N c_i^k}$$

K=3

$$c_i = \frac{\alpha}{\alpha + \gamma} + \frac{\delta}{\beta + \delta}$$

α : number of hit (fcst=yes, obs=yes)

β : number of false alarm (fcst=yes, obs=no)

γ : number of miss (fcst=no, obs=no)

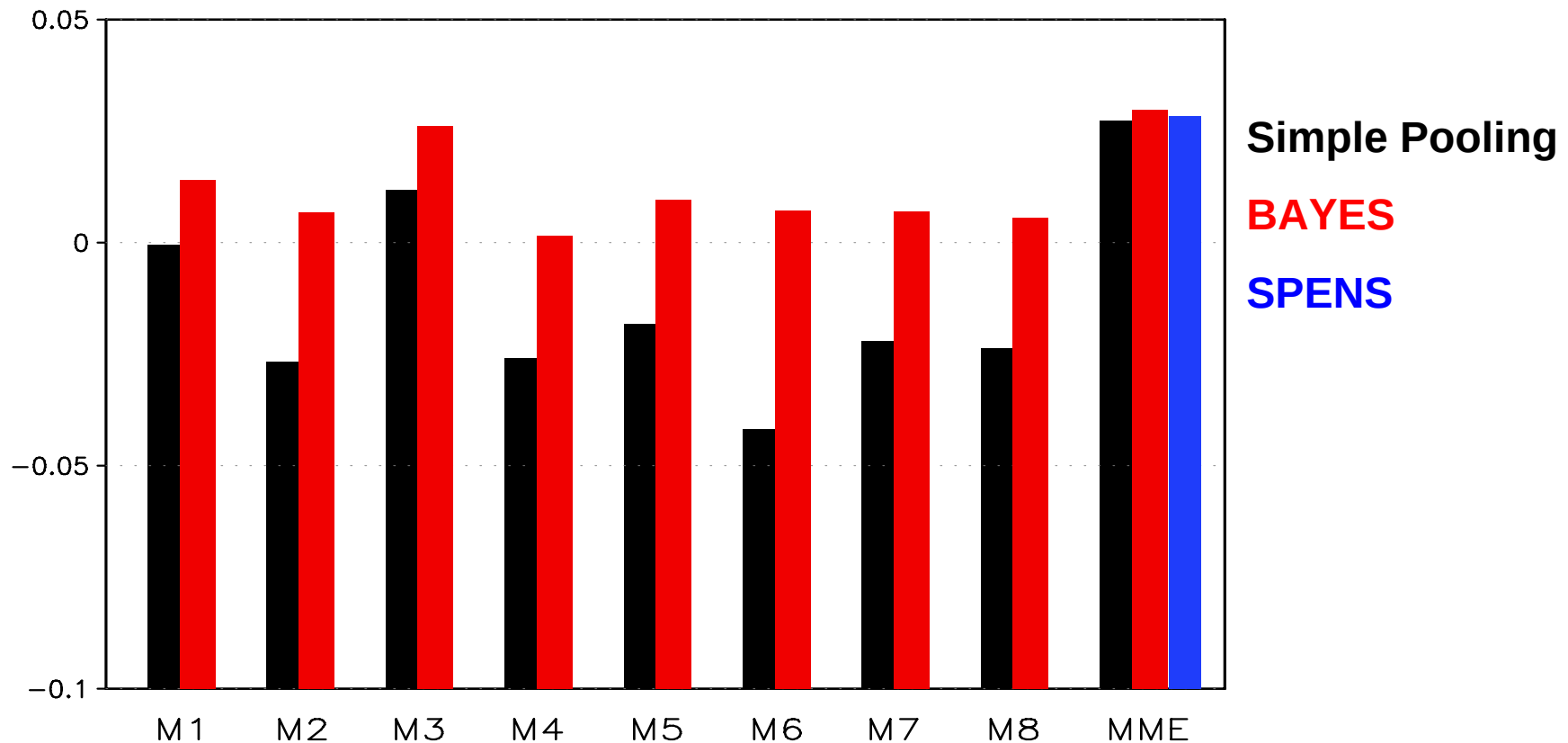
δ : n. of correct rejection (fcst=no, obs=yes)



Mean RPSS

seasonal mean upper level streamfunc. / 20 members / total 240 seasons

Training: 120 seasons, Verification: 120 seasons

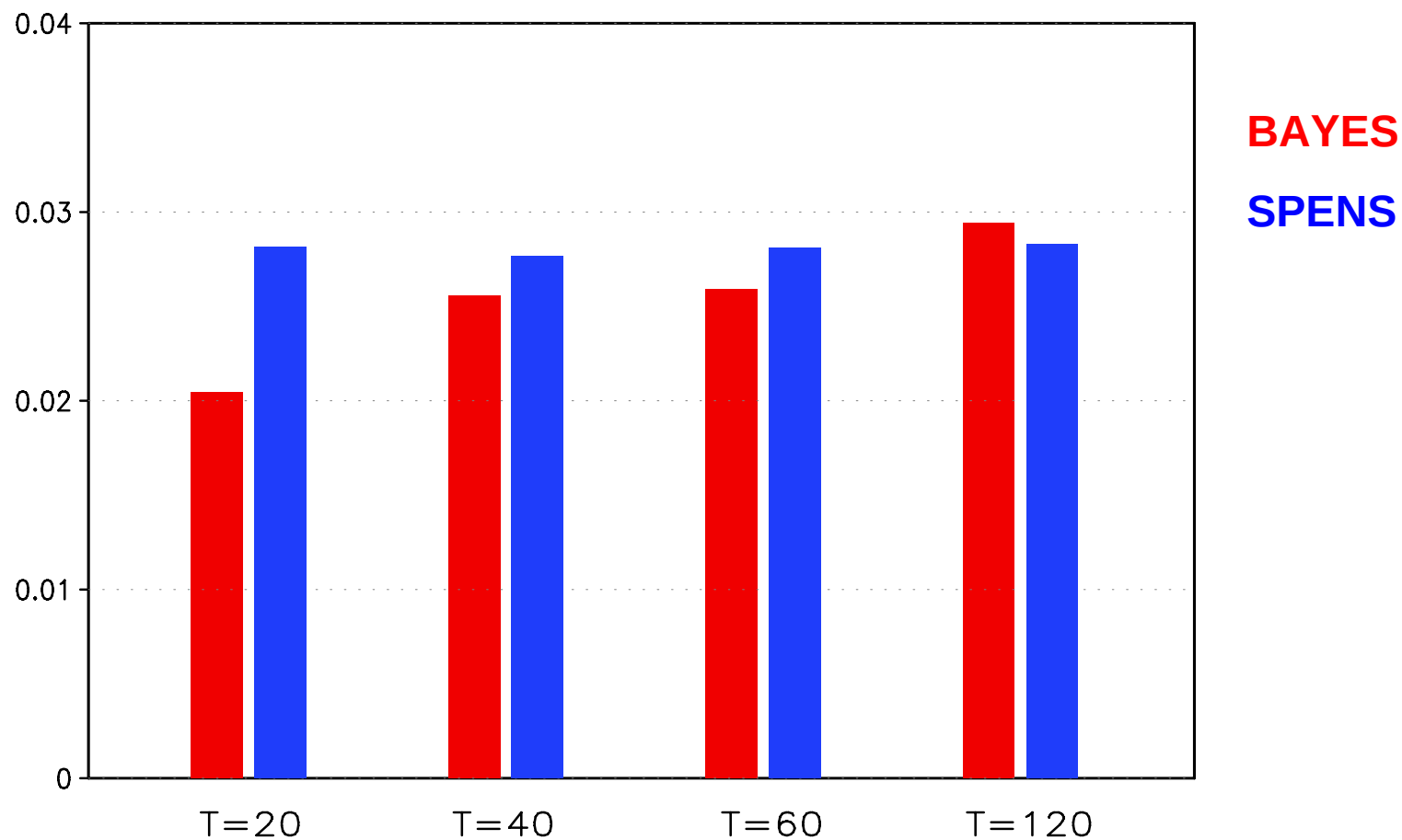


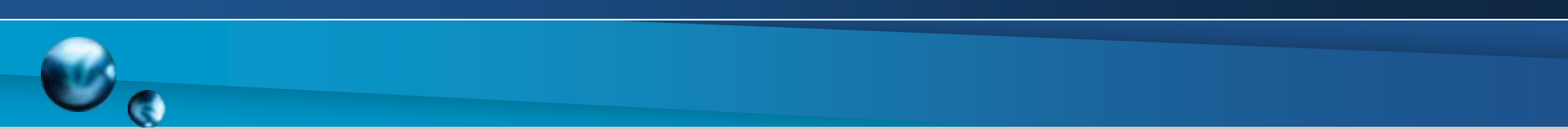
Very good simple pooling MME : either of Impact of ensemble size or well distributed different model

Weighted MME is better than/comparable to the pooling



Mean RPSS w.r.t. different training sample size (year)





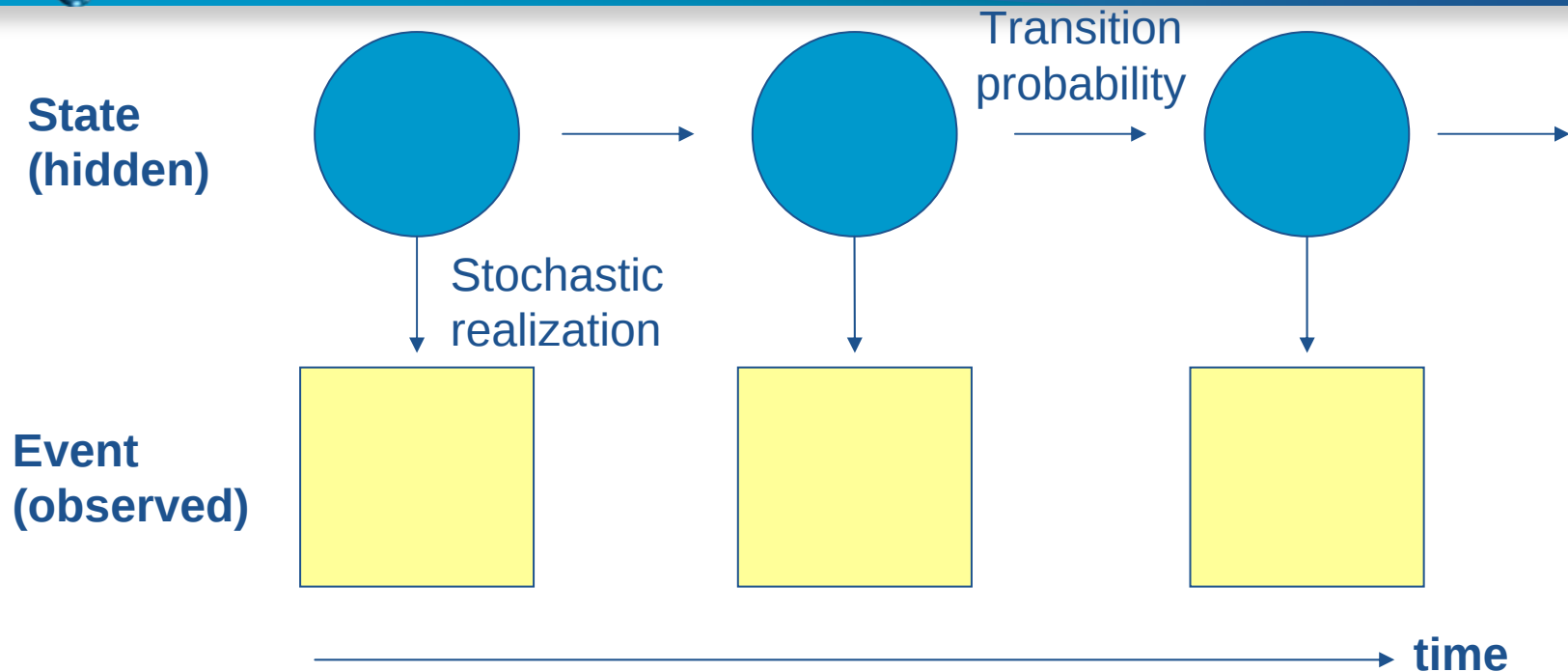
Seasonal Prediction

- **Seasonal mean**
- **Daily or pentad variations for a season**

Frequency vs Intensity



Hidden Markov Model



Cluster analysis + transition property among clusters

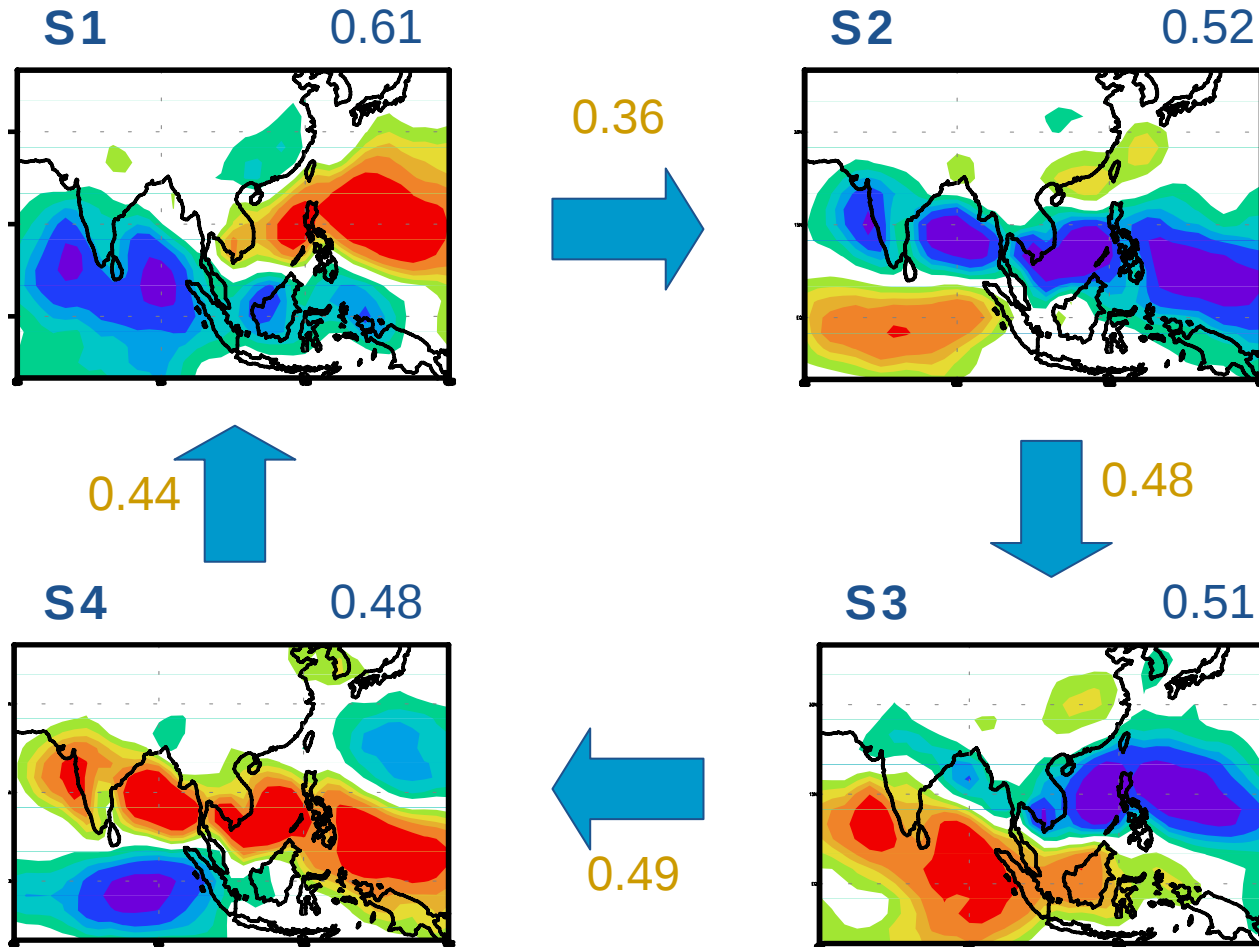
Application of HMM to ISO

- Statistical analysis of ISO
- Link to dynamical seasonal forecast : Utilize as a post-process



Estimated States & transition probabilities

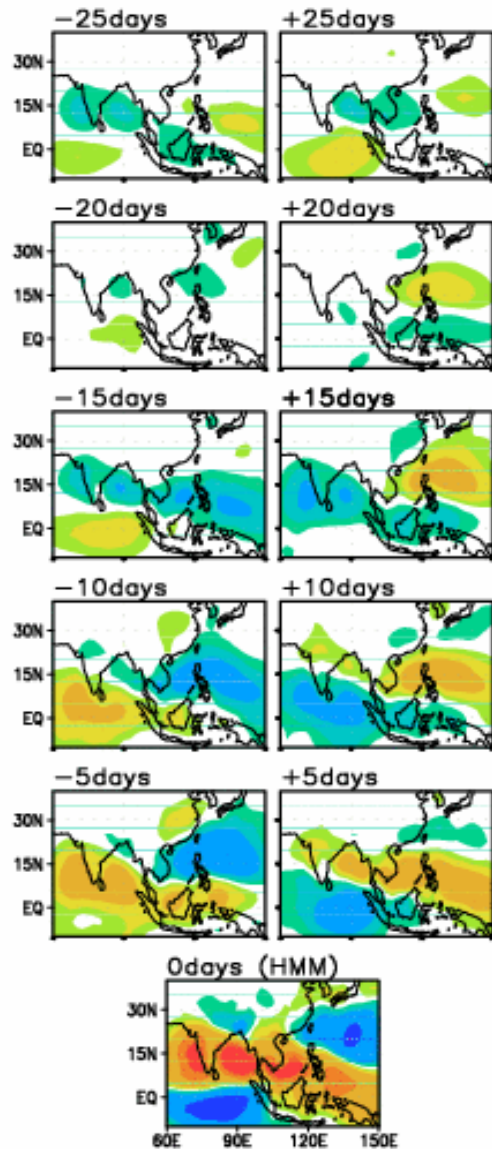
Map: Pentad Precipitation anomaly corresponding to each state





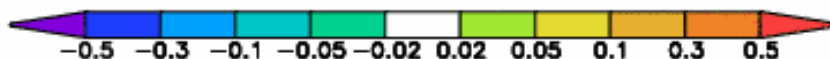
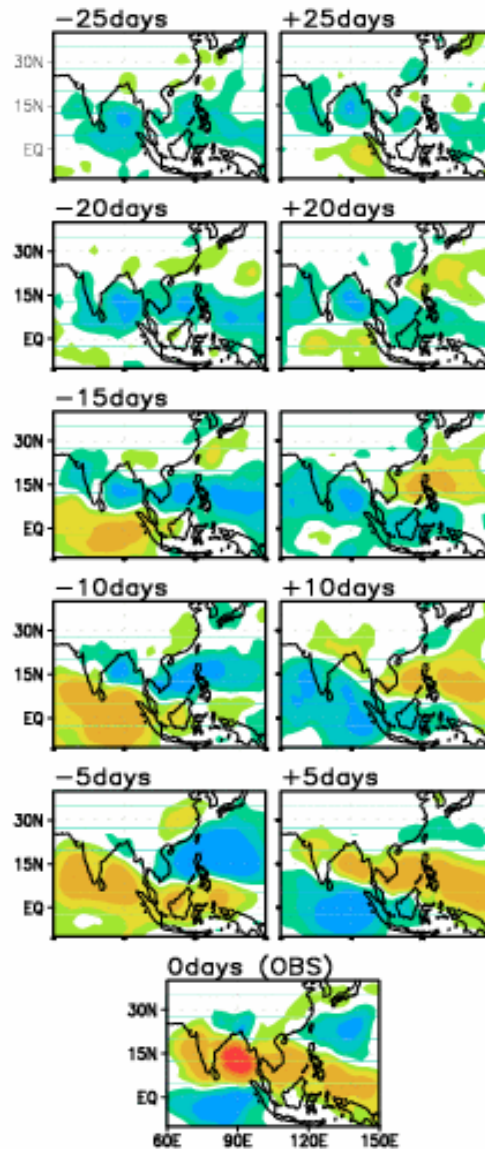
Stochastic simulation of ISO with HMM

HMM



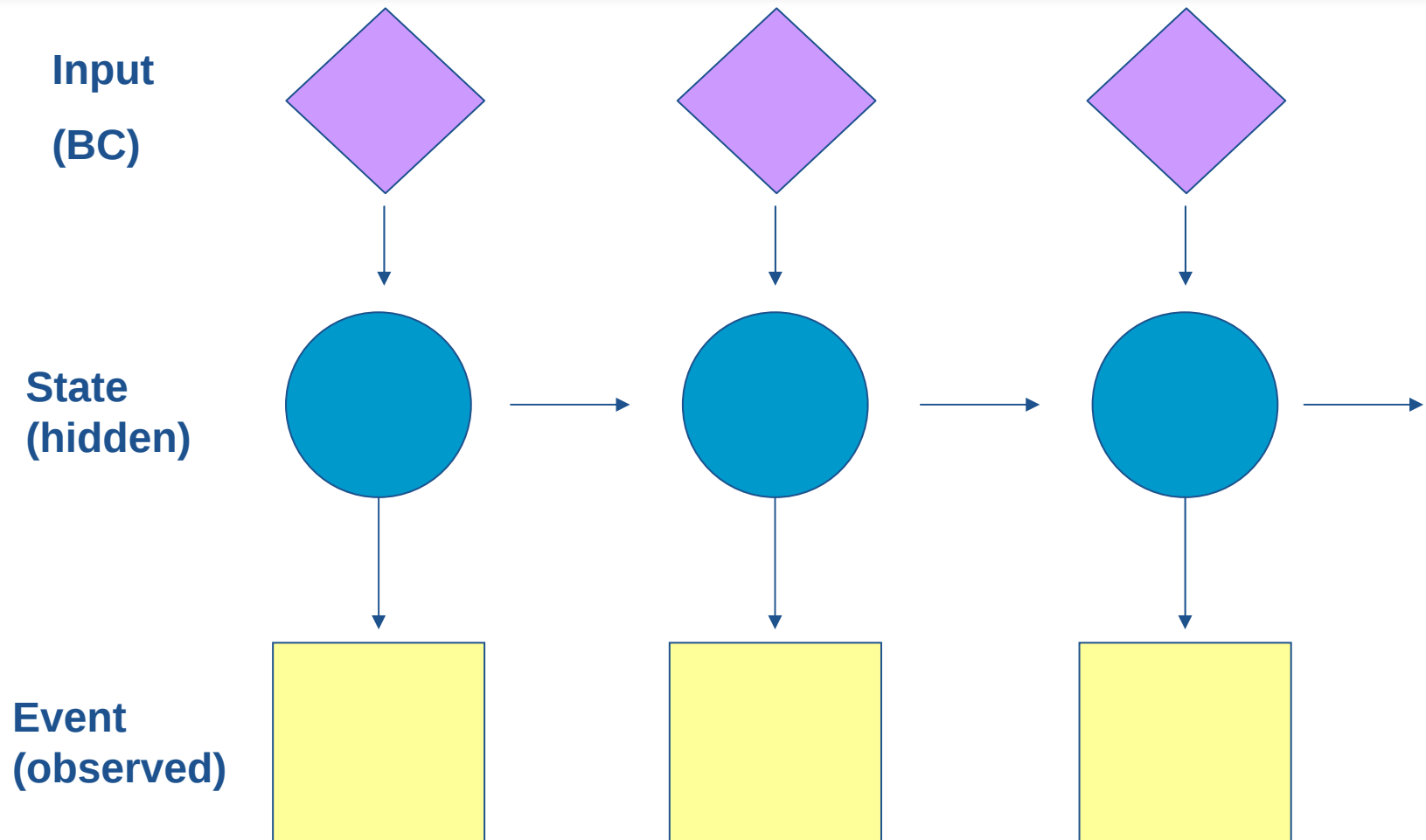
OBS

Lead-Lag one
point regression
map





Nonhomogeneous HMM (NHMM) with input



Considering impact of Input(BC) in transition probability / states occurrence

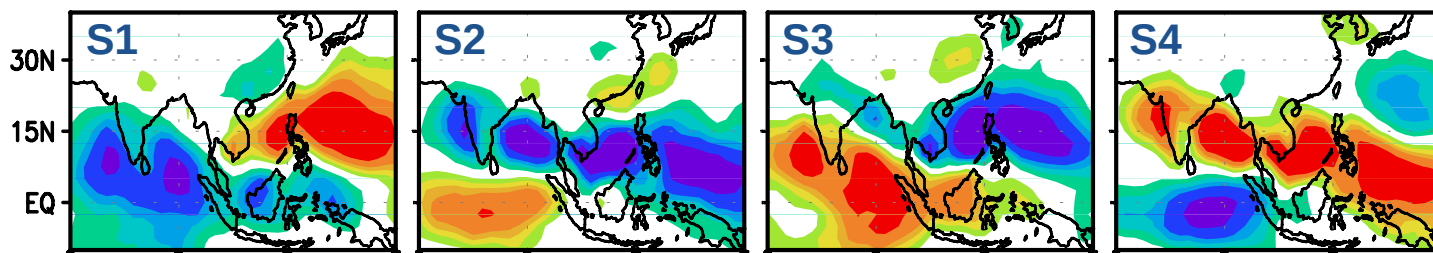
→ Linkage to GCM forecast



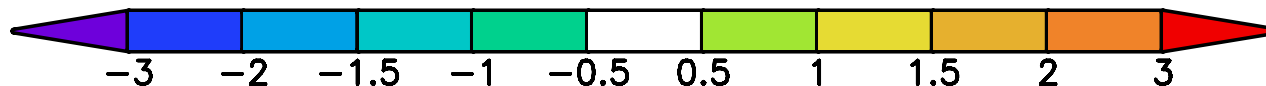
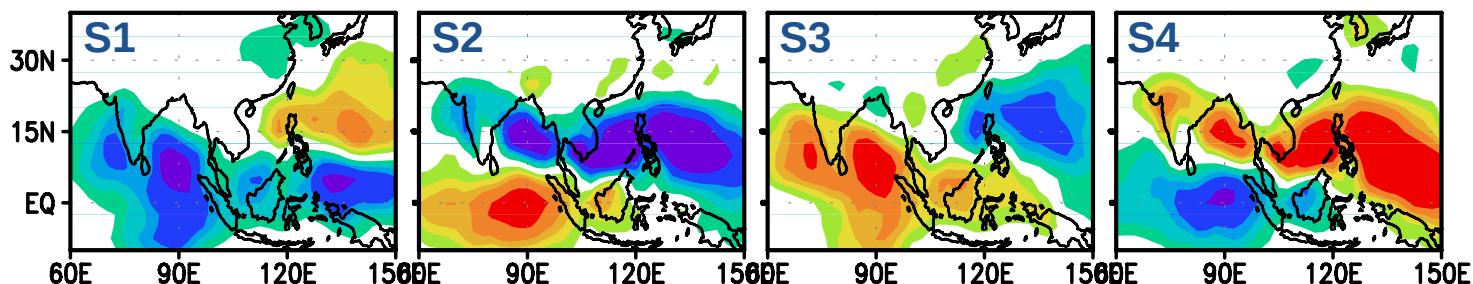
NHMM with summer mean Nino3.4 SSTA

Map: Pentad Precipitation anomaly corresponding to each state

HMM



NHMM (with NINO3.4)

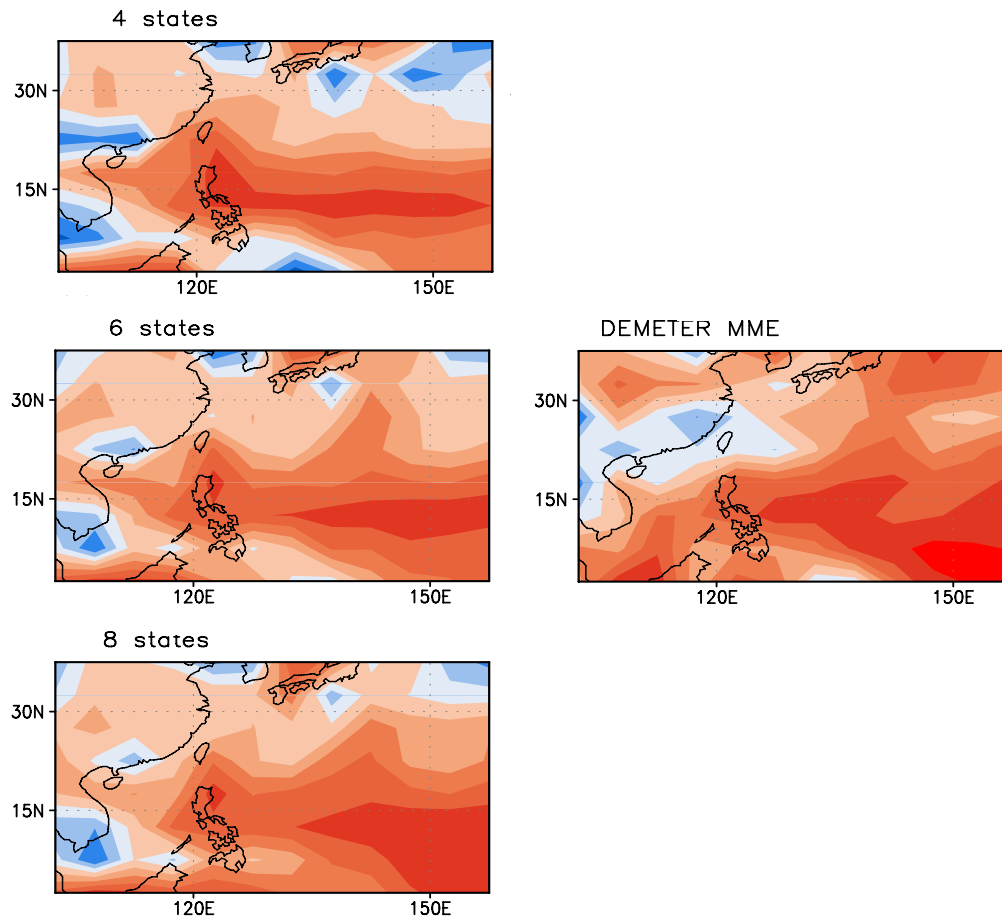


States picked up by NHMM resembles those of HMM



First attempt of post-process : anomaly correlation skill

seasonal mean precip. generated by NHMM with GCM forecast as a input



Input variable of NHMM :
3 leading PCs of GCM
(DEMETER) MME monthly
mean forecast of
precipitation over same
domain

Simulating Pentad
precipitation anomalies
with NHMM and make
seasonal average of them

Cross-validation

Thank You !

