

# Seasonal Prediction (1) : Introduction/Predictability

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# Overview

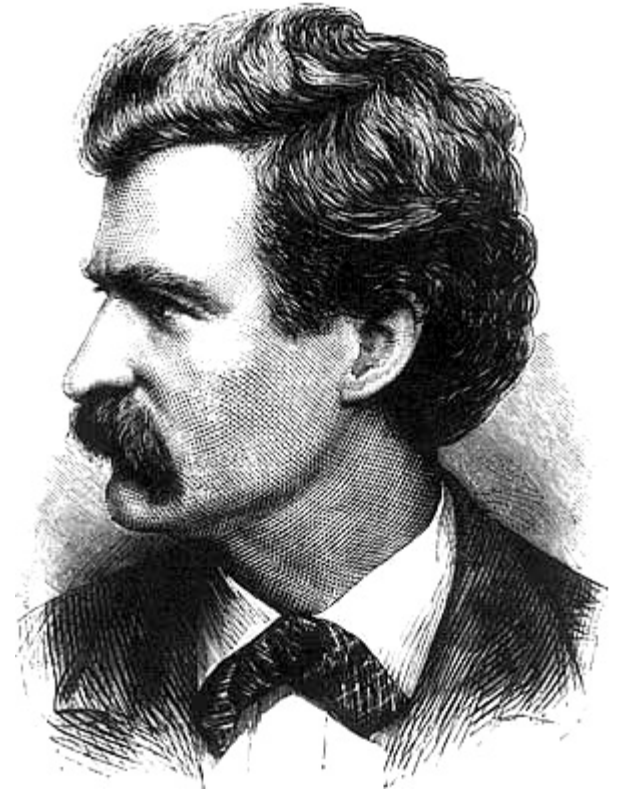
- Predictability
- Methods
- Verification + Downscaling
- Operation

# Climate prediction

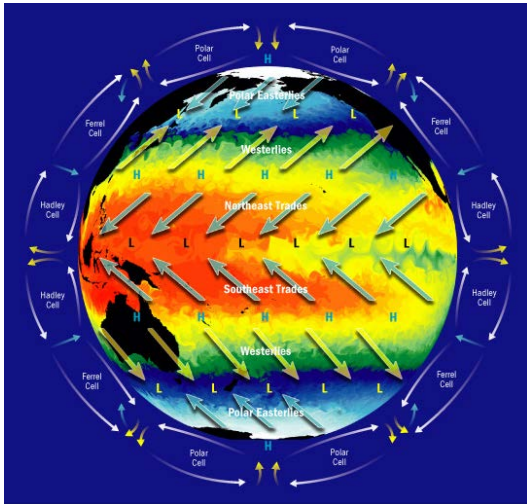
# Climate

**Climate is  
what we expect,**

**Weather is  
what we get**



# Climate = Expectation



**Climate Change = We need to change our Expectation**

**Climate prediction = Expectation of Expectation**

**How uncertain!**

# Prediction

a rigorous, (often quantitative), statement forecasting **what** will happen **under specific conditions**

# Prediction (in Meteorology)

a rigorous, (often quantitative), statement forecasting **what** will happen **under specific conditions**

What : atmospheric state  
Conditions??

# Atmosphere is dynamical system

$$\frac{d\vec{X}}{dt} = F(\vec{X}, a)$$

$$\vec{X}(t_0 + \tau) = \vec{X}(t_0) + \int_0^\tau F(\vec{X}(t), a(t)) dt$$

# Prediction (in Meteorology)

a rigorous, (often quantitative), statement forecasting **what** will happen **under specific conditions**

What : atmospheric state (weather)

Conditions: Current state, Physical rules, external forcing factors

# Determinism

$$\frac{d\vec{X}}{dt} = F(\vec{X}, a)$$

Perfect prediction is possible when we have knowledge of all necessary “conditions”

# Chaos

Small difference in the initial state cause huge difference later even in the deterministic nonlinear system.

$$\frac{d\vec{X}}{dt} = F(\vec{X}, a)$$

# Our knowledge is never perfect!

→ perfect forecast is impossible

How well we can predict?

“Predictability”

# Predictability

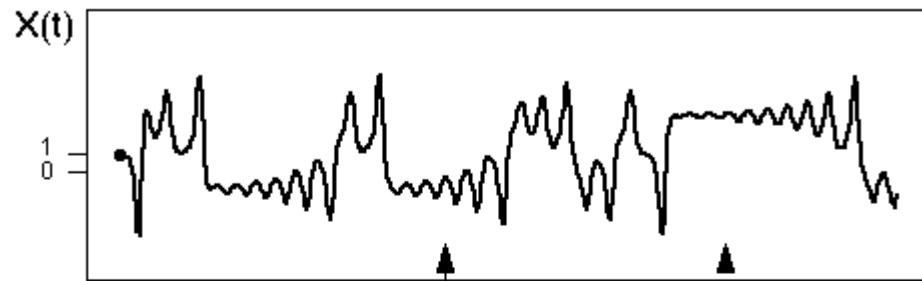
Depends on *what to predict*

*Prediction of*

- 1. Temperature of this room tomorrow*
- 2. Temperature of this room in 30days later*
- 3. Temperature of this room in 30years later*

**Lead time( $\tau$ )**

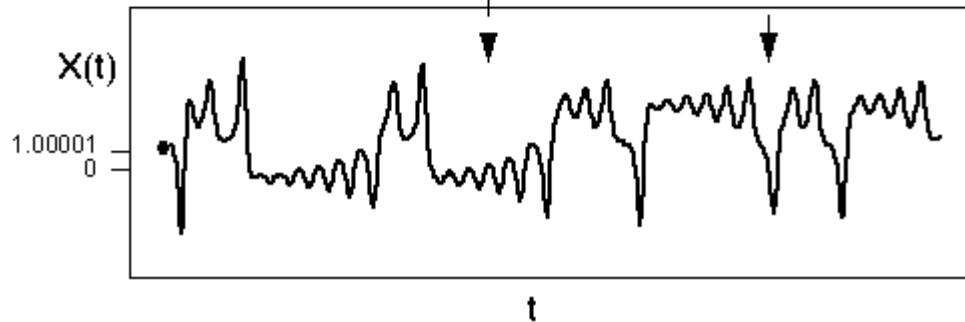
$$X(\text{initial}) = 1.$$



same

different

$$X(\text{initial}) = 1.00001$$



# Predictability

Depends on *what to predict*

*Prediction of*

- 1. Temperature of Busan*
- 2. Temperature of Jakarta*
- 3. Temperature of London*

**Location**

# Predictability

Depends on *what to predict*

*Prediction of*

- 1. Temperature*
- 2. rainfall*
- 3. wind speed*

**Physical variables**

# Why Predictability is varying with location/variables

## Characteristics of variability is different

- Tropics : weather = local convection (time scale ~ few hours)
- Extratropics : weather = synoptic system (time scale ~ few days)
- Daily rainfall is more chaotic (highly nonlinear) than temperature/pressure

# Predictability

Depends on *what to predict*

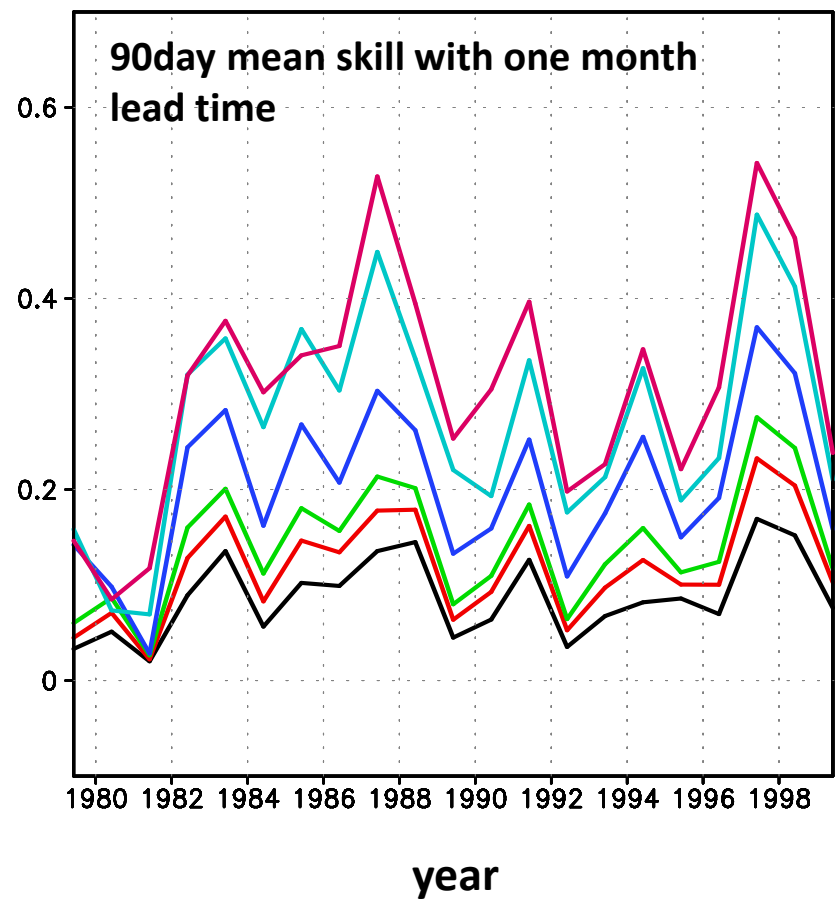
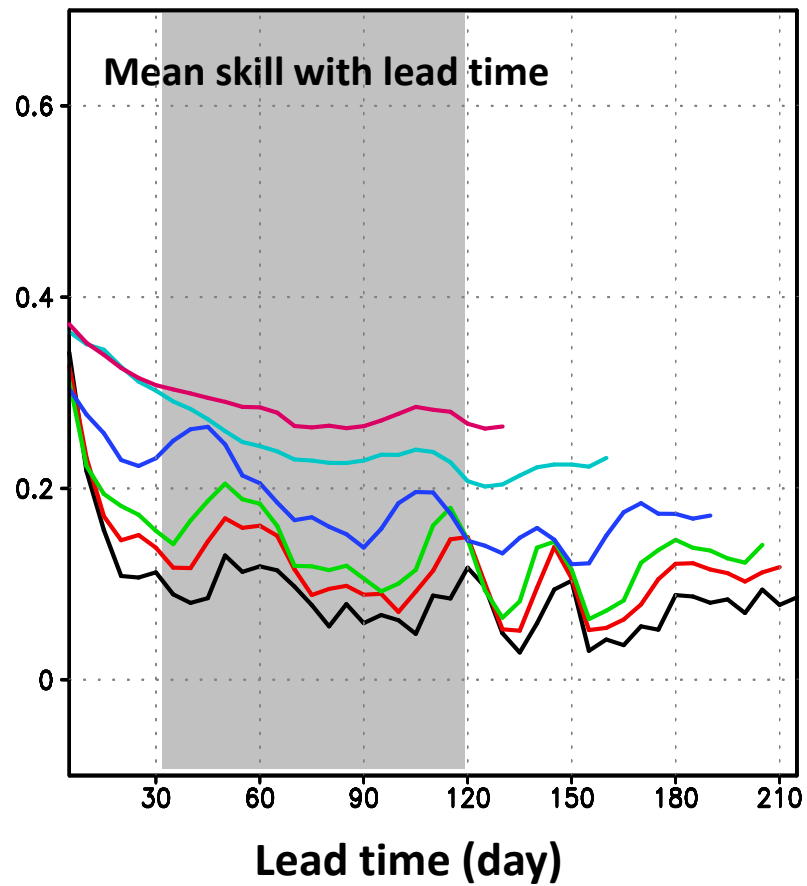
*Prediction of*

- 1. Mean Temperature during a day*
- 2. Mean Temperature during a month*
- 3. Mean Temperature during a century*

**Time scale of predictand**

# Seasonal mean and Intraseasonal predictability

## Global pattern correlation skill of GPCS precipitation forecast (SMIP)



5day, 10day, 15day, 30day, 60day, 90day averaged field

*How long?*

*Time mean of weather*

# Climate prediction

# Seasonal forecast



# Seasonal Prediction

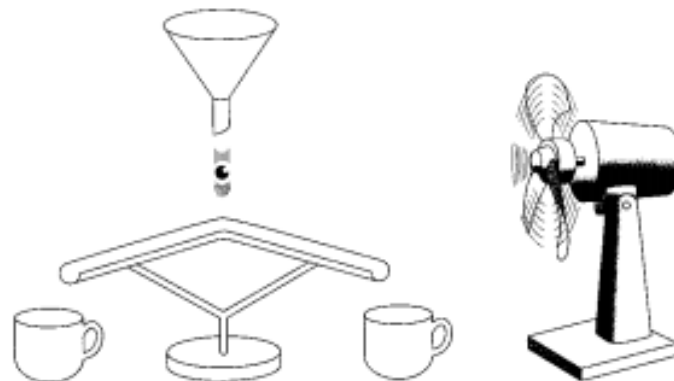
What : state of atmosphere **during a season**

Condition : Current state, Physical rules, external forcing factor

Lead time ~ 1 month (e.g. DJF forecast at Nov)

# History of Short-term (Seasonal) Climate Prediction

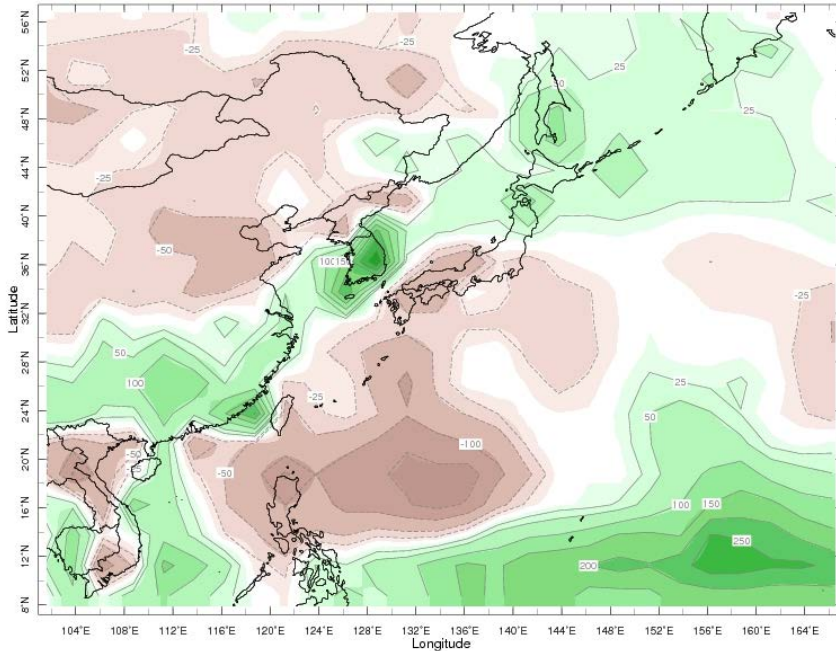
- 1960's : Hypothesis proposed
- 1980's : **ENSO** prediction + Atm. LFV. (PNA..)
- 1990's : (Experimental) Dyn. Seasonal Fcst.
- 2000's : International collaboration (MIPs)
- 2010's : Operation (GFCS, RCOFs/WMO)



T. Palmer (1998)

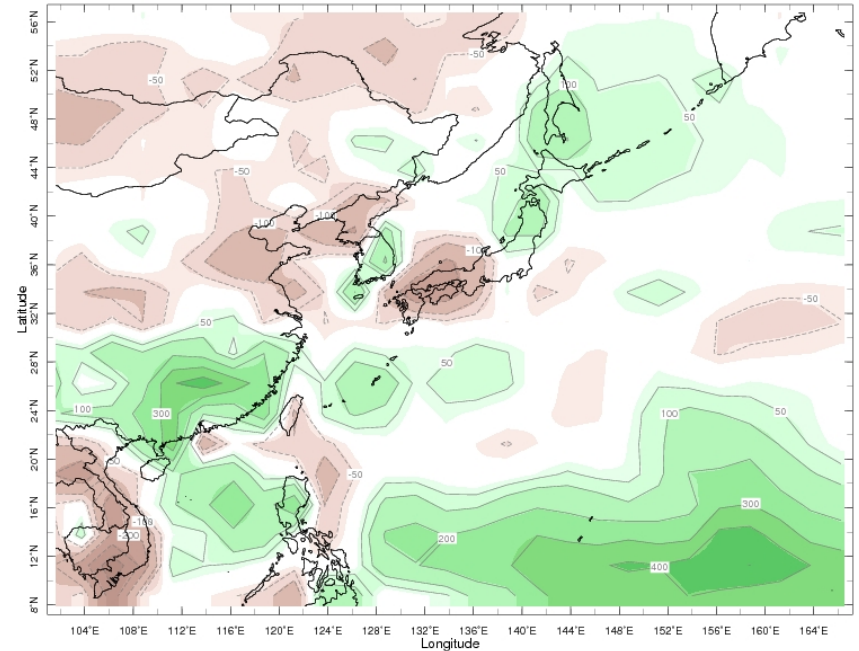
# 2002 summer rainfall

## Monthly mean prec. (Aug)



Aug 2002

## Summer mean prec.

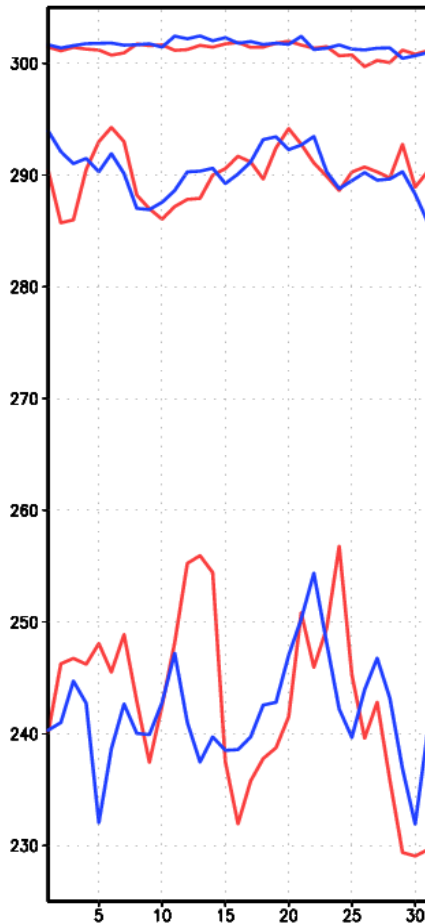


Jun-Aug 2002

**Typhoon "RUSA" passed at 8/31 (1000mm a day)**

# Seasonal forecast

How is the seasonal mean determined?

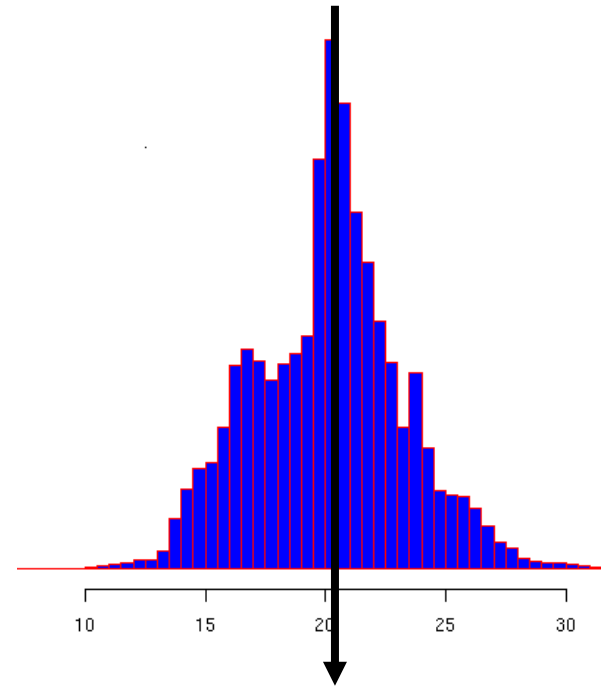
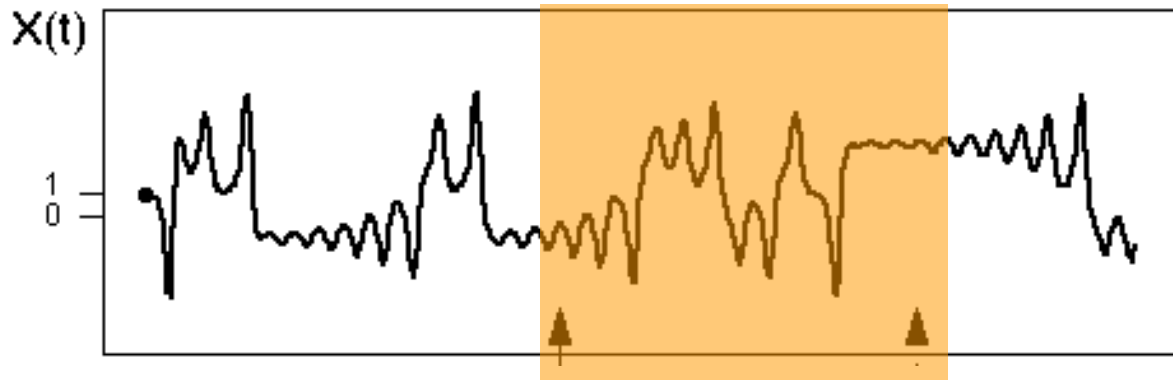


What causes change (variability) of the mean?

- By chance?
- By “something”?



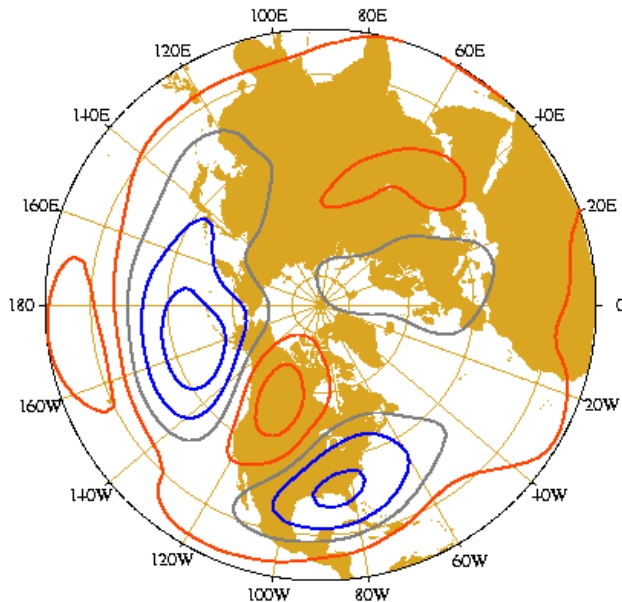
# Weather statistics



Primary seasonal weather statistics : seasonal mean

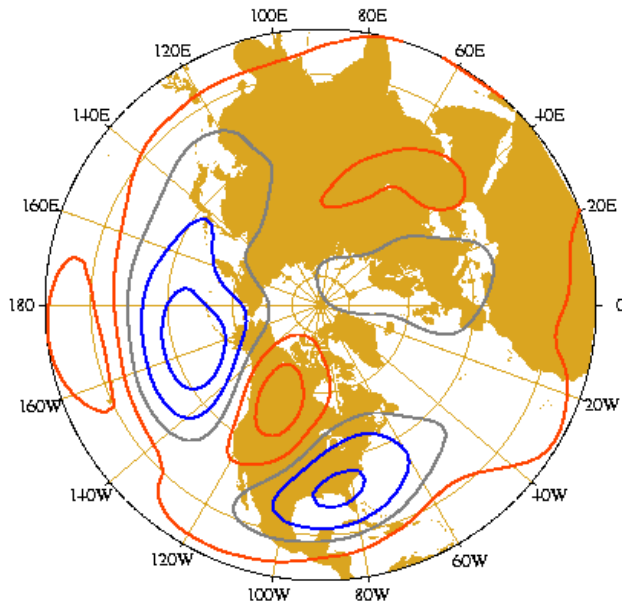
Seasonal mean

# PNA debates



1. Forced by El Nino
2. Atmospheric internal variability (random)

# PNA debates



1. Forced by El Nino  
**Predictable (signal)**
2. Atmospheric internal  
variability (random)  
**Unpredictable (noise)**

**Matter  
of  
Signal  
&  
Noise**

$$X = X_s + X_n$$

# Potential predictability

Measured by relative magnitude (variance) of signal and noise

**Signal >> Noise : more predictable**

**Signal << Noise : less predictable**

# Signal in Seasonal prediction

- What is the **Signal**? (How we can “see”?)
  - Tendency of weather that has be physically caused by slow varying processes
- What derives the Signal?
  - External forcing (or interaction)
  - Slow varying processes (ENSO)

# Mechanisms of Variability

## Internal

## External

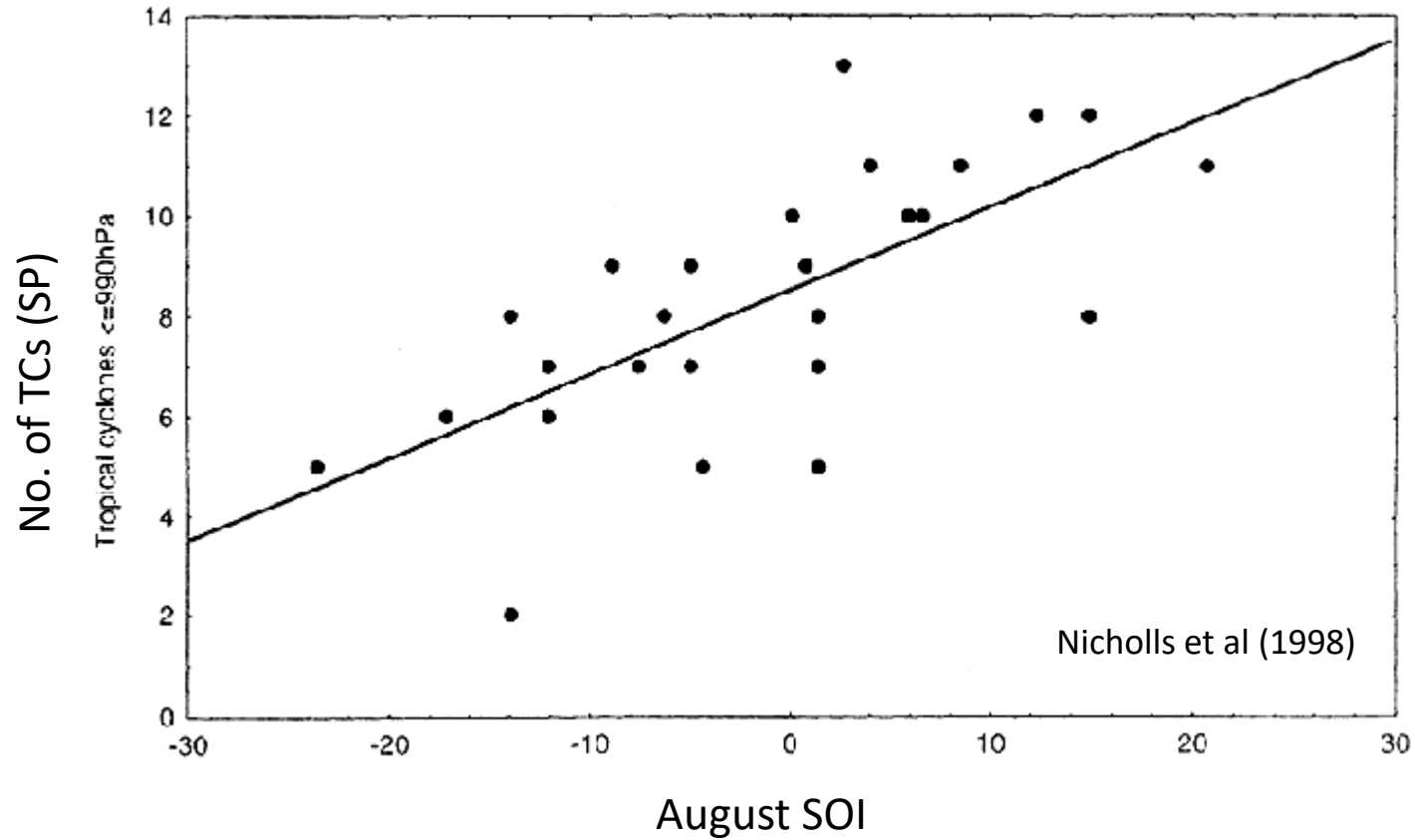
<b>Weather:</b>	<b>1. Internal Dynamics of Atmosphere</b>	<ul style="list-style-type: none"><li>• Boundary Condition of SST, Soil wetness, Snow, Sea ice, etc.</li></ul>
<b>Climate:</b> (seasonal-decadal)	<b>2. Internal Dynamics of Coupled Ocean-Land-Atmosphere</b>	<ul style="list-style-type: none"><li>• Solar, Volcanoes</li></ul>
<b>Climate Change:</b>	<b>3. Internal Dynamics of Sun-Earth System</b>	<ul style="list-style-type: none"><li>• Human effects: (Greenhouse gases, land use changes)</li></ul>

From J. Shukla (2007)

# Two scales

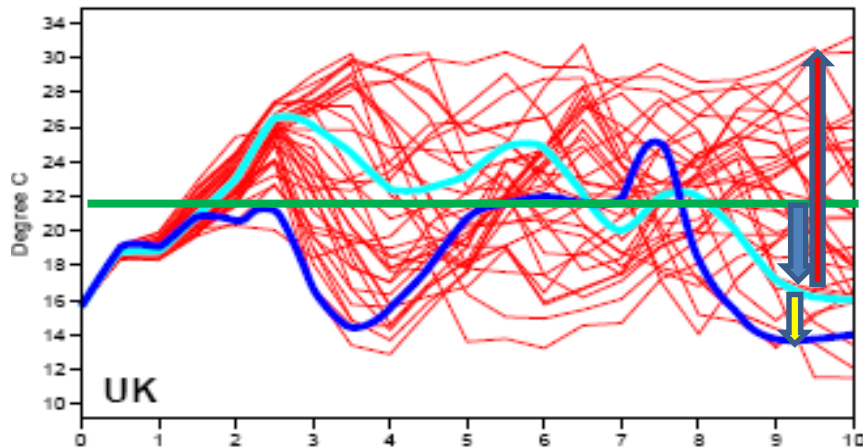
- **Fast and small** scale processes : noise
  - Weather, Tropical cyclone
- **Slow and large** processes : signal
  - Climate, ITCZ, ENSO

# Two scales



# Predictability

- Relative ratio between signal and noise
- BUT we don't know actual signal
  - Estimation of potential predictability by models
  - Ensemble prediction

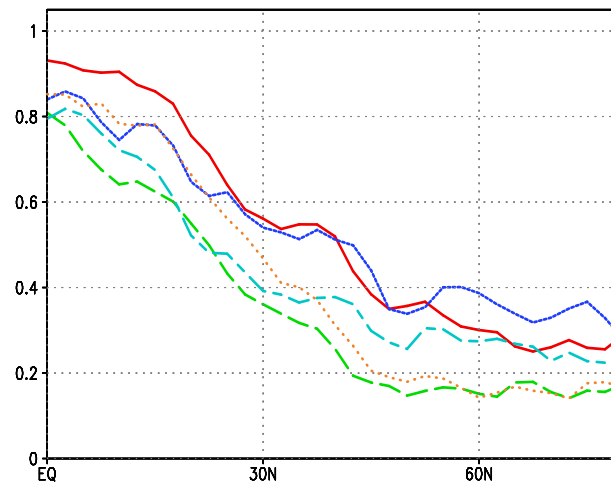
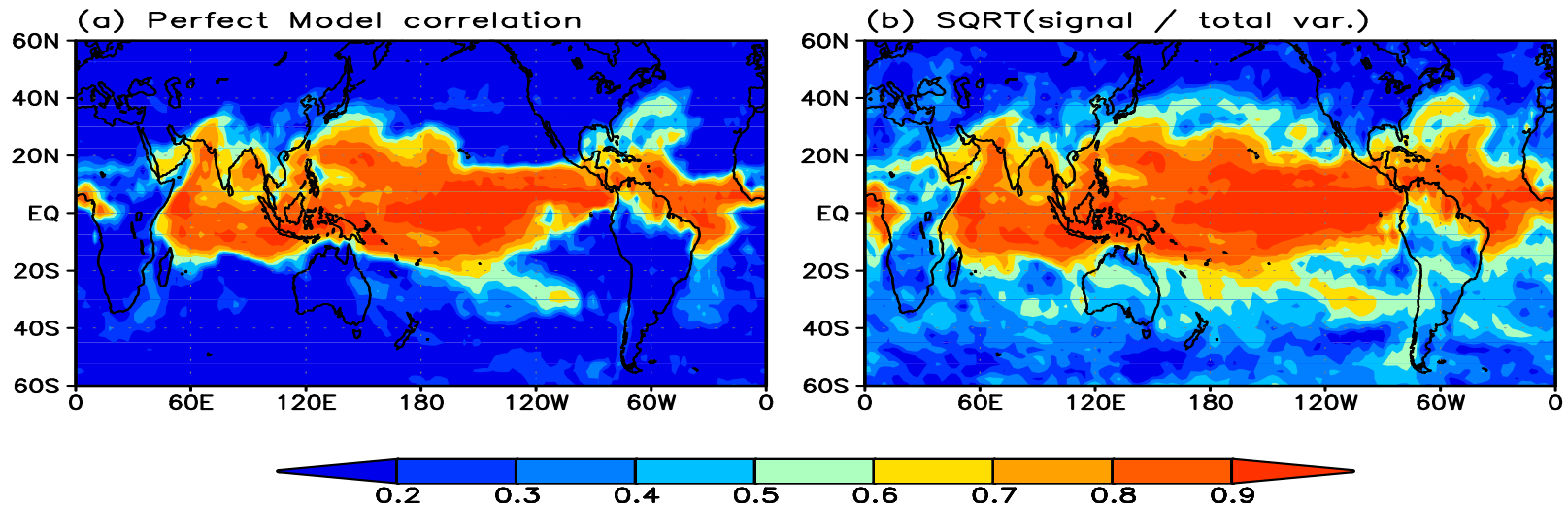


$$X = X_s + X_n$$

$X_s$  : ensemble mean

$X_n$  : deviation from ensemble mean

# Estimated potential predictability of rainfall



# Potential predictability

- Estimated limit of the predictability given prediction methods (model)
  - Depends on **nature** itself as well as prediction **model**
  - We cannot change the nature but model is our product
  - Potential predictability may be able to be improved (or not) if our model is improved

# Seasonal Prediction (2) : Methods

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# Methods

- Statistical (Empirical)
  - Use observed relationship of climate system to predict future
  - Linear
- Dynamical
  - Based on “physical law” of climate system and expect to mimic “the memory”
  - Nonlinear

# Which one is better?

## Statistical

- Simple and cheap
- Based on data
- Data is real thing but do we have enough?

## Dynamical

- Complex and expensive
- Based on Law
- Is our understanding accurate?

# Statistical forecasting

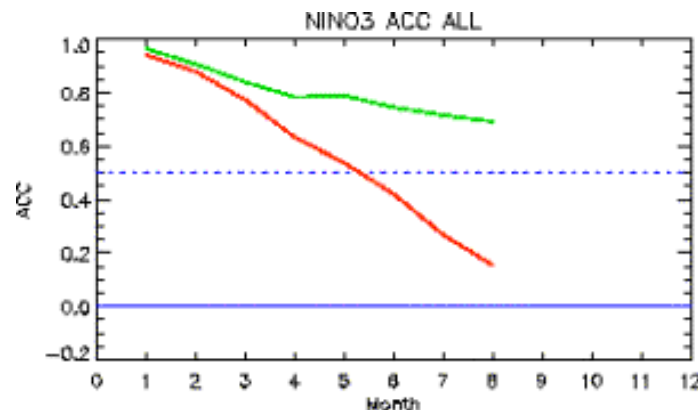
- (0) Climatology

$$x(t + 1) = \bar{x}$$

- Baseline of seasonal forecasting
- “Nothing particular, Sir.”
- Deterministic forecast
  - Rainfall amount will be similar to 30year average
- Probabilistic forecast
  - Near normal ?
  - I don't know? (33%:33%:33%)

# Statistical forecasting

- (1) Persistence  $x'(t + 1) = x'(t)$ 
  - Assume that future will be same as it is now
  - ANOMALY !
  - Often Close to people's expectation
  - Effective when the autocorrelation is large
    - Often used for ENSO forecast (Nino3.4)

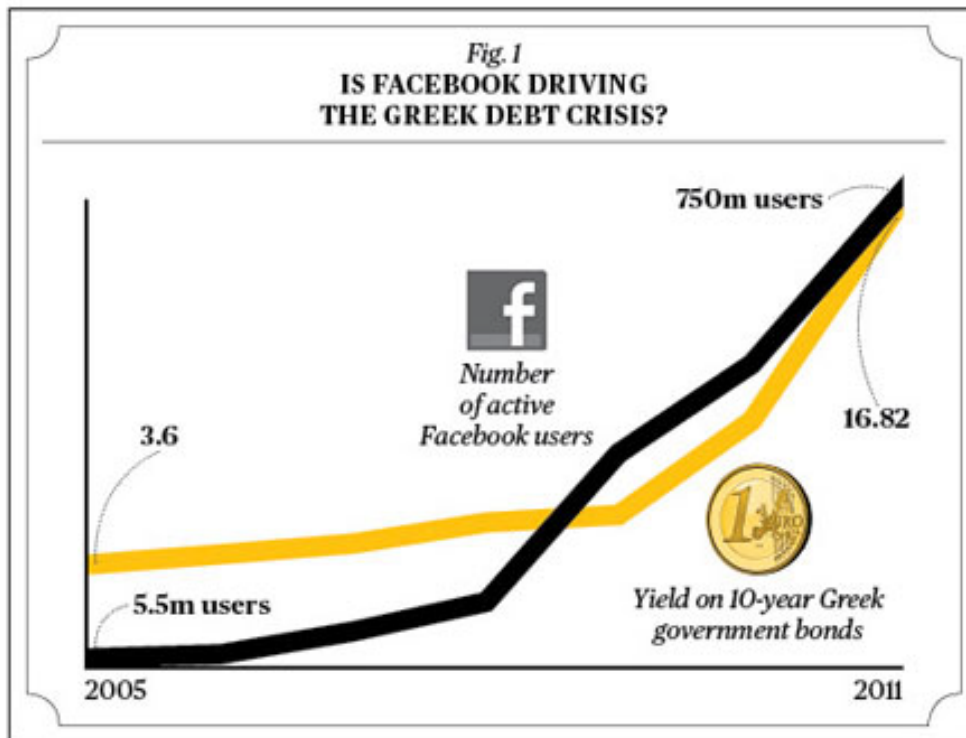


# Statistical forecasting

- (2) Regression  $x'(t + 1) = ay(t) + b$ 
  - The most popular method and many variations
  - $x$  : predictand (e.g. rainfall at a station)
  - $y$  : predictor (e.g. NINO3.4 SST)

# Predict yield of Greek bonds with Facebook users

- Is it appropriate?



If yes, why?

If not, why?

From *business week*

# Regression based forecast

- Question #1  $x'(t + 1) = ay(t) + b$ 
  - How to define predictor ( $y$ )?
  - By definition, predictor should cause some changes in variation of predictand
  - Predictand : my mood in the morning
  - Predictor?

# Regression based forecast

- Question #2

$$x'(t + 1) = ay(t) + b$$

- How to define **a** and **b**?
- your choice. Linear, nonlinear, single, multi....
  - Complex one is not necessarily better.
- Predictand : my mood in the morning
- Predictor :
- a , b?

# Regression based forecast

- Question #1 : Predictor selection
  - Should be based on Physical relationship between predictors and predictands
  - Predictor cannot be tiny signal in the seasonal forecast
  - Keep “doubt” on the possibility of selection by chance
  - Selected predictor should be validated with separate data

# Regression based forecast

- Question #2 : appropriate Function

$$x'(t + 1) = ay(t) + b$$

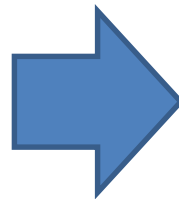
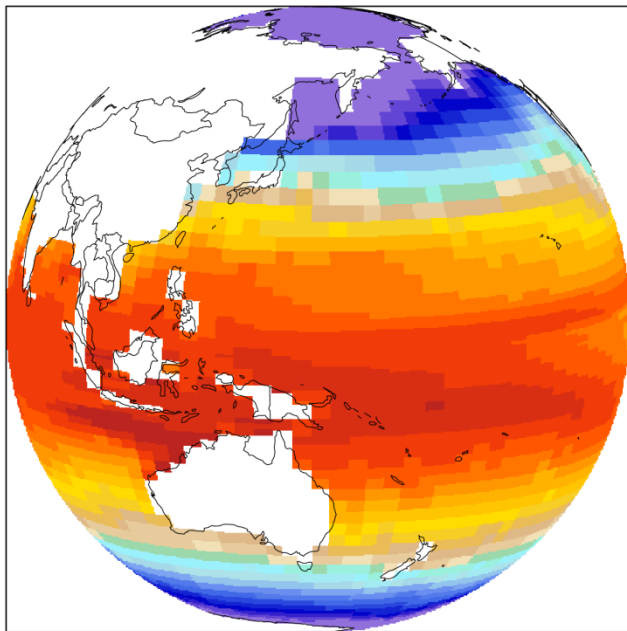
$$x'(t + 1) = a_1y_1(t) + a_2y_2(t)b$$

$$x_1'(t + 1) + x_2'(t + 1) = a_1y_1(t) + a_2y_2(t)b$$

- One to One : often not very satisfactory, limited cases
- One to Multi : easy to overfit (lie)
- Multi to Multi : looks nice but often produce nothing practical
- If they gives similar result, the simpler is the better

# Dynamical forecast

- Use GCM : Global Climate Model
  - It used to be called “General Circulation Model”



# Dynamical forecast

- Governing Equations
  - Written as computer program code (NWP)

$$\frac{\partial \mathbf{u}}{\partial t} + (\mathbf{u} \cdot \nabla) \mathbf{u} = \nabla \Phi - 2\Omega \times \mathbf{u} - \frac{1}{\rho} \nabla p + \mathcal{F}$$

$$\frac{\partial \rho}{\partial t} + \bar{\nabla}(\rho \bar{\mathbf{u}}) = 0 \quad \Leftrightarrow \quad \frac{D\rho}{Dt} = -\rho \nabla \cdot \mathbf{u}$$

$$\frac{\partial \theta}{\partial t} + \bar{\mathbf{u}} \cdot \bar{\nabla} \theta = l$$



```
//Behradek functions:
//
//   DTstage(T+0.11)^-2.05
//
MinTime=pow(T1]+9.11, -3.05); //Minimum time to advance to stage (in days)
for(k=0;k<numLifeStage;k++)
{
  MaxRate[k]=MinTime+DTstage[k];
  MaxRate[k]=MaxRate[k]*ToSecs; //Convert to seconds
  MaxRate[k]=1.0/MaxRate[k]; //Convert to rate
}

//Parameters for Ivlev functions controlling food dependence
//
//   R=1-exp(-b*(food-c))--development rate (days^-1)
//
// But, idea is that temp sets max growth rate, and food tells us how close
// we get to the max. In this sense, a=1 (Campbell figured an absolute
// rate, we're essentially normalizing his rates by rate at 40C.
//
//b=[ones(1,6)*params.bnaup,ones(1,6)*params.bcop];

for(k=0;k<6;k++)
  Rfood[k]=(1.-exp(-(F[j]-c)*params.bnaup));
for(k=6;k<12;k++)
  Rfood[k]=(1.-exp(-(F[j]-c)*params.bcop));

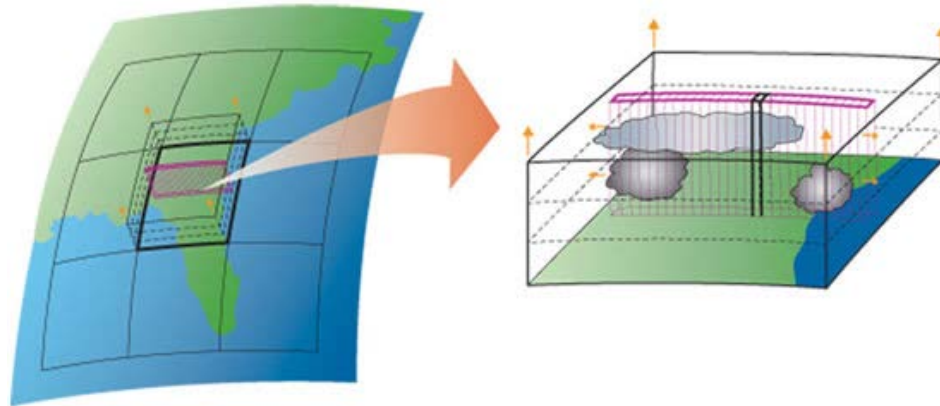
//Multiply Rfood by MaxRate to get the actual rate.
for(k=0;k<12;k++)
  R[k]=MaxRate[k]*Rfood[k];

R[12]=0.; //adults don't molt

//M[k]=mortality rate for stage k at node j
//
gammaT=gamma0*(1.-gamma0)+pow(T[j]/Tc,2);
//gammaT=0.1; //Override temp dependent mortality
```

# Numerical modeling

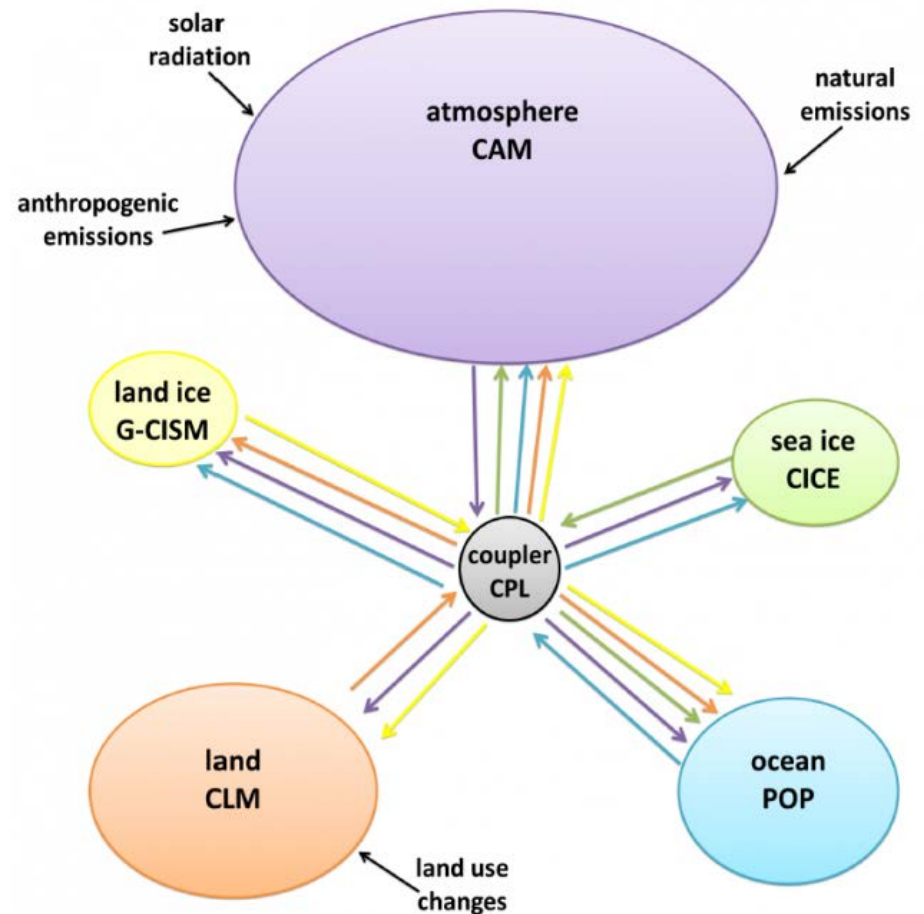
- Issue
  - Digitization (physical variable is continuous, but computer needs digitization”
    - Resolution, subgrid-scale parameterization



- Unknown processes, tunable parameters
- Initialization (for forecasting)

# GCMs

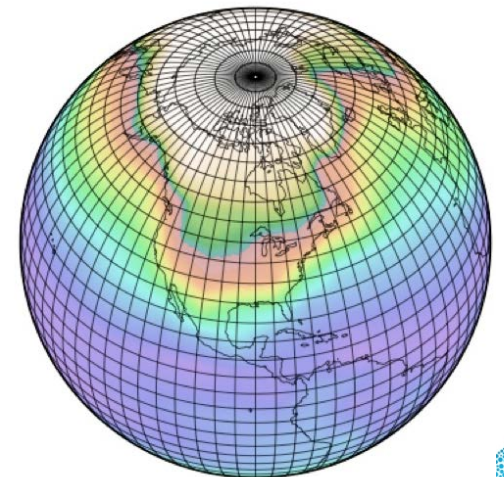
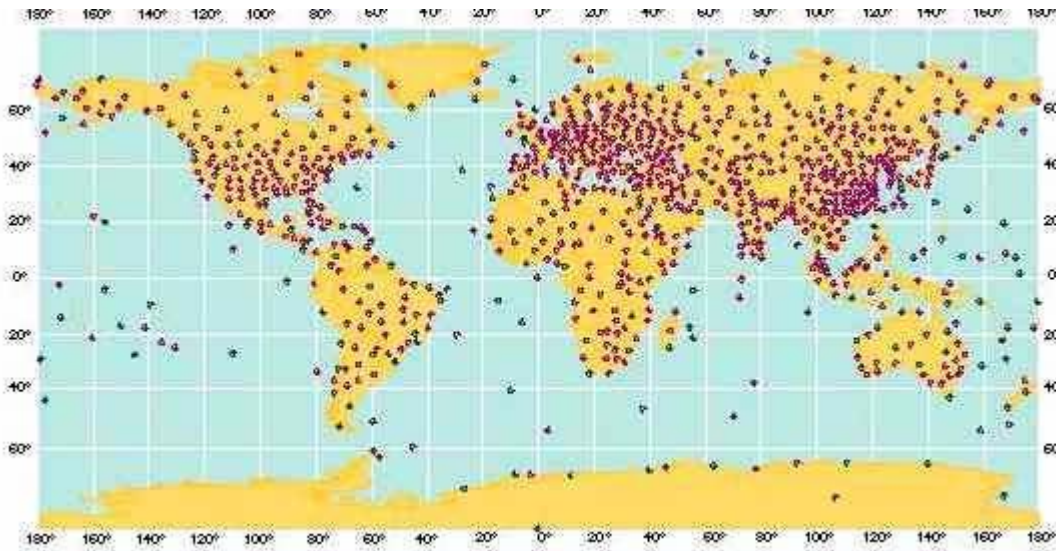
- Coupled GCM
  - Atmosphere
  - Ocean
  - Sea-Ice
  - Land surface
  - Chemistry
  - Biosphere



# Initialization

Estimating Current status of climate system

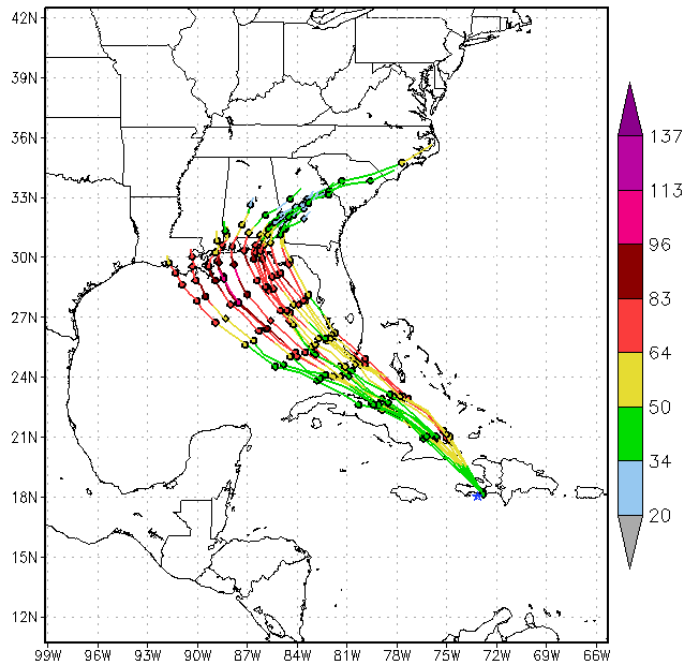
- Preparing the beginning climate state of GCM with available observation
  - Balance between Wrong GCM vs Wrong OBS.
  - Balance between components (Atm, Ocn)



# Ensemble Forecasting

- Run many times
  - Starts from slightly different initial conditions

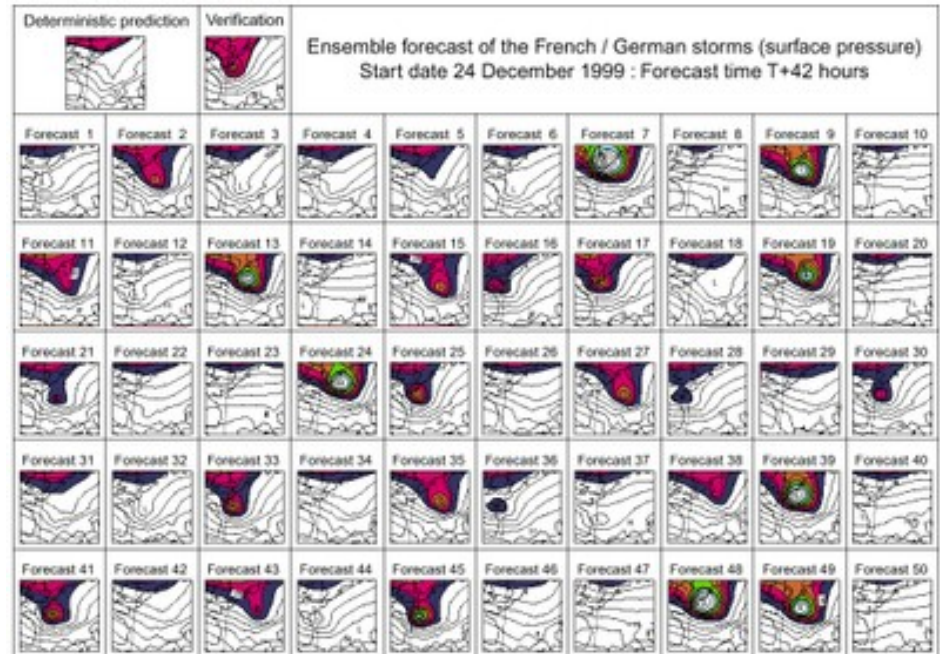
6-hourly Track and Intensity (kt) for ISAAC09L  
 GFDL ensemble forecast for the 126 hrs from 06Z25AUG2012



of missing members (out of 16) at t=0: 0  
 indicates ISAAC09L observed center at initial time

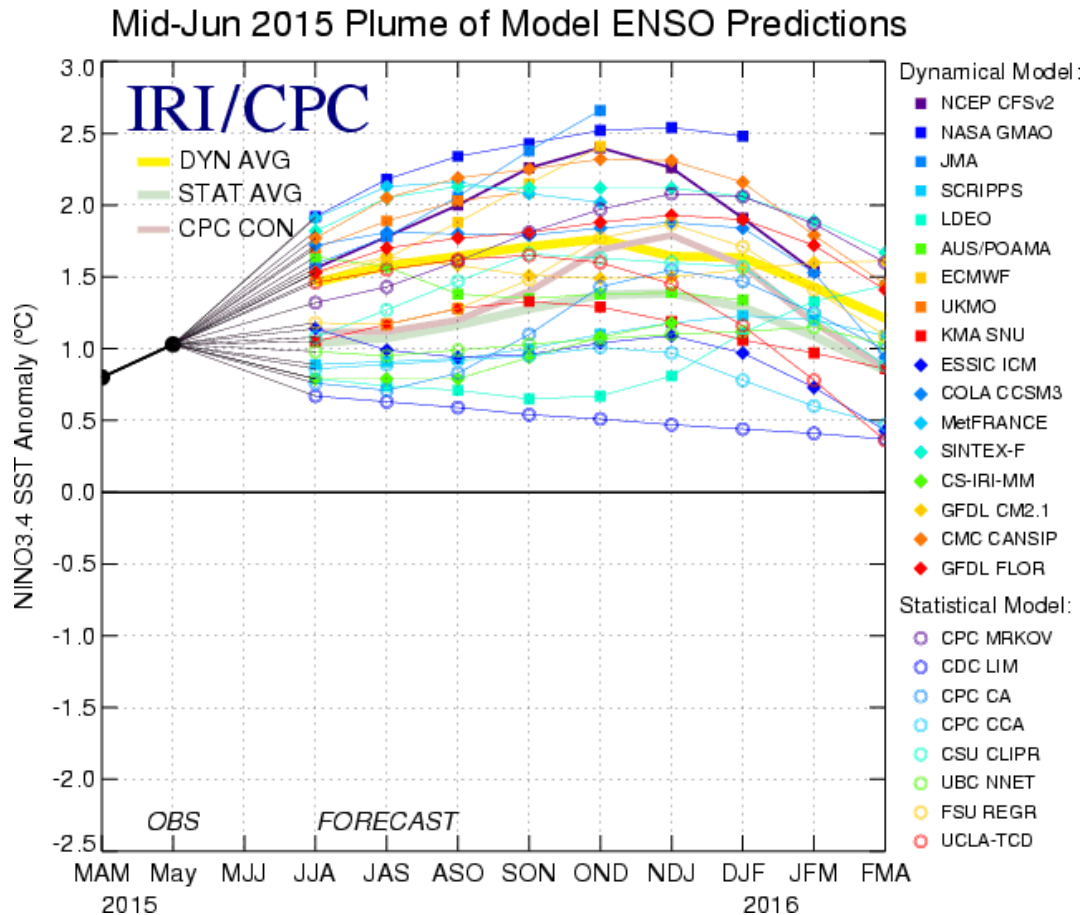
Track forecast positions are marked every 12 hrs

GFDL Hurricane Dynamics Group



# Multi Model Ensemble Forecasting

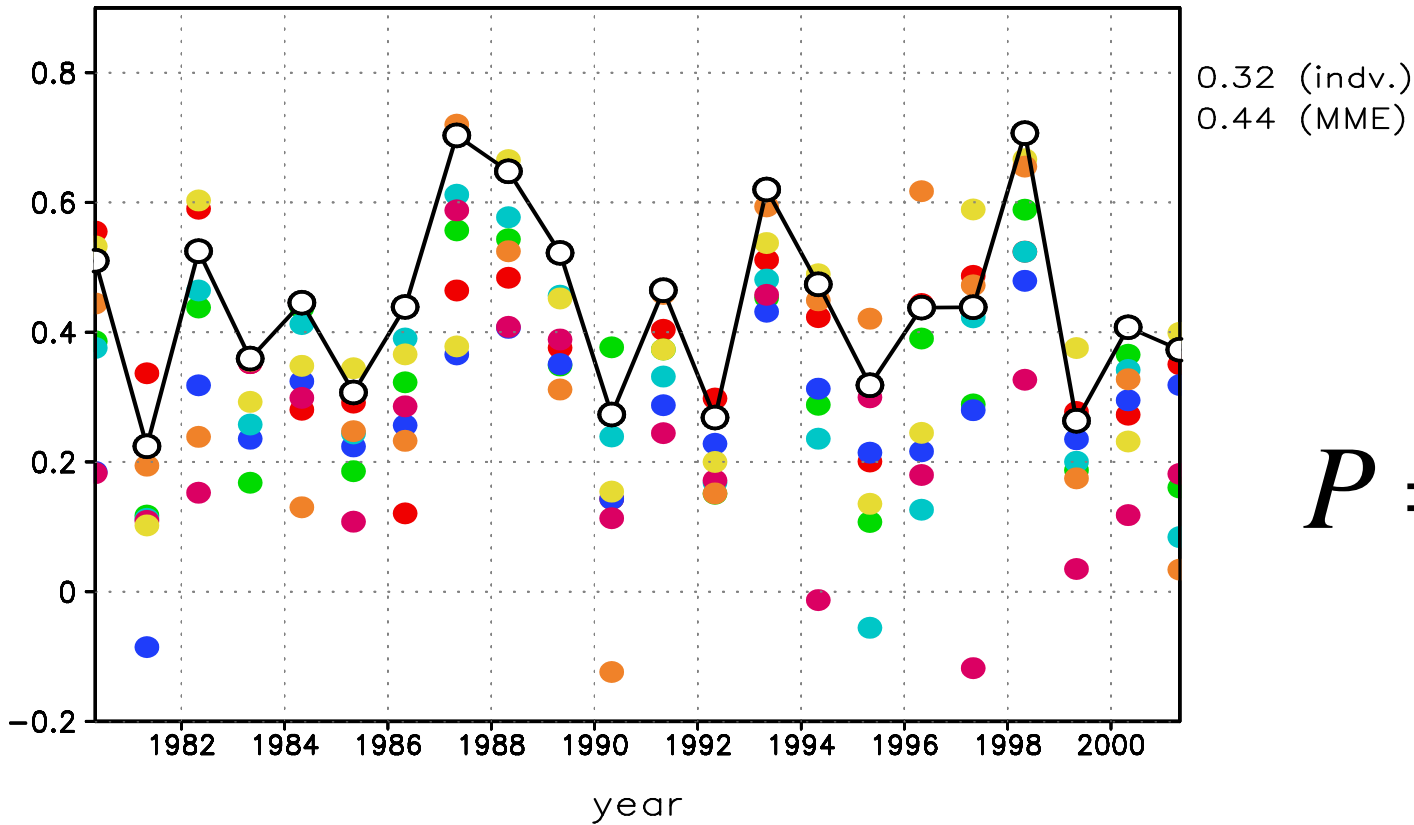
- Run with many models



Which one??

# Use all!

Pattern correlation : summer monsoon precip.



$$P = \sum_i a_i F_i$$

# Predictability of Multi Model Ensemble

Correlation skill of a single model

$$R_i = \frac{\overline{xy_i}}{\sqrt{V(x)V(y_i)}}$$

Correlation skill of MME

$$\langle y \rangle = 1/M \sum_{i=1}^M y_i$$

$$R_{MM} = \frac{x \langle y \rangle}{\sqrt{V(x)V(\langle y \rangle)}} = \frac{1}{M} \sum_{i=1}^M \left( R_i \sqrt{\frac{V(y_i)}{V(\langle y \rangle)}} \right) = \langle R \rangle \sqrt{\frac{\langle V(y) \rangle}{V(\langle y \rangle)}}$$

$$\langle R \rangle = \frac{1}{M} \sum_i R_i$$

$$V(\langle y \rangle) = \langle V_{Single} \rangle - \frac{M-1}{M} \langle V(y_n) \rangle - \frac{M-1}{M} \langle (V(e) - C(e)) \rangle$$

$$R_{MM} = \frac{\langle R \rangle}{\sqrt{V(\langle y \rangle)}} = \frac{\langle R \rangle}{\sqrt{\langle r \rangle}}$$

$$\langle r \rangle = \frac{1}{M^2} \sum_i \sum_j \frac{\overline{y_i y_j}}{V}$$

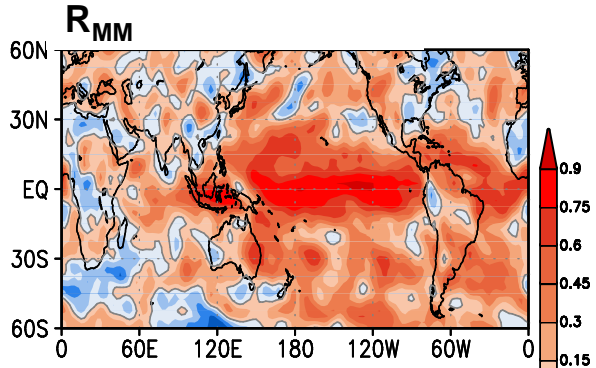
$$E_{MM} = \langle V_{Single} \rangle (1 + \langle r \rangle - 2 \langle R \rangle)$$

Observation :  $x = x_s + x_n$   
 Forecast :  $y = y_s + y_n = x_s + e + y_n$

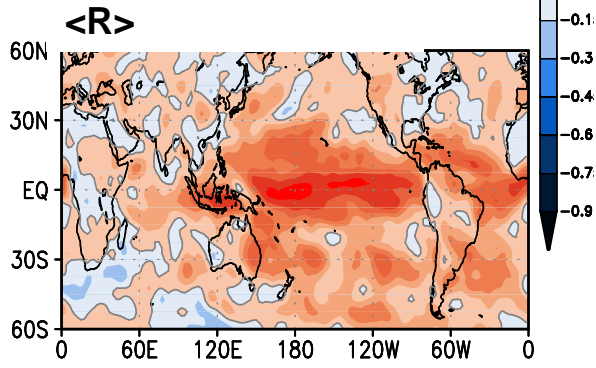


# Temporal correlation skill (SUMMER MEAN PRCP)

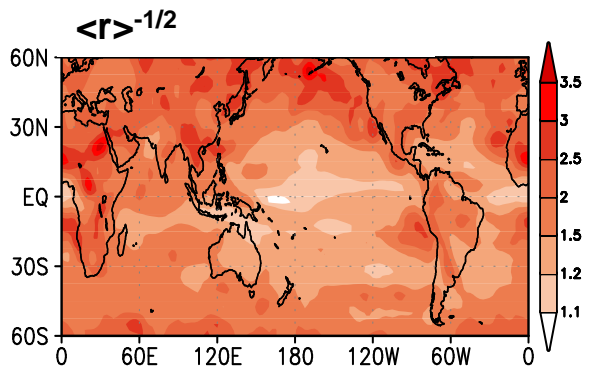
**Multi-model ensemble correlation skill**



**Mean correlation skill of individual models**

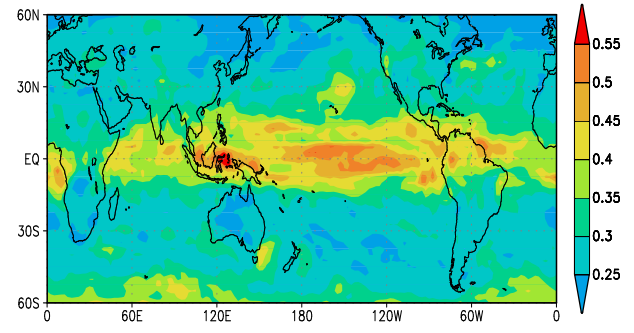


**Inflation factor of correlation skill by multi-model ensemble**



$$V(\langle y \rangle) = V_{Single} - \frac{M-1}{M} \langle V(y_n) \rangle - \frac{M-1}{M} \langle V(e) - C(e) \rangle$$

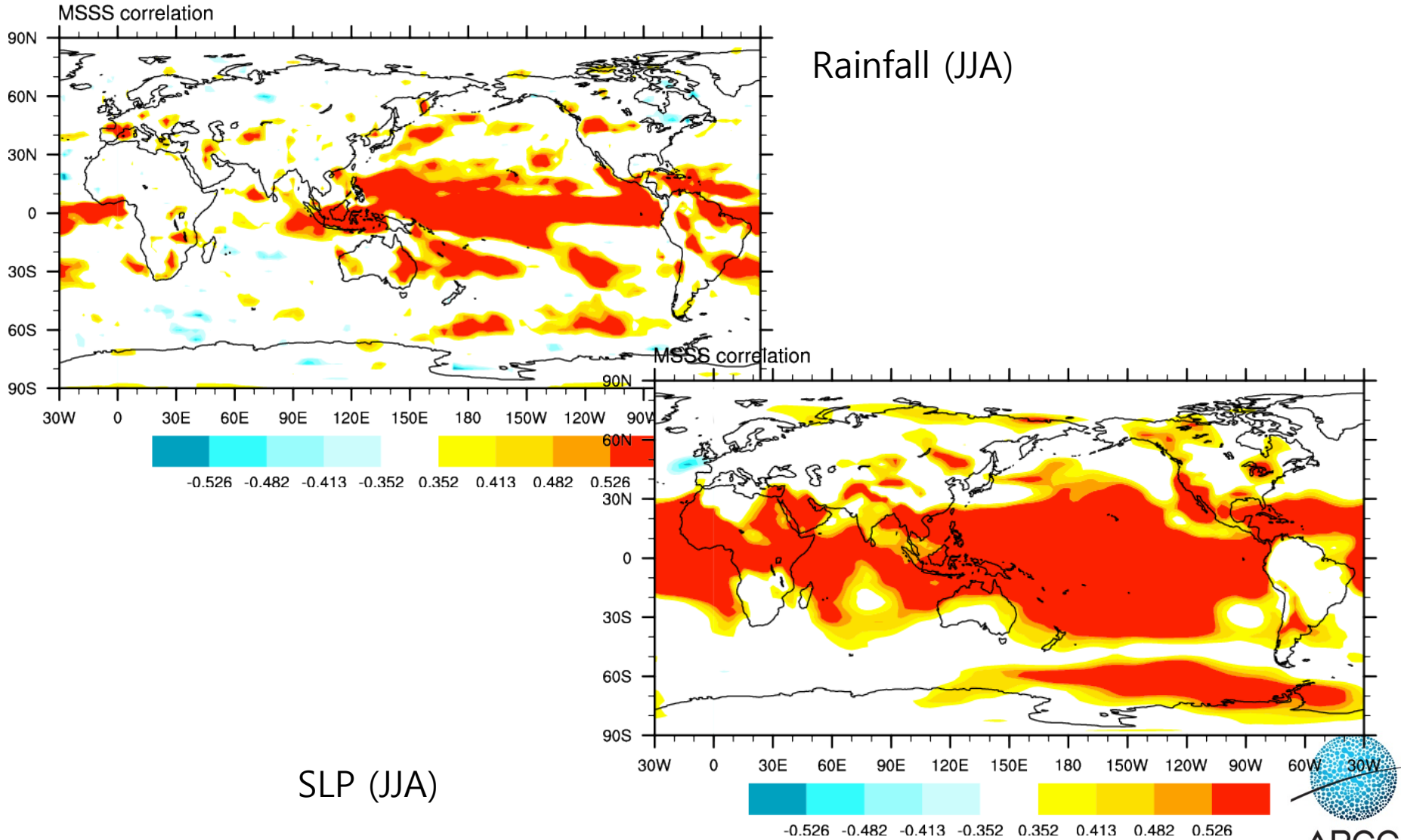
**Contribution of systematic error (conditional) cancellation**



$$R_{MM} = \frac{\langle R \rangle}{\sqrt{V(\langle y \rangle)}} = \frac{\langle R \rangle}{\sqrt{\langle r \rangle}}$$

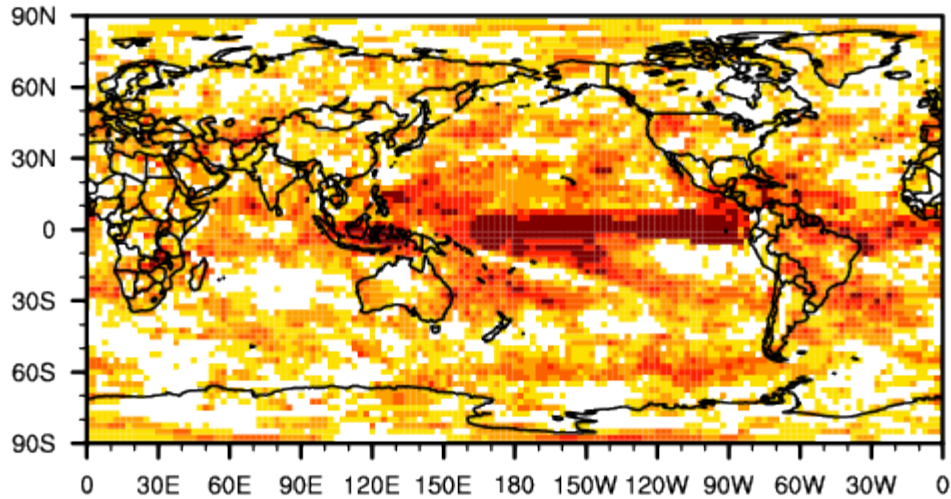
**Independent and good models : Best forecast result (on average)**

# APCC MME (TCC)

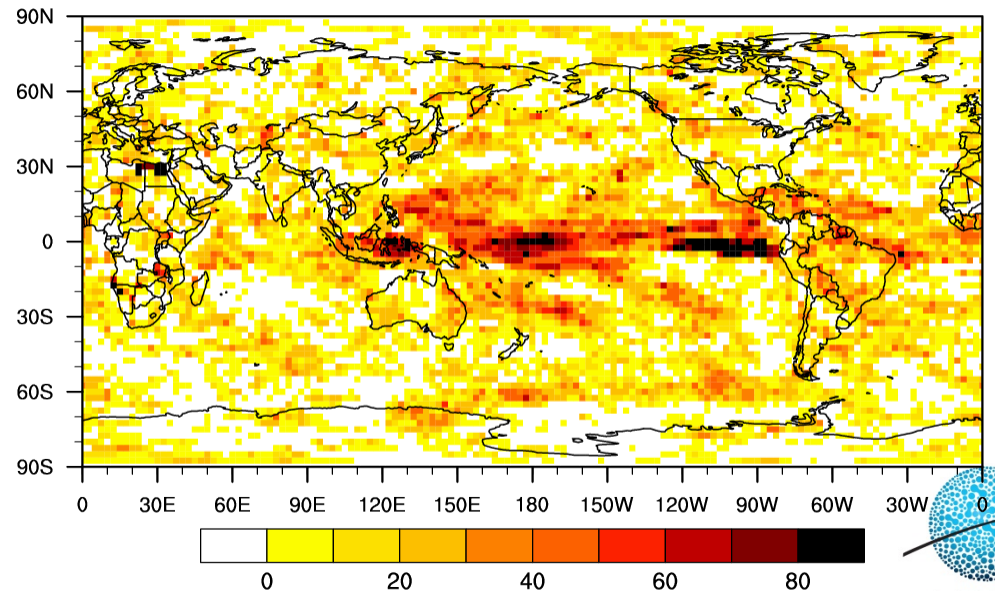


# ROC Score : PREC, JJA (1983-2005)

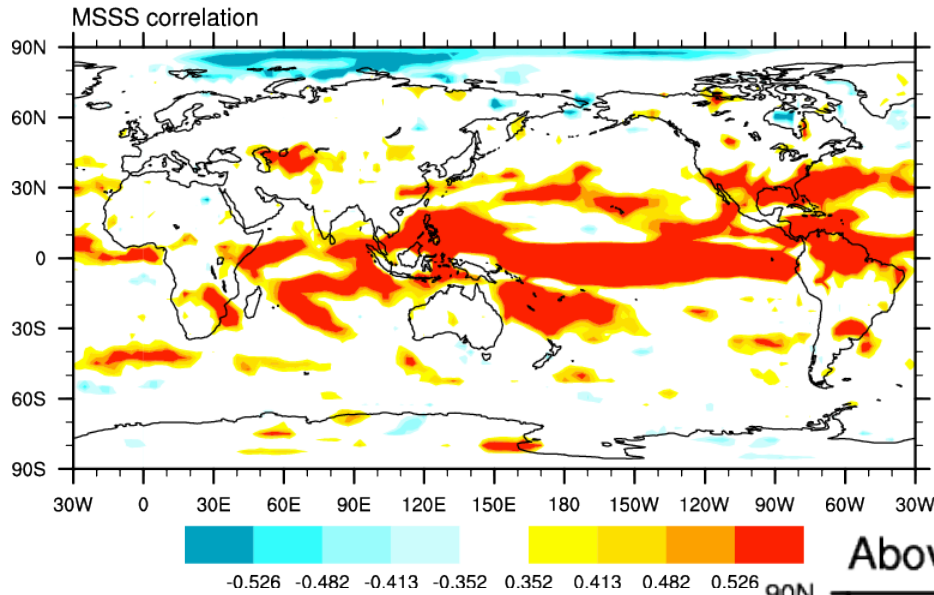
## Above-Normal



## Heidke Skill Score : PREC, JJA (1983-2005)

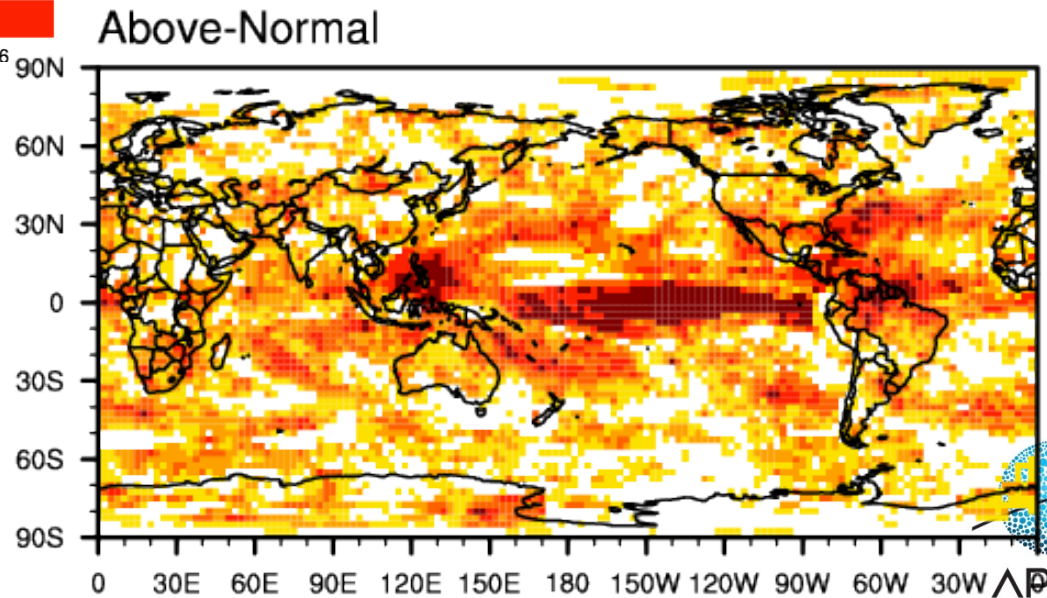


# DJF season

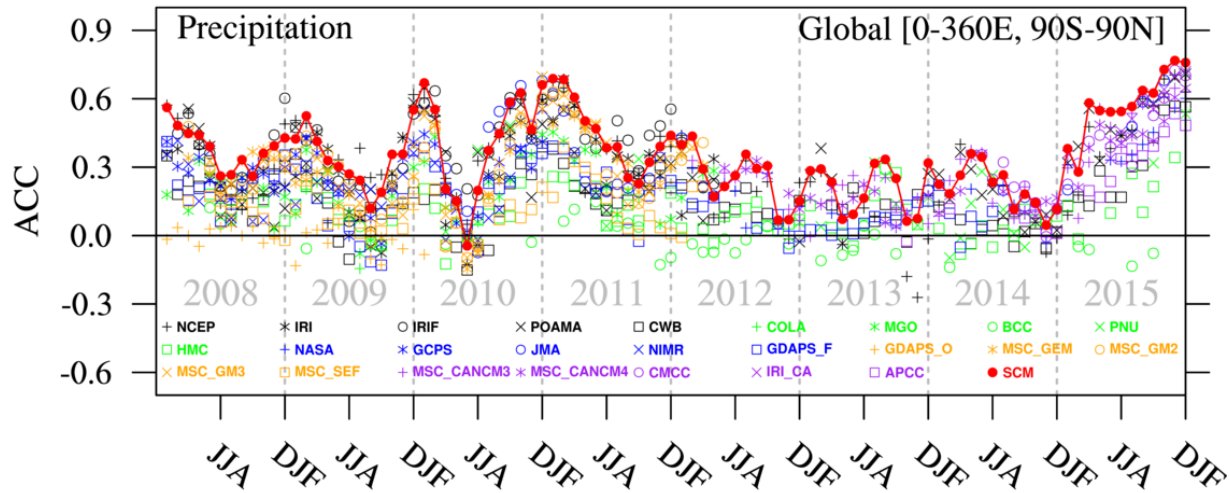


Rainfall (JJA)

ROC score  
Rainfall (DJF)



# APCC operational forecast



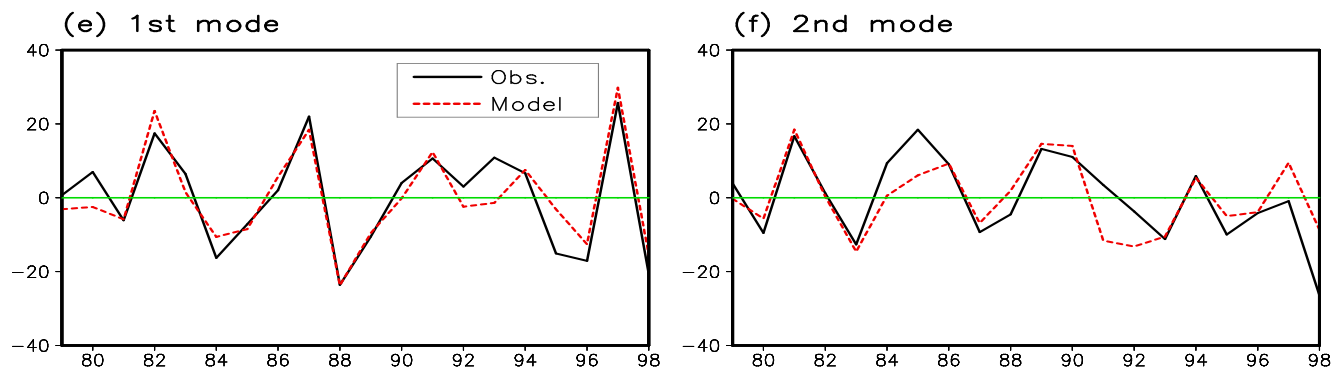
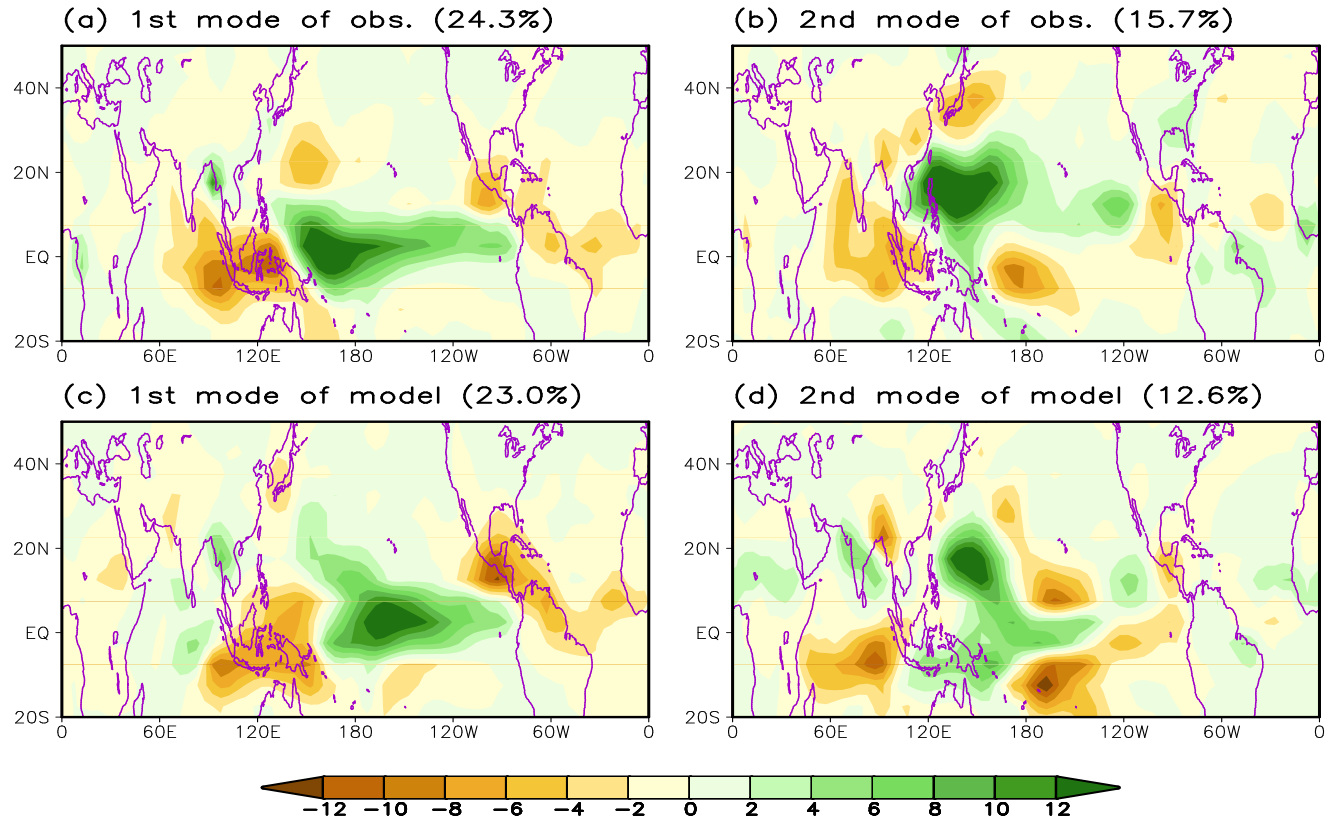
	APCC	WMOLC	ECMWF	NCEP	UKMO	JMA
AN	0.569457	0.541897	0.535531	0.52996	0.528975	0.531497
NN	0.520962	0.521424	0.537661	0.519823	0.524022	0.514656
BN	0.567702	0.533777	0.516511	0.535767	0.516994	0.534244

Realtime rainfall forecast for last 4 years (12-15)  
 ROC score : Perfect = 1, Meaningless(no skill) =0.5,

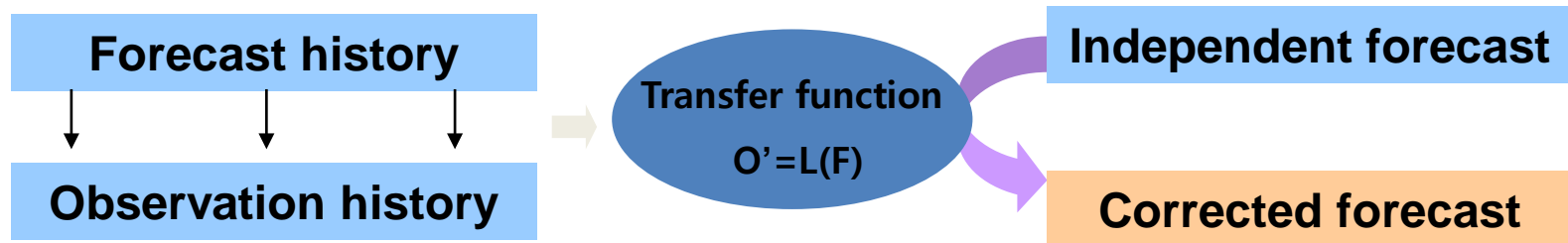
# Even with MME,

- Still many region in the world, predictability is low
- Any room for further improvement?
  - Post process

# EOFs of Summer Mean Precipitation



# Statistical downscaling : CLIK



There are many approaches in post-process, All of them share similar assumption. :  
**Statistics between forecast and observation is stationary**

If statistics is not stationary, post-process will not work in independent forecast

Thus, statistical stability is a rule of thumb in the statistical post-process (avoiding overfitting)

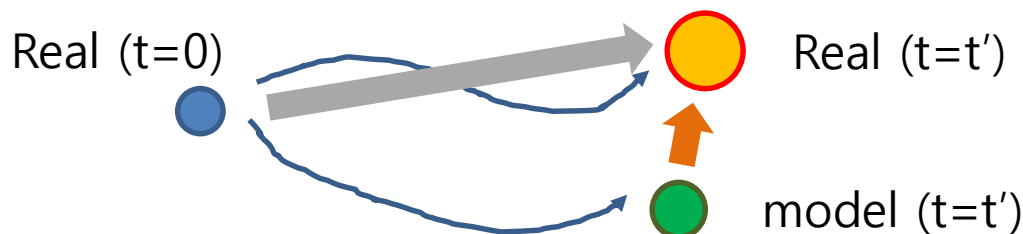
# Approach

## ■ Statistical forecasting based on past forecast

$y(s, t)$  : observation

$x(s, t)$  : forecast

$$y'(t) = f(x(t), \alpha), \alpha = g(x(1 : t - 1), y(1 : t - 1))$$



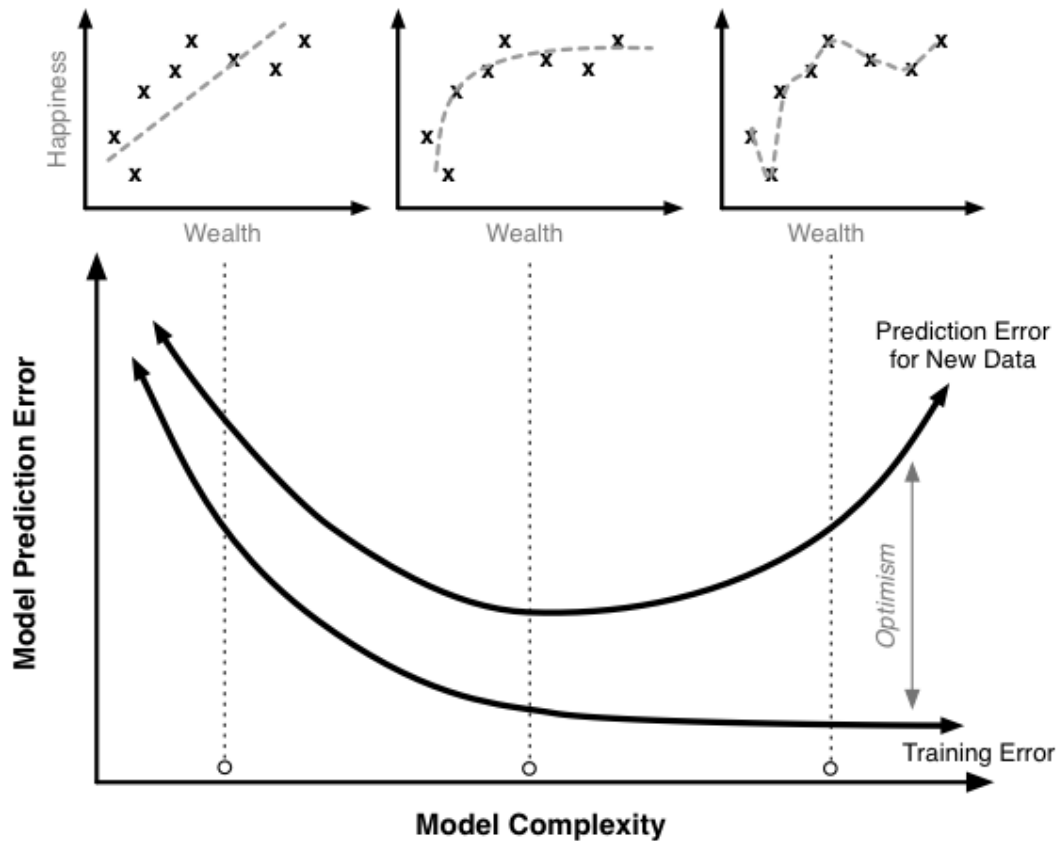
## ■ The most common way : Regression

$$\sum_j b_j y_j = \sum_i a_i x_i + \epsilon$$

- If  $i \text{ \& } j = 1$  : Linear regression
- $i > 1, j = 1$  : Multiple regression
- $i \text{ \& } j > 1$  : CCA, SVD, etc

# Weakness : overfitting

## ■ Consider potential predictability



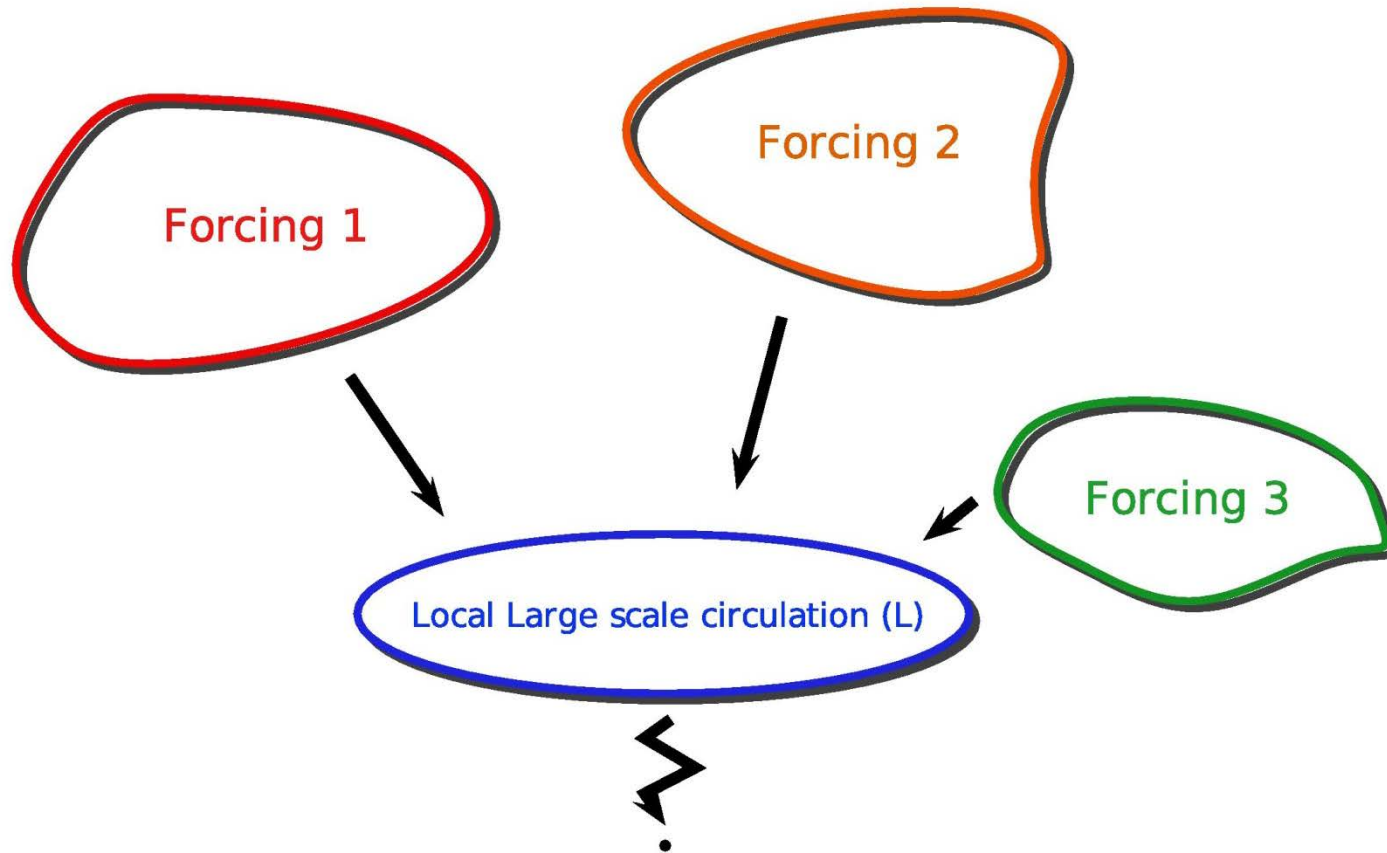
If model output is fitted to the unpredictable noise : Overfitting.  
What if we remove “noise” in the observation?

# Downscaling (post-process) should be based on

- Physical understanding of;
  1. What weather event/system consists of your seasonal climate (LOCAL, predictand)
  2. What external (slow varying factor) controls the weather system (GLOBAL, predictor)

And, whether model is able to predict 1 or 2

# Local large scale circulation



Local weather statistics (Korean summer rainfall)

# Local large scale circulation

- Local climate (i.e. seasonal mean) is defined by how weather behaved during a season (statistics)
- Therefore, understanding weather behavior is the first step of seasonal forecast (often ignored..)
- In many cases, local large scale pattern that directly affect local weather is visible in seasonal time scale
  - Question is whether we can predict that large scale pattern directly or via teleconnection

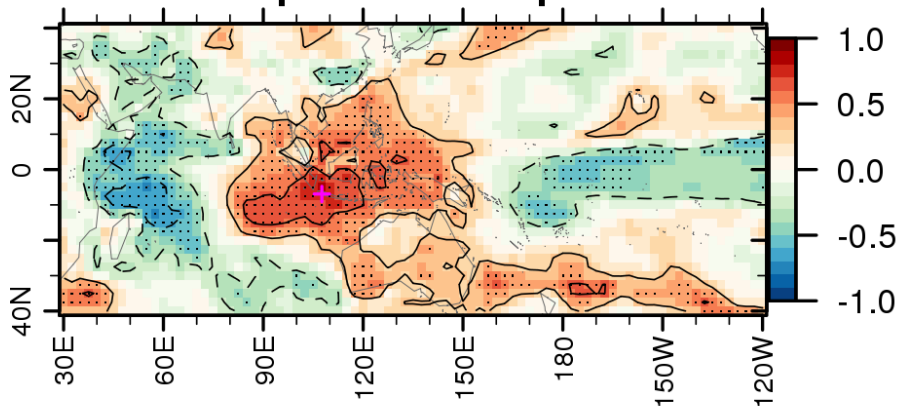
# LARGE SCALE PATTERN ASSOCIATED WITH RAINFALL

Local large circulation and Teleconnection

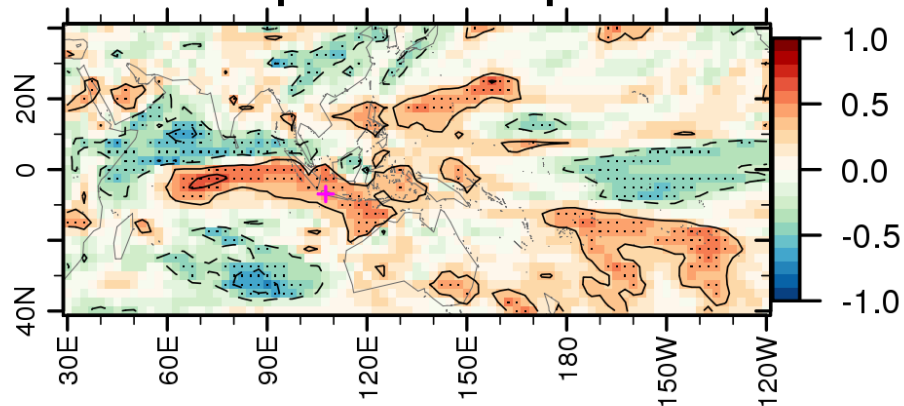
One Point Correlation map with seasonal mean local rainfall (APRODITE or CRU data) with other variables

# SON [Jakarta]

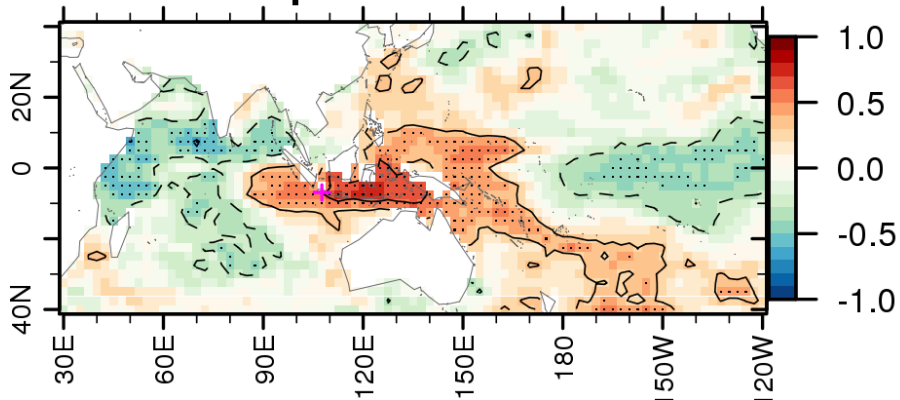
### stn prec. VS obs prec



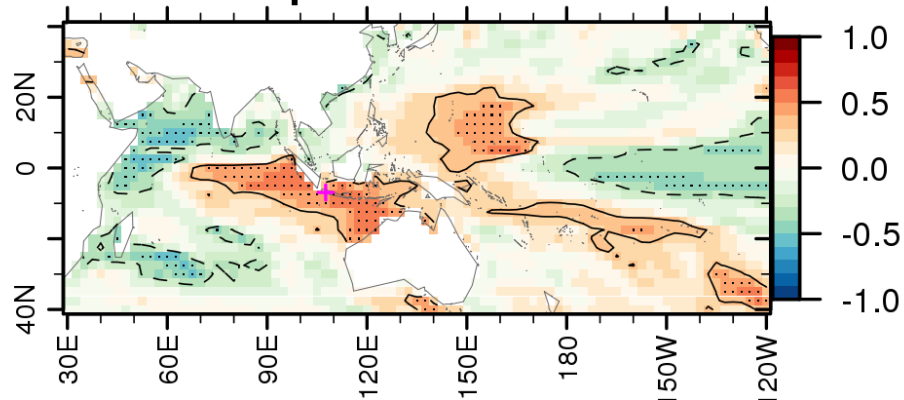
### stn prec. VS scm prec



### stn prec. VS obs sst



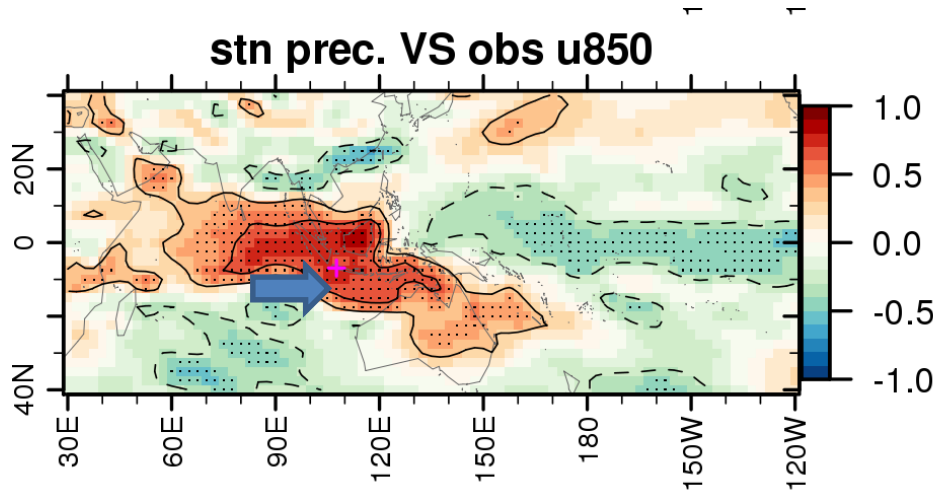
### stn prec. VS scm sst



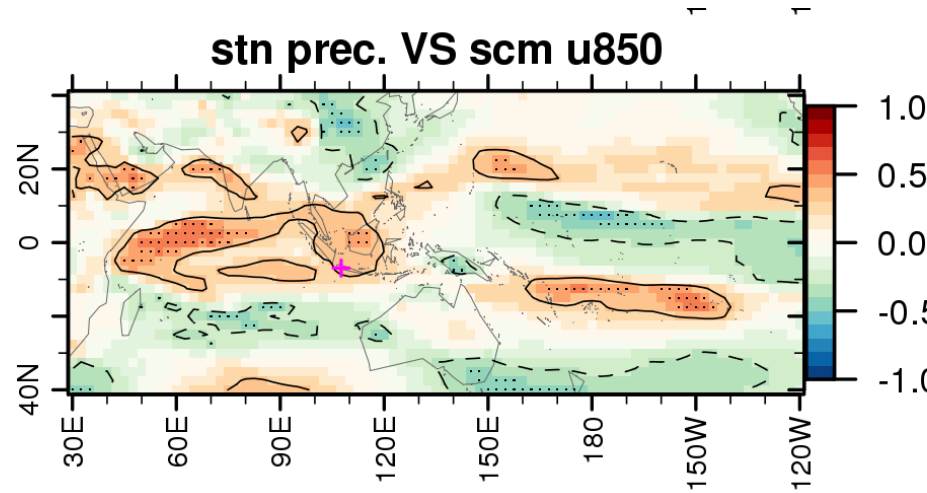
**La Nina (and IOD) signature**

# SON(Jakarta)

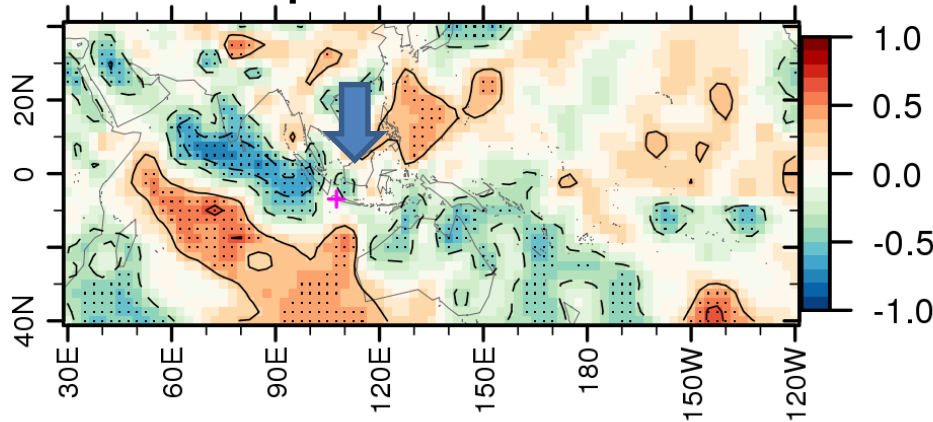
## stn prec. VS obs u850



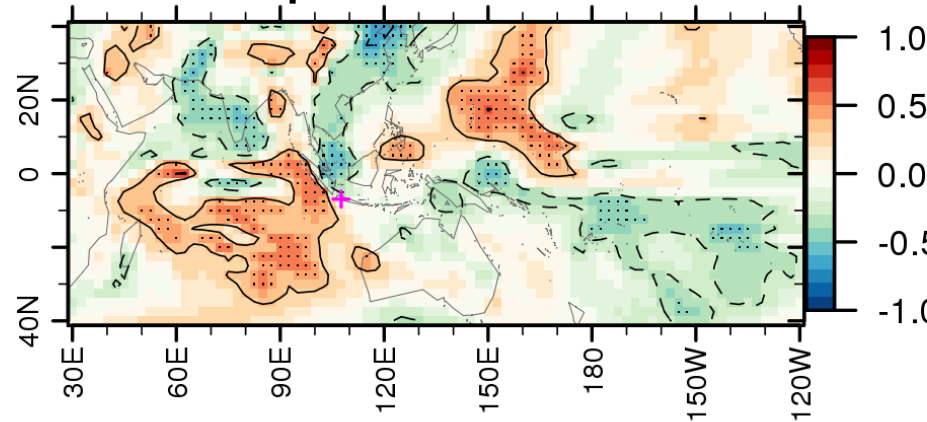
## stn prec. VS scm u850



## stn prec. VS obs v850

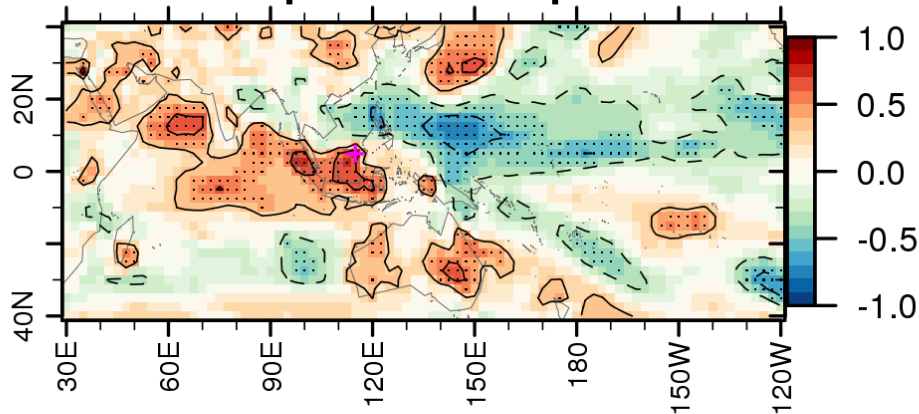


## stn prec. VS scm v850

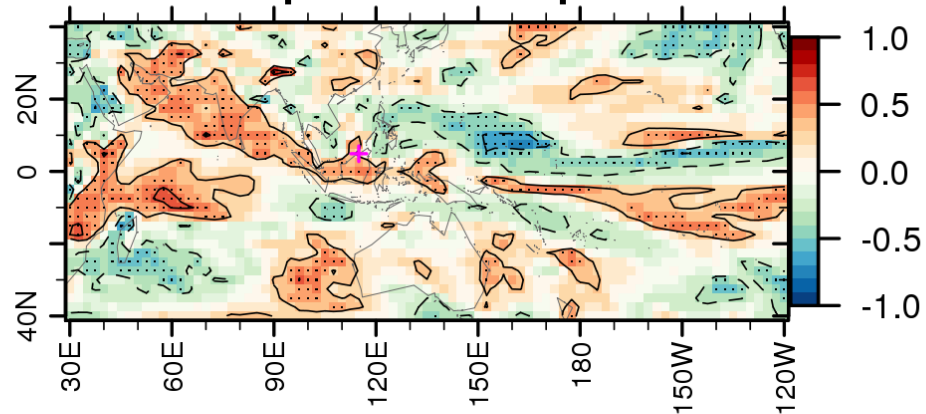


# JJA [Bandar\_Seri\_Begawan]

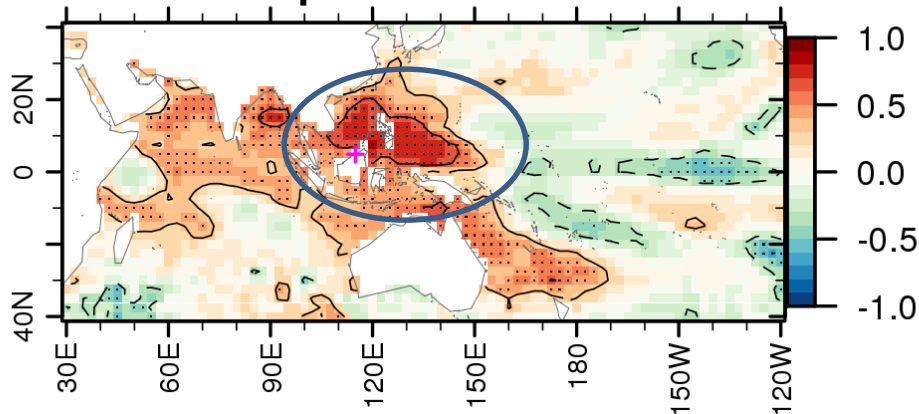
## stn prec. VS obs prec



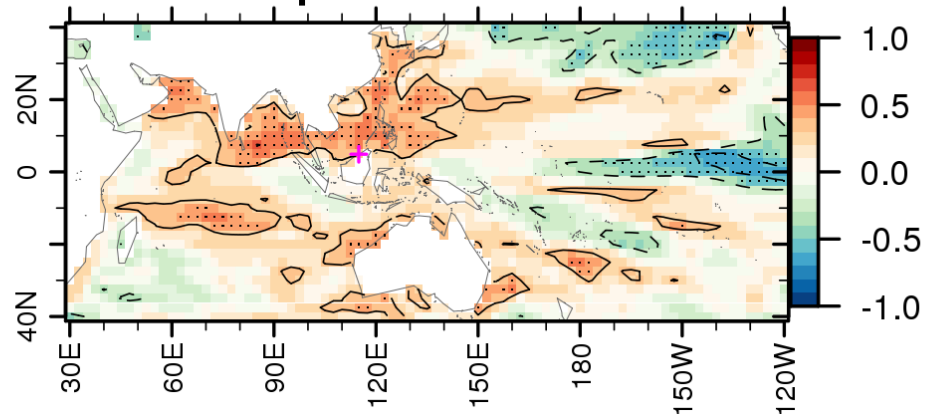
## stn prec. VS scm prec



## stn prec. VS obs sst

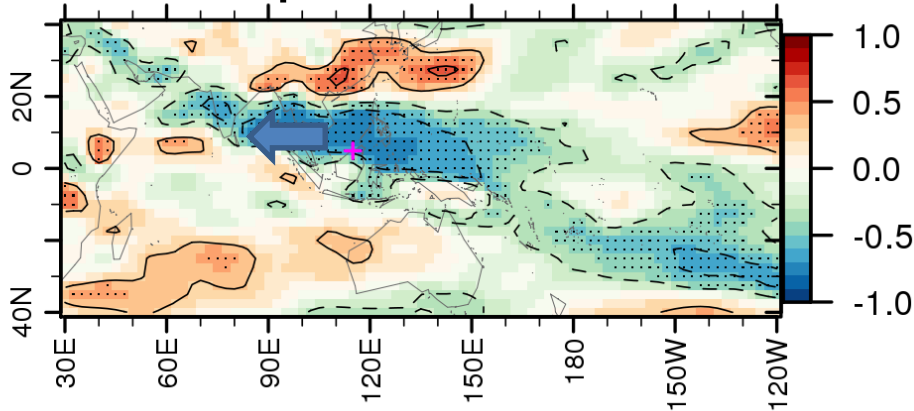


## stn prec. VS scm sst

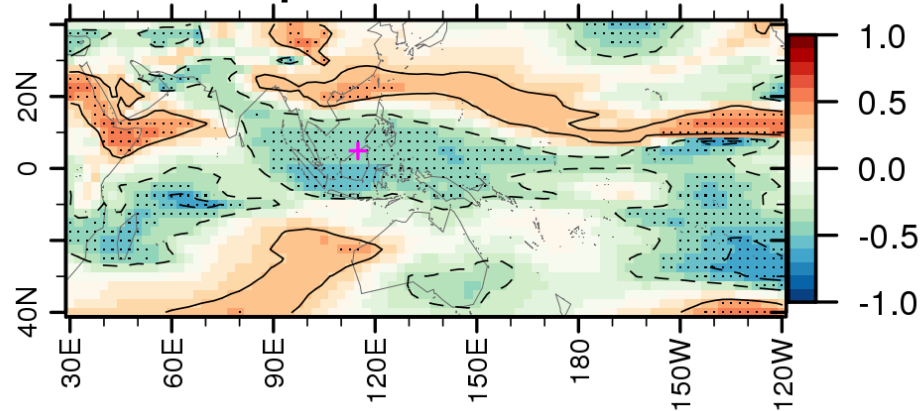


# JJA(Bandar\_Seri\_Begawan)

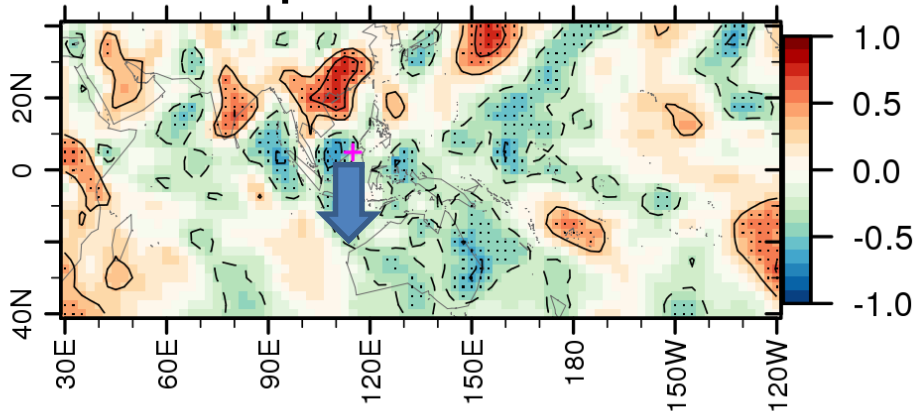
## stn prec. VS obs u850



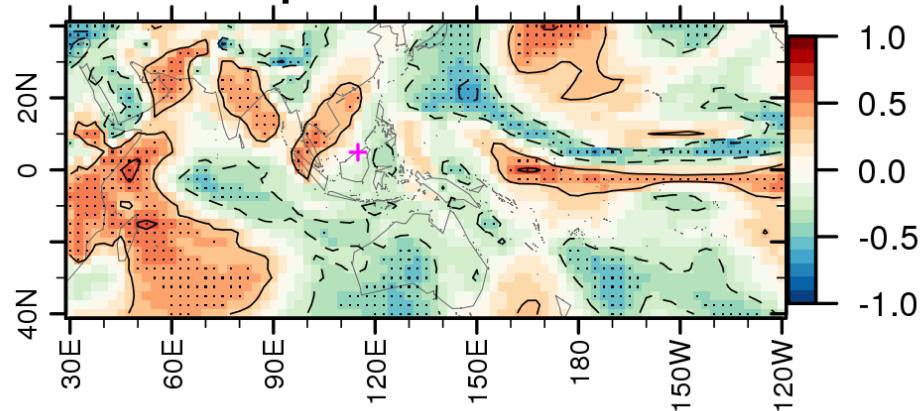
## stn prec. VS scm u850



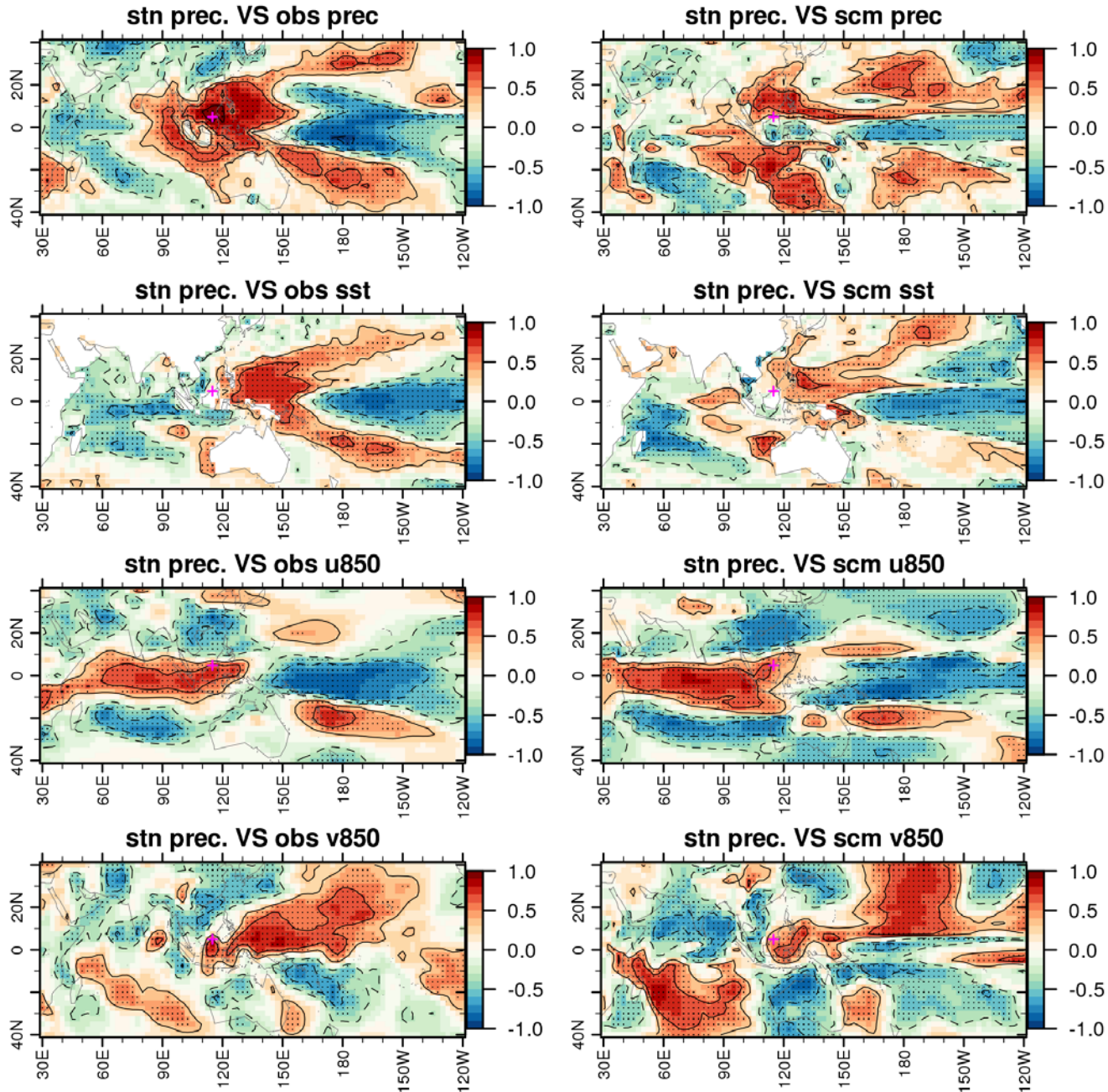
## stn prec. VS obs v850



## stn prec. VS scm v850

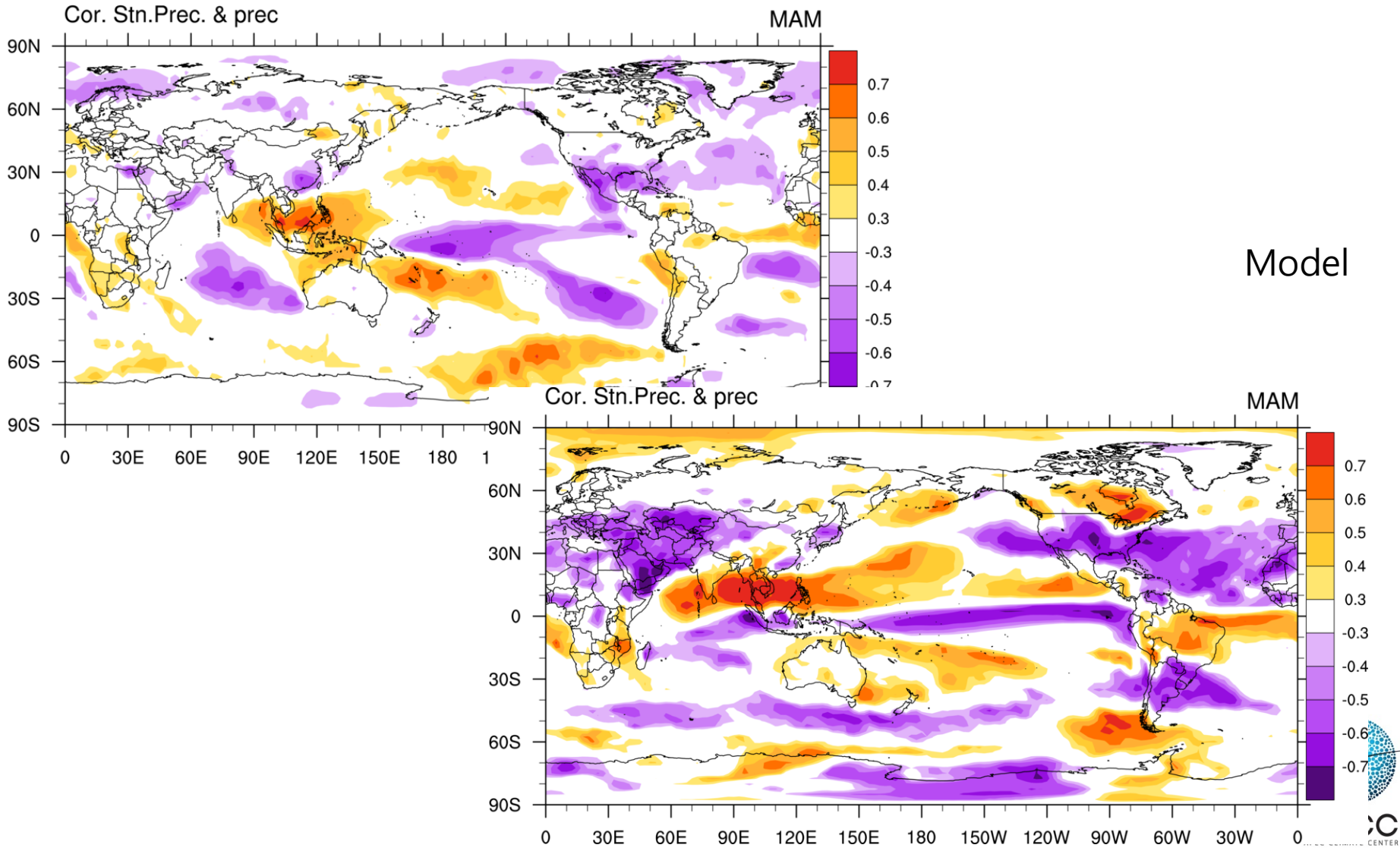


# DJF [Bandar\_Seri\_Begawan]

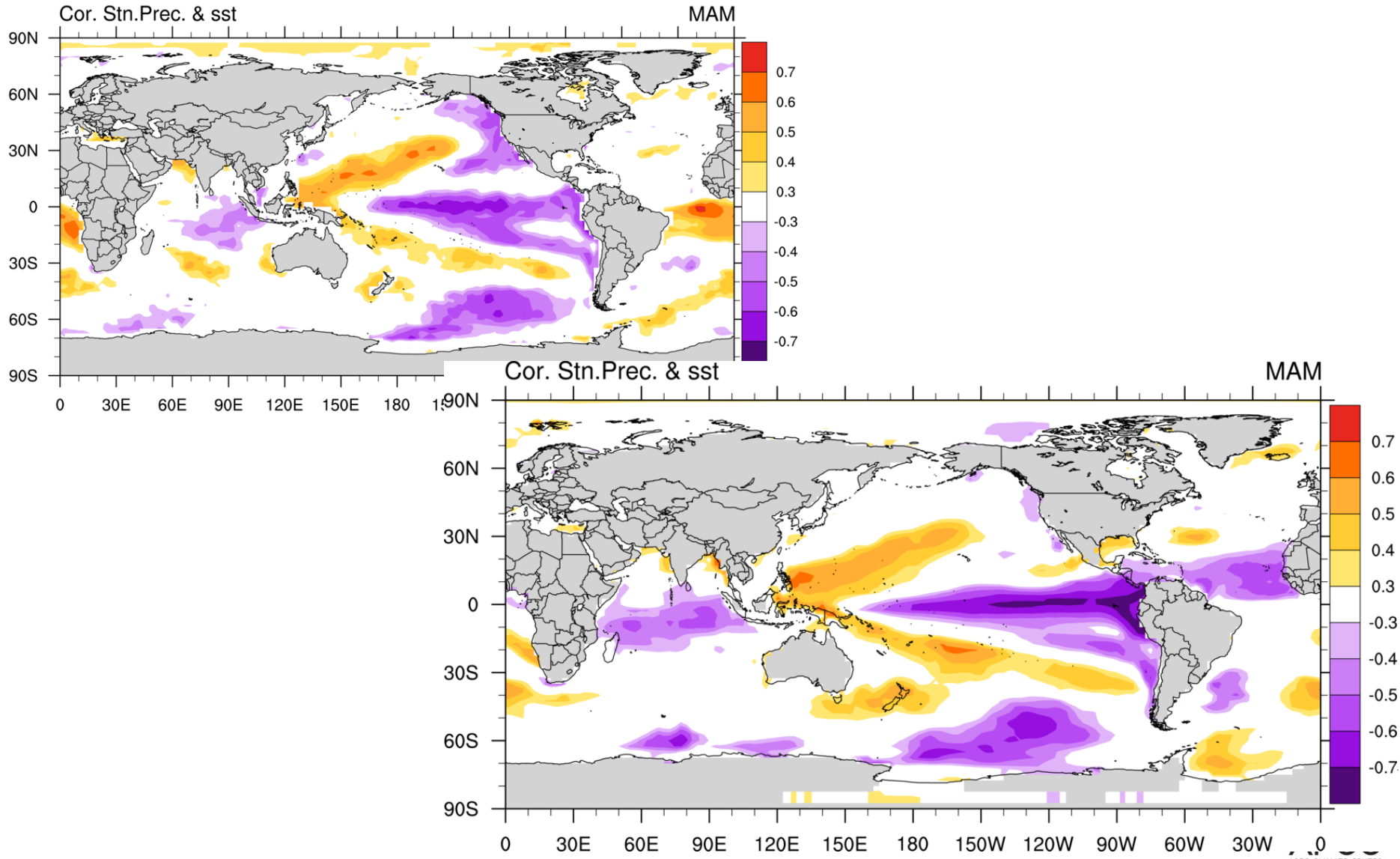


**La Nina!**

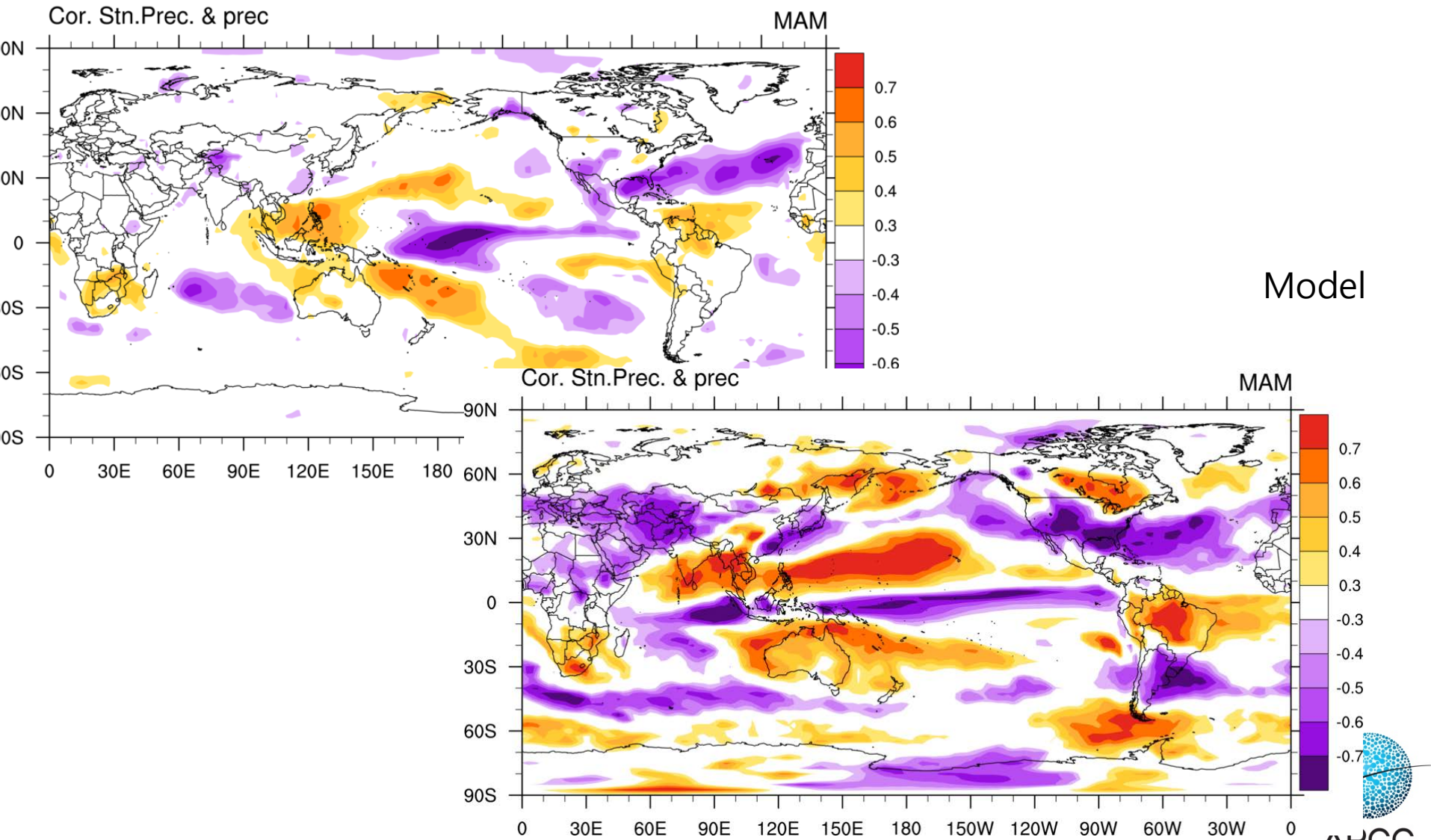
# Bangkok (MAM)



# Bangkok (MAM)

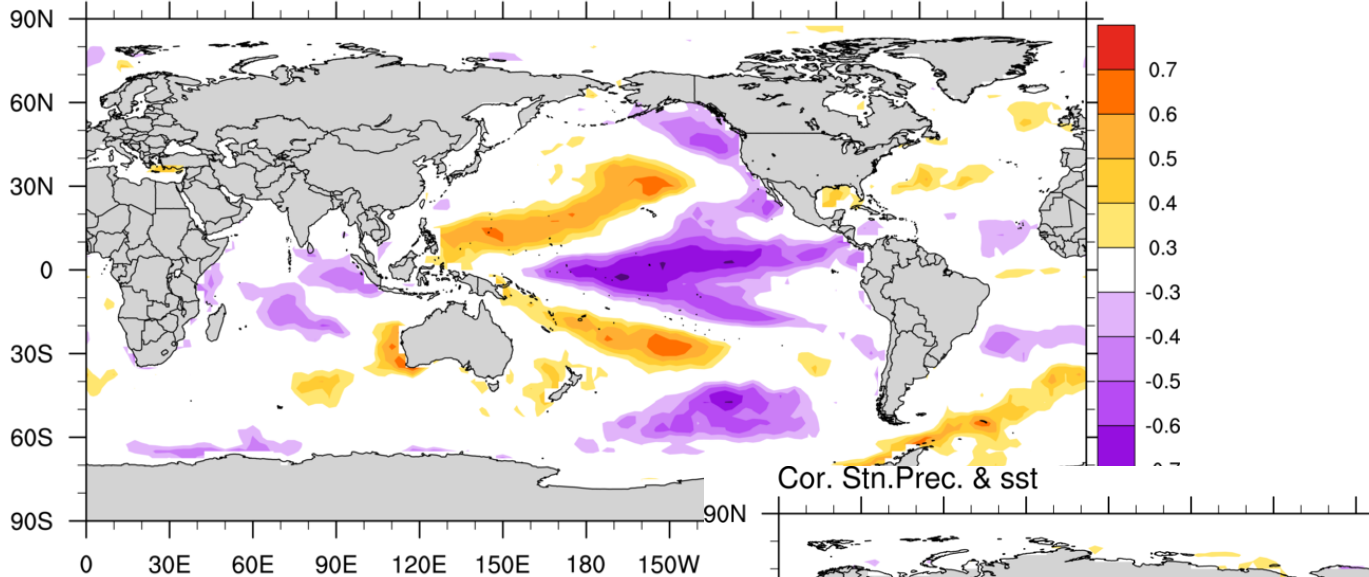


# Hochiminh



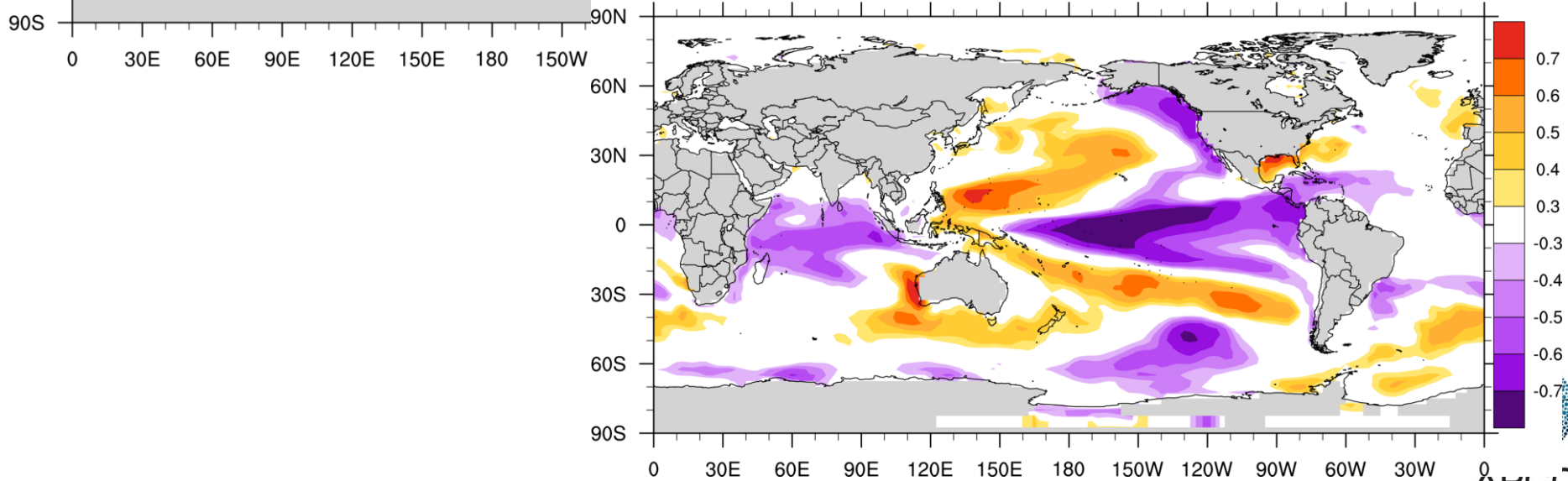
# Hochiminh

Cor. Stn.Prec. & sst MAM



Cor. Stn.Prec. & sst

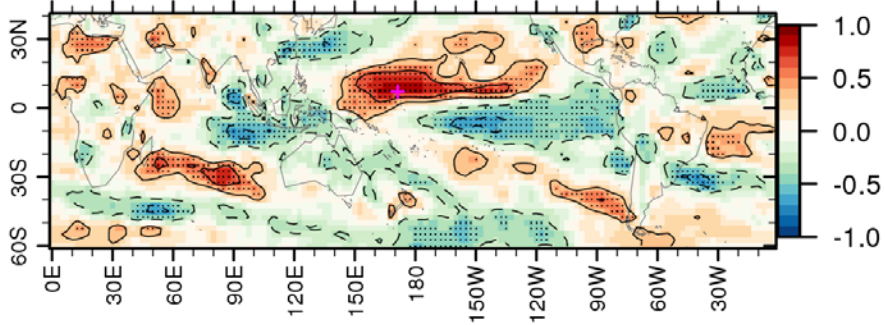
MAM



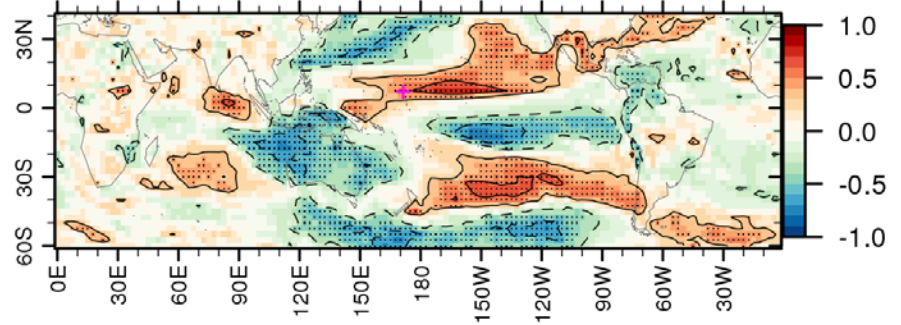
# Majuro

prec, AMJ [Marshall\_Islands, 91376]

NCEP\_R2

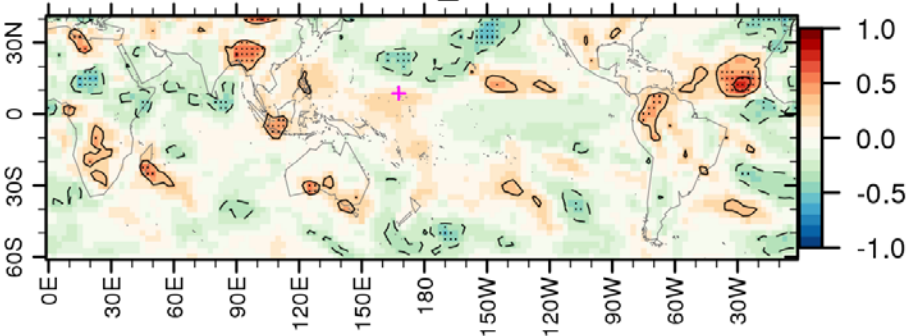


SCM

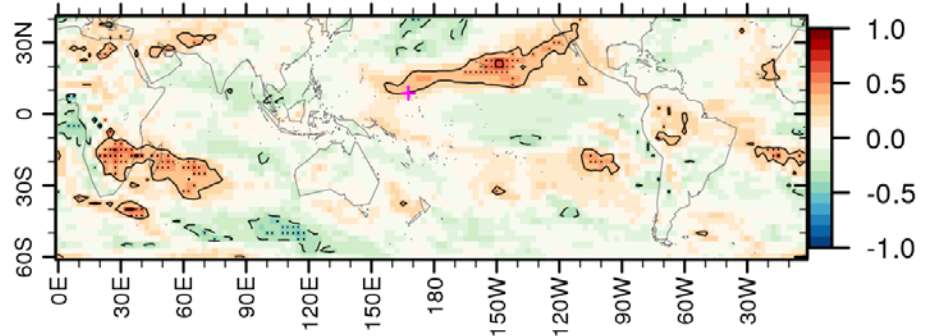


prec, OND [Marshall\_Islands, 91366]

NCEP\_R2



SCM



# Note that,

- YOU should have an “Guess field” that is associated with your seasonal mean climate variability (“positive SST over certain region causes more rainfall at our station”)
- Model should be able to mimic that physical relationship even with some error
- CLIK will work if you can find a predictor satisfying above two thing

# Downscaling in CLIK

- Use “observed” large scale pattern (X) associated with climate variability at stations
- X needs to be predicted by GCMs to some degree
  - X becomes predictor (user selected area)
- CLIK does not provide any prior information for selection of predictor (to avoid overfitting)
  - Basic knowledge on Local large scale circulation and associated global teleconnection is necessary

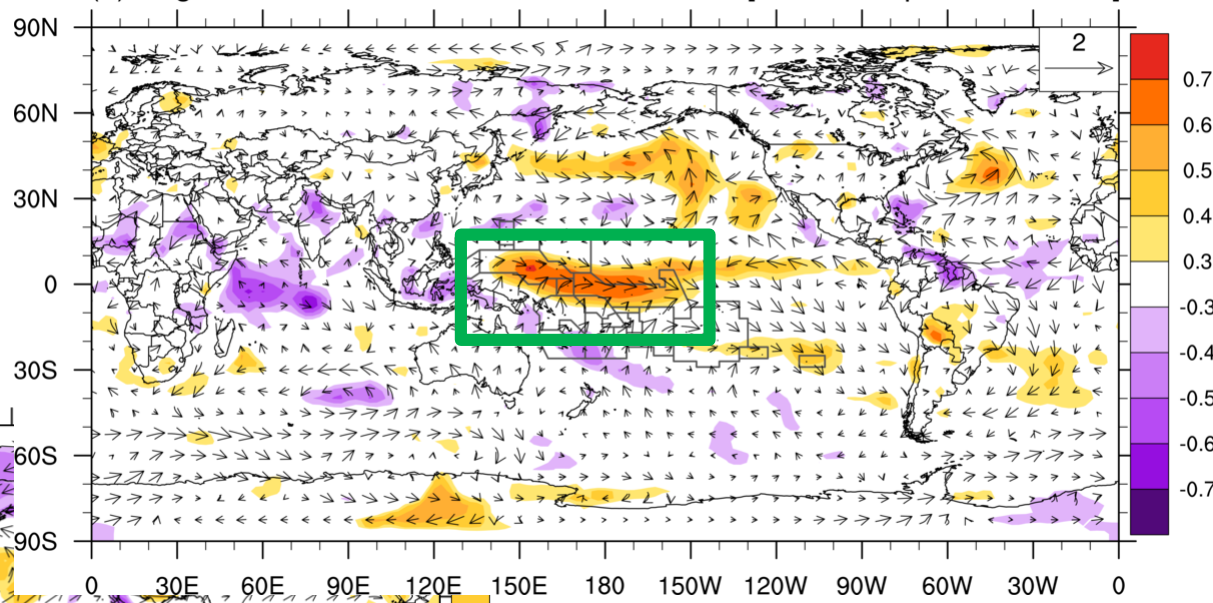
# Predictor selection

Meaningful pattern? (hopeful)  
: significance score

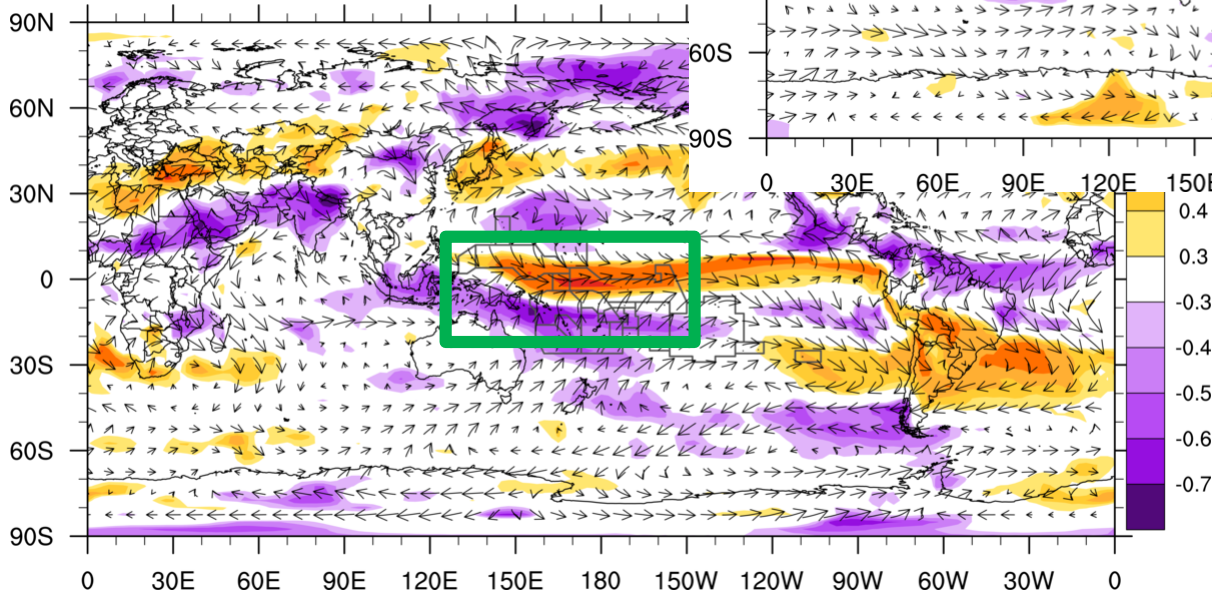
Station data 



(a) Reg. between Obs. & Station 91348 [JJA - Precipitation & Wind]



(a) Reg. between MME & Station 91348



Consistency between obs.  
and GCMs (good)  
: pattern score

The most important thing you need is,

**Patience**

