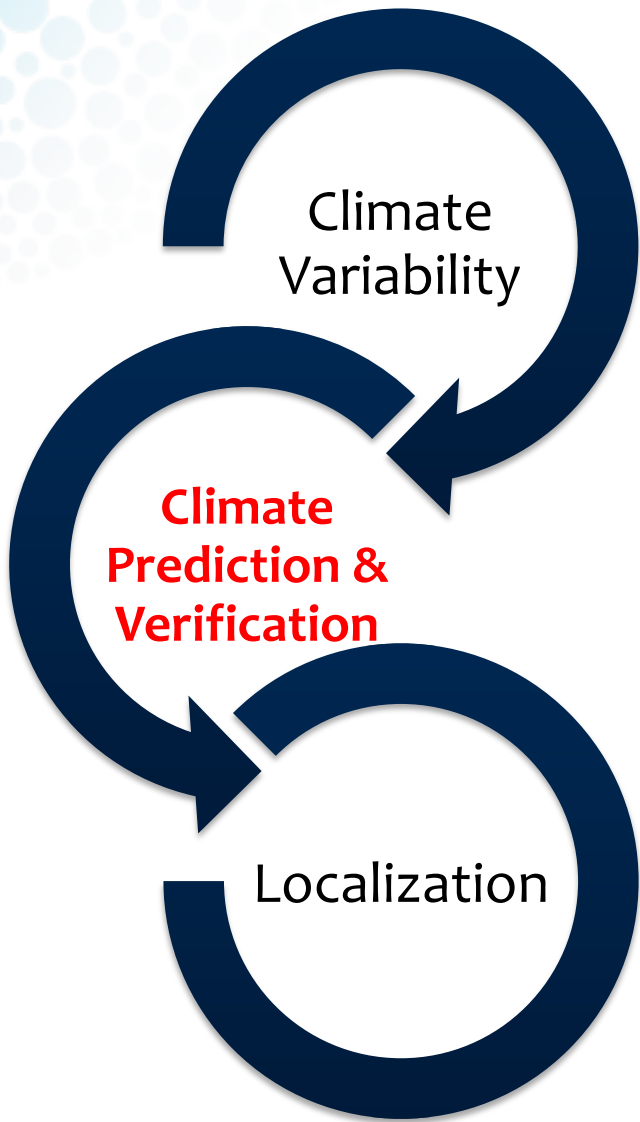


# **MME Seasonal Prediction & its Localization using CLIK**



&



**Generating  
Seasonal Outlook**

# Climate Prediction 101

Yun-Young Lee



**CLIMATE?**

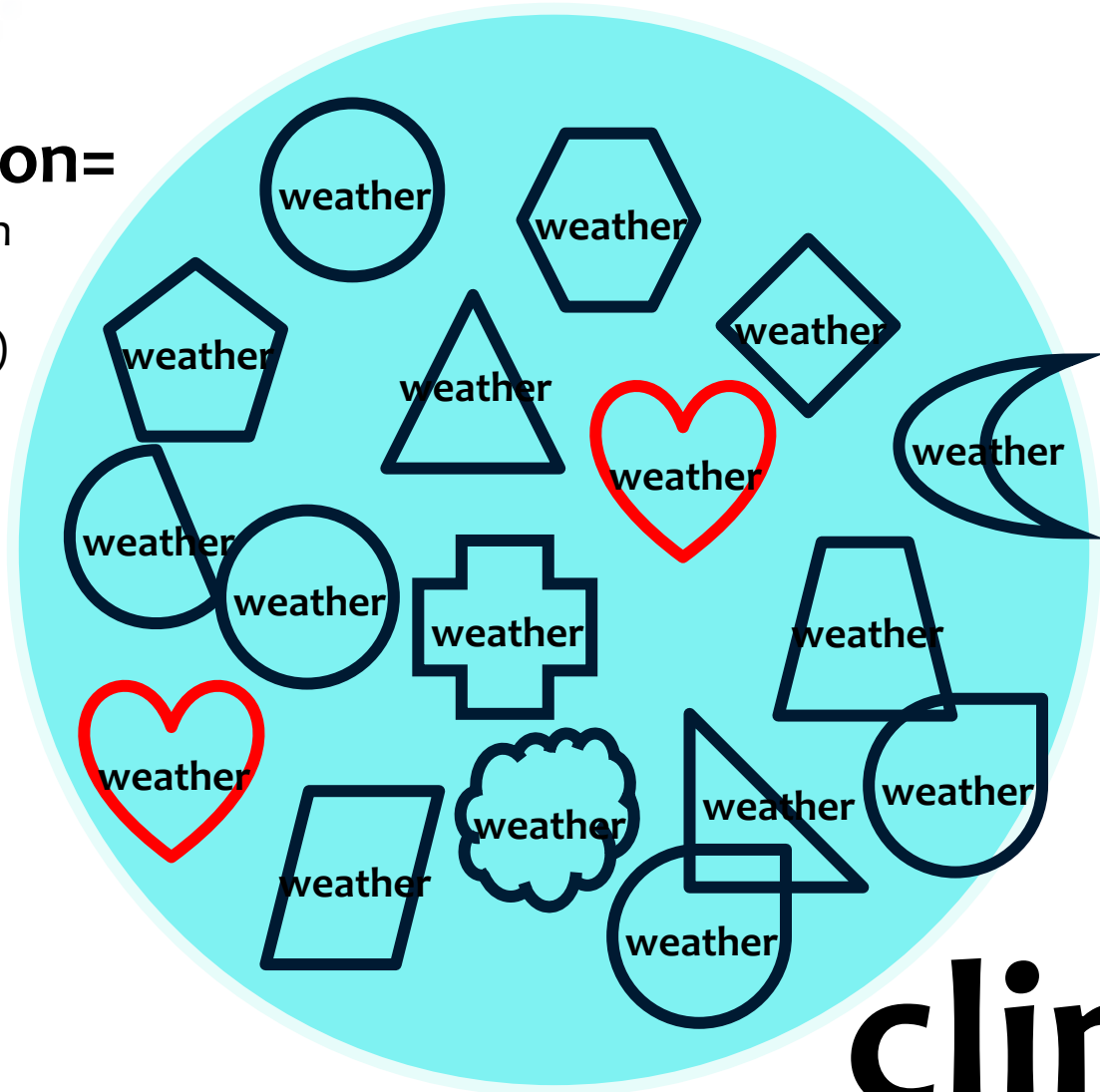


**Weather is what we get,  
Climate is what we expect!**

# Weather summary = Climate

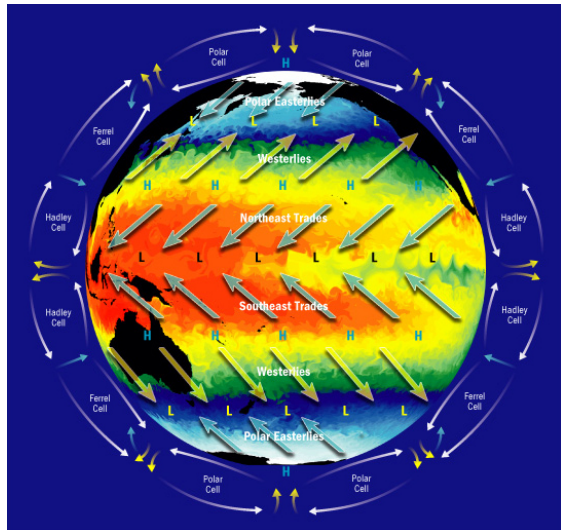
## Expectation=

mean condition  
of atmosphere  
(temp. & Prcp.)



# climate

# Climate = Expectation



**Climate** = **Expectation**  
*Change* *Should be*  
*changed!*



**Climate** = **Expectation**  
*Prediction* *of*  
*Expectation*

**How uncertain!**

# Prediction

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

(in meteorology)

- What : atmospheric state (weather)
- Conditions:  
*current state, physical rules, external forcing factors*

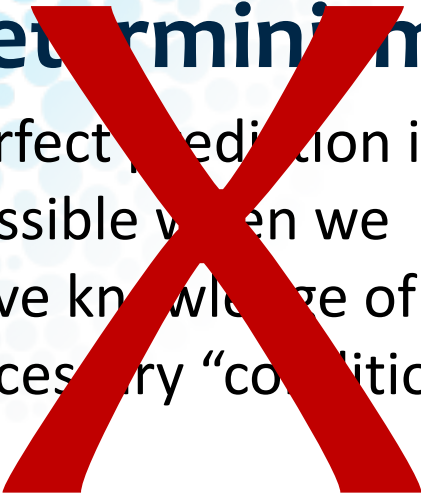
**Atmosphere is dynamical system!**

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

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

# Determinism

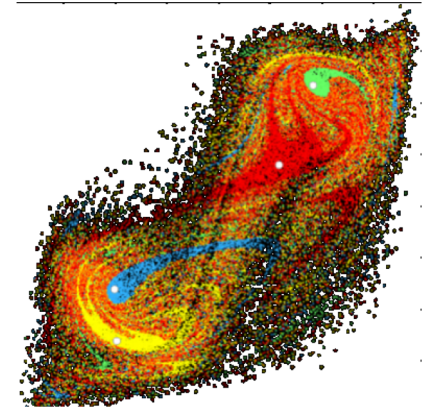
Perfect prediction is possible when we have knowledge of all necessary "conditions"



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

# Chaos

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



**Our knowledge is never perfect!**

**→ perfect forecast is impossible...**

# Predictability

Depends on **what to predict**

## Lead time( $\tau$ )

- ✓ *Temperature of this room tomorrow*
- ✓ *Temperature of this room in 30days later*
- ✓ *Temperature of this room in 30years later*

## Location

- ✓ *Temperature of Busan (Korea)*
- ✓ *Temperature of Antofagast (Chile)*
- ✓ *Temperature of Villa Las Estrellas (Antarctica)*

## Predictability

- ✓ *Temperature*
- ✓ *rainfall*
- ✓ *wind speed*

## Physical variables

- ✓ *Mean Temperature during a day*
- ✓ *Mean Temperature during a month*
- ✓ *Mean Temperature during a century*

## Time-scale of predictand

# Signal & Noise

## Two scales

- **Fast and small** scale processes : **noise**
  - Weather by tropical cyclone etc.
- **Slow and large** processes : **signal**
  - Climate by **ENSO**, ITCZ, monsoon, **MJO** and so forth

- What is the **Signal**? (How we can “see”?)
  - Tendency of weather that has to be physically caused by **slow varying processes**

# Potential predictability

**Matter of**

**Signal**

**&**

**Noise**

$$X = X_s + X_n$$

Measured by relative magnitude  
(variance) of signal and noise

**Signal >> Noise : more predictable**

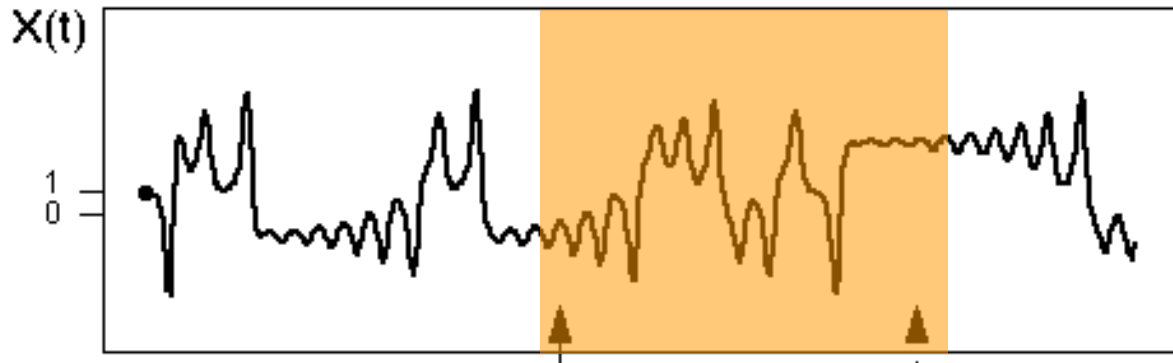
**Signal << Noise : less predictable**

How long  
(time domain)?

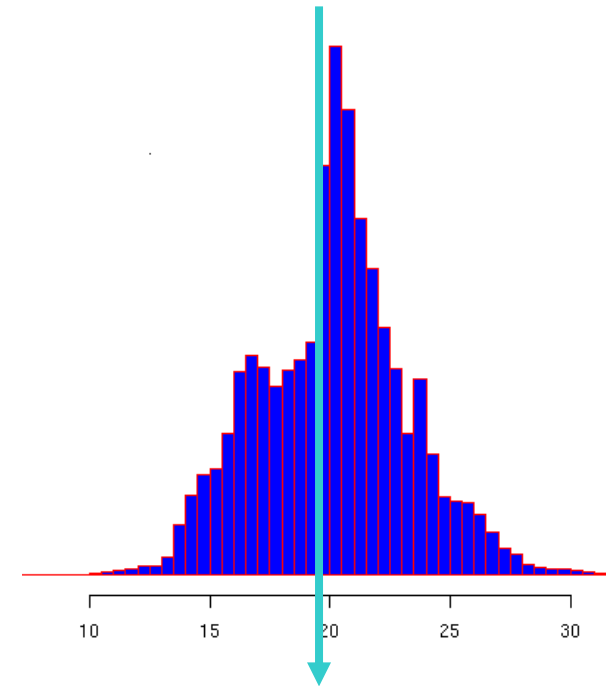
Time mean of  
weather

# Subseasonal climate prediction

# Weather statistics



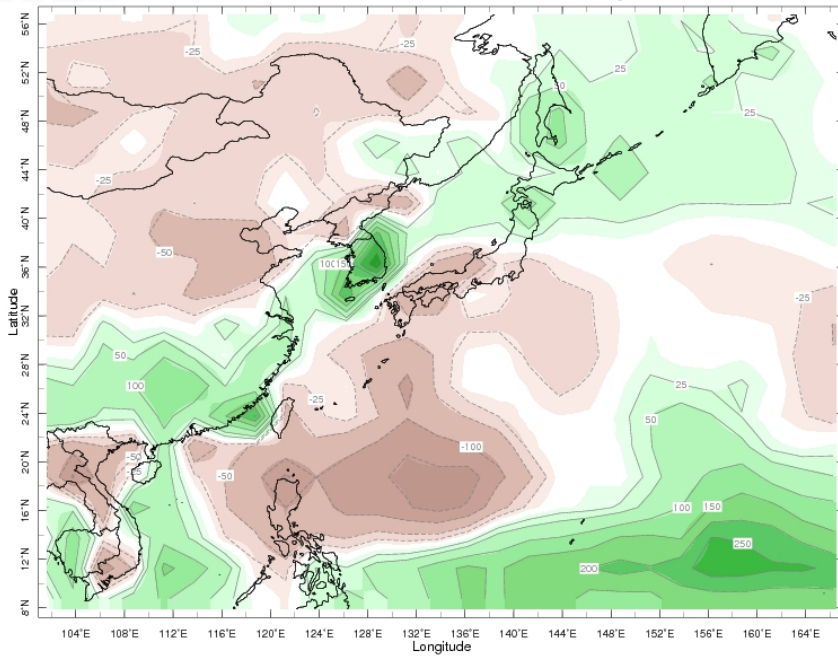
Primary seasonal weather statistics :  
seasonal **mean**



Seasonal  
**mean**

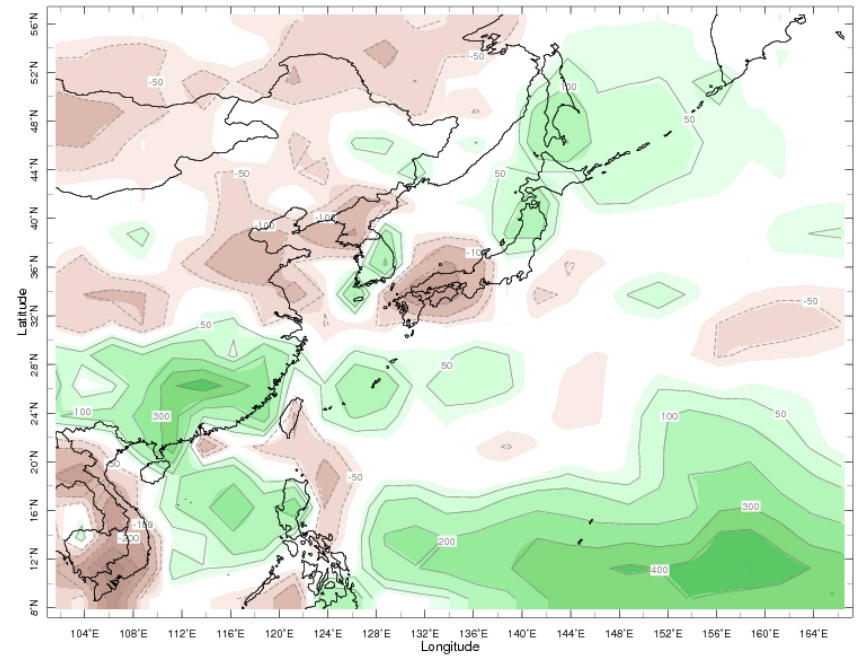
# 2002 summer (JJA) rainfall

## Monthly prec. Anomaly (Aug)



Aug 2002

## Summer mean prec. anomaly



Jun-Aug 2002

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

# 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

# Pros/Cons

## Statistical/Empirical

- Simple and cheap
- Based on (observation) data
- Short observing history. Do we have enough?
- Unprecedented events predictable ????

## Dynamical

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

# Statistical forecasting

## (0) Climatology

- Baseline of seasonal forecasting
- “Nothing particular, Sir.”

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

- ✓ Rainfall amount will be similar to 30 year average.
- ✓ I don't know? (33%:33%:33%) or Near Normal?

## (1) Persistence

- Assume that future will be the same as it is now.

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

- ✓ Often Close to people's expectation.
- ✓ Effective when the autocorrelation is large (e.g. ENSO forecast)

## (2) Regression

- The most popular method and many variations

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

$x$  : predictand (e.g. rainfall at a station)

$y$  : predictor (e.g. NINO3.4 SST)

# Regression based forecast

## Question #1 : Predictor selection

- How to define **predictor (y)**?
- By definition, predictor should cause some changes in variation of predictand.

## Question #2 : appropriate Function

- How to define **a** and **b**?
- *Your choice*: linear, nonlinear, single, multi...complex ones are not necessarily better.

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

*Predictand : my mood in the morning*  
*Predictor? Relationship?*

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

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

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

One to One : often not very satisfactory

One to Multi : easy to overfit (lie)

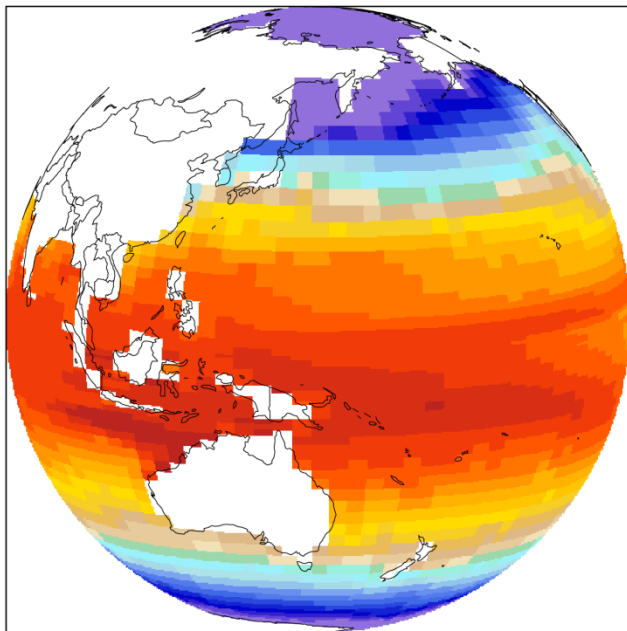
Multi to Multi : looks nice but often produce nothing practical

- ✓ If they give similar results, **the simpler is the better!**

- ✓ 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

# 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+9.11)^-2.05
//
MinTime=pow(T[j]+9.11, -2.05);//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=a[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];

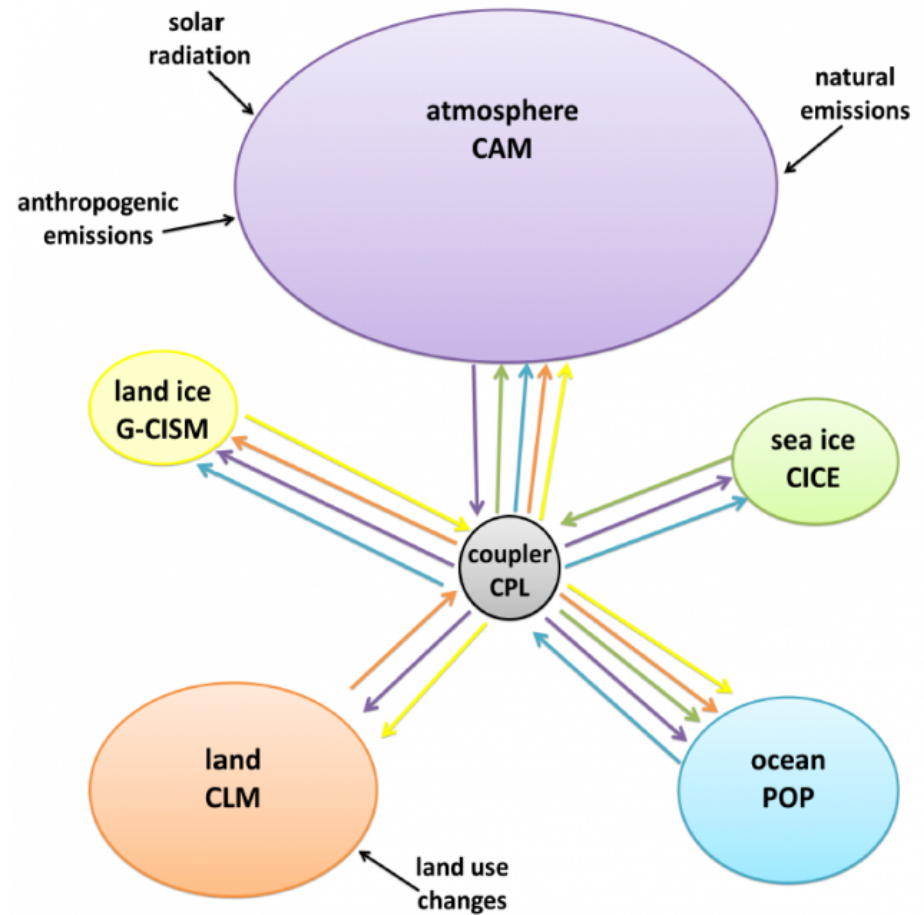
R[12]=0.;//adults don't molt

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

# GCMs

## ■ Coupled GCM

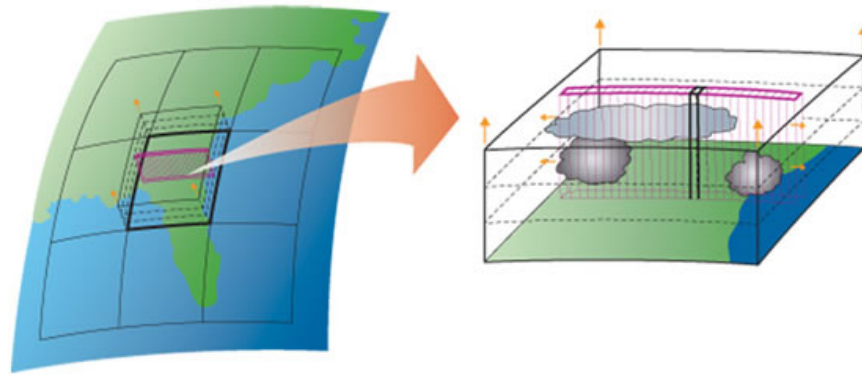
- Atmosphere
- Ocean
- Sea-Ice
- Land surface
- Chemistry
- Biosphere



# Numerical modeling

## ▪ Issue

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



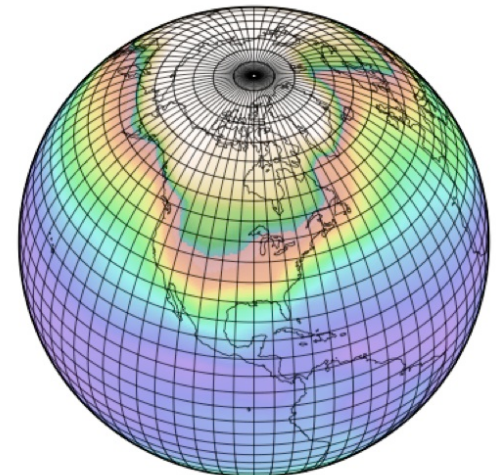
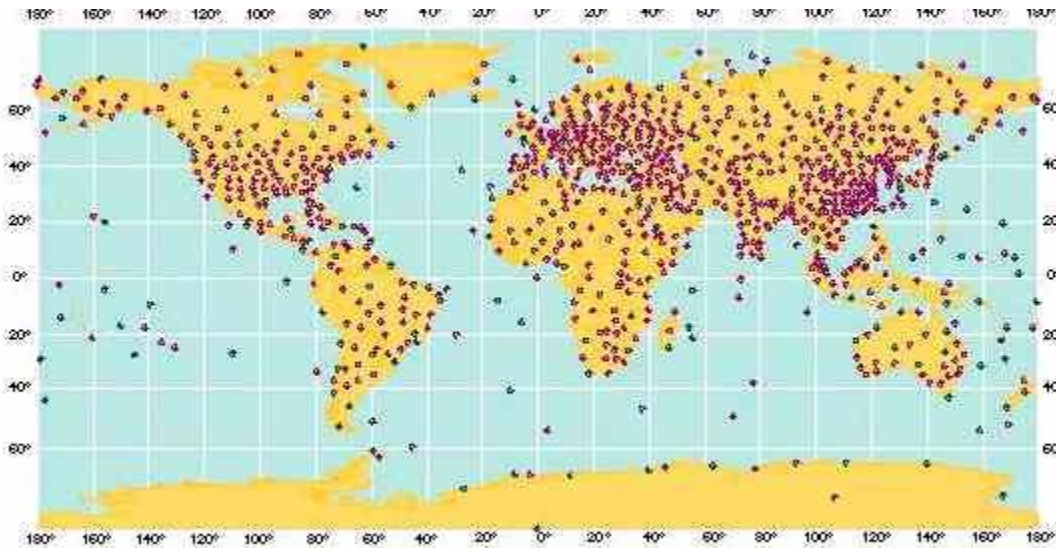
- Unknown processes, tunable parameters
- Initialization (for forecasting)

**NOT the same with NATURE**  
**NO perfect GCM**

# Initialization

Estimating Current status of climate system

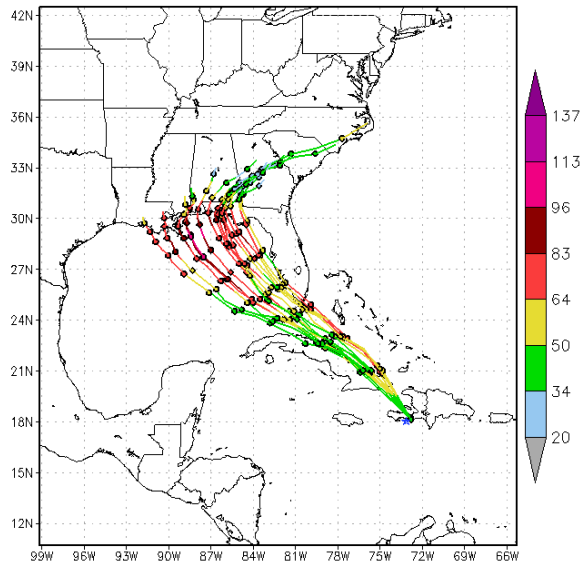
- Preparing the beginning climate state of GCM with available observation
  - Balance between Wrong GCM vs Wrong OBS.
  - Balance between components (Atm, Ocn)



# Ensemble Forecasting

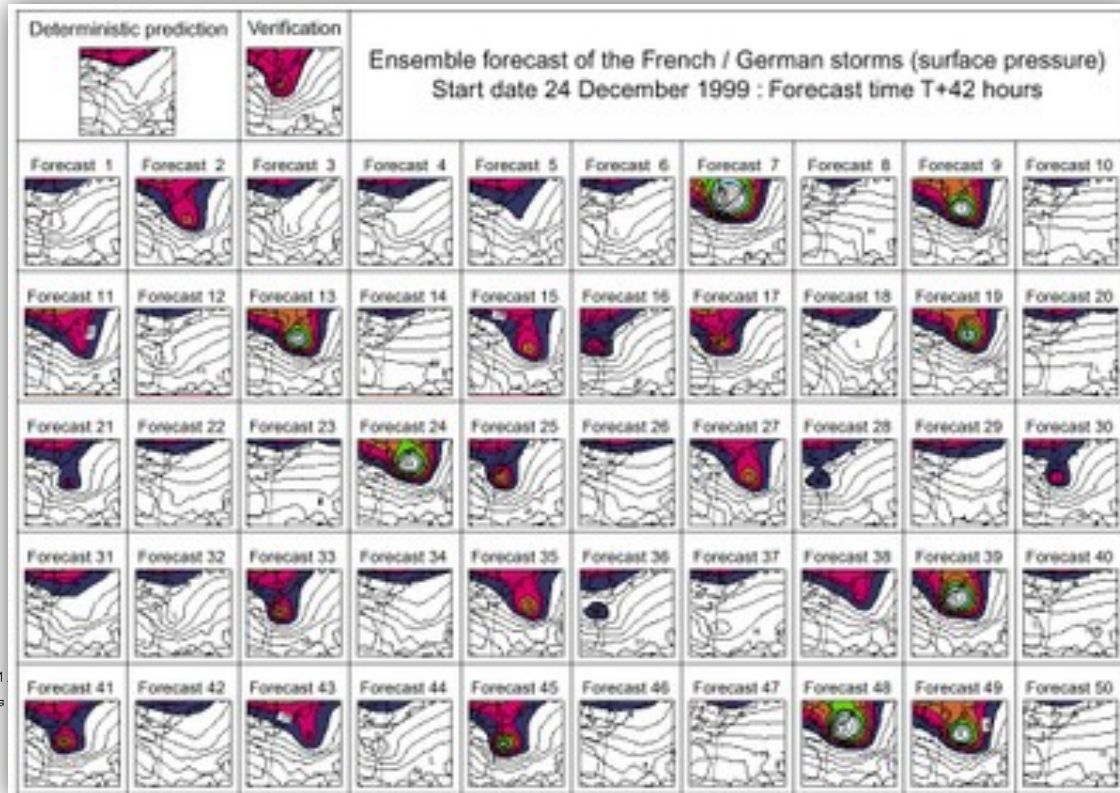
- Run many times
  - Starts from slightly different initial conditions

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



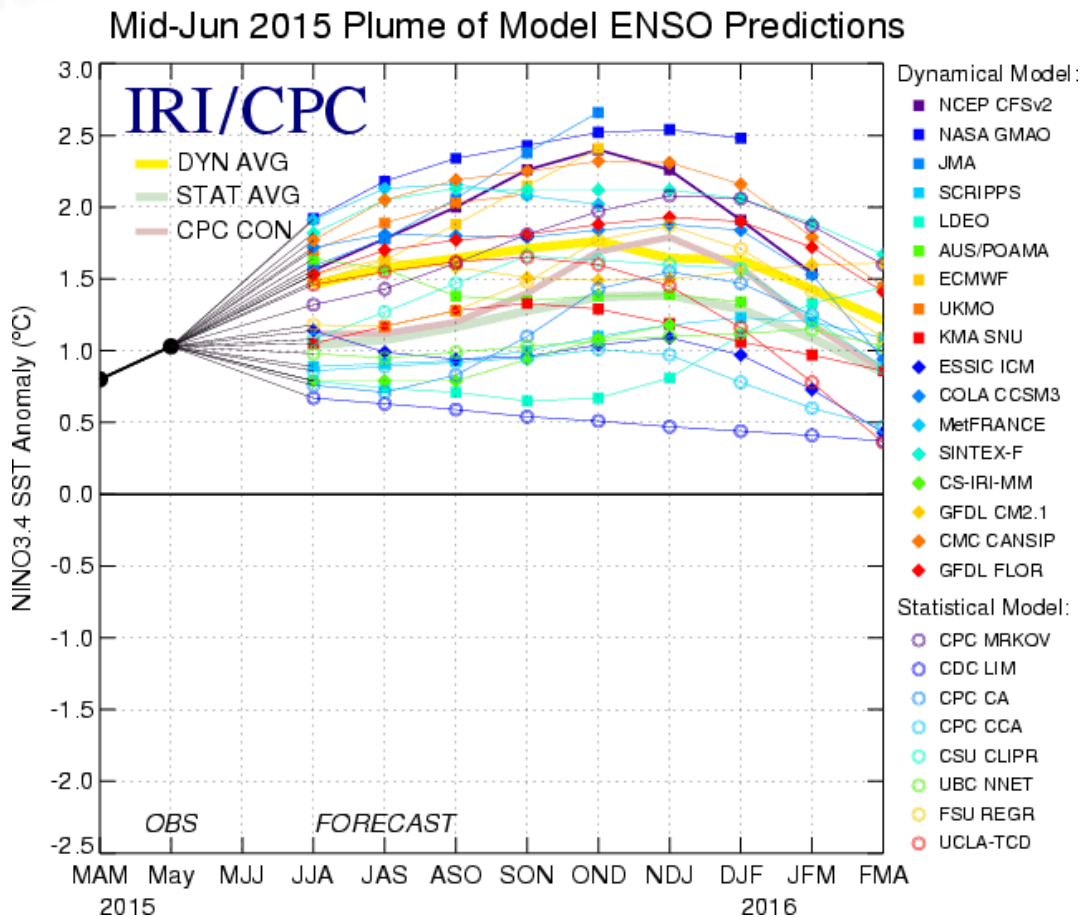
missing members (out of 16) at t=0: 0  
 indicates ISAAC09L observed center at initial time

Track forecast positions are marked every 1  
 GFDL Hurricane Dynamics



# Multi Model Ensemble Forecasting

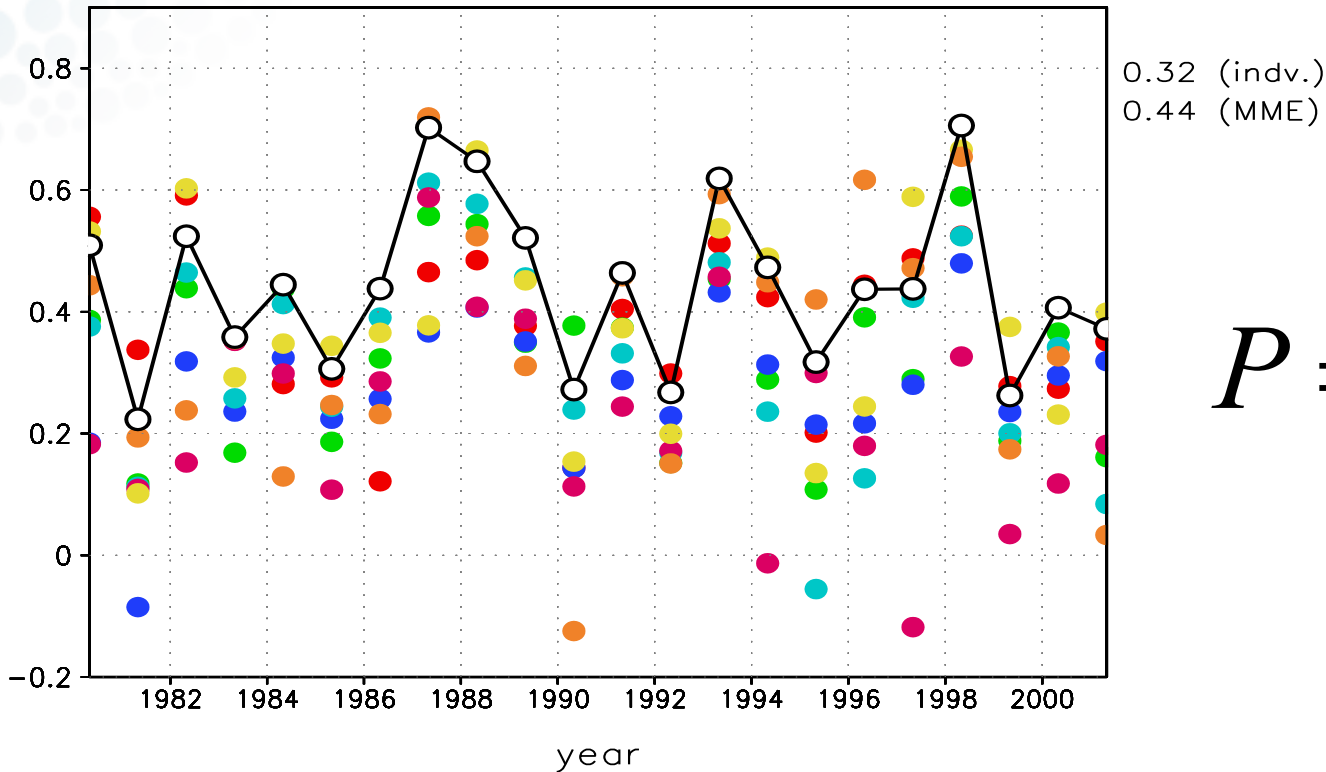
- Run with many models



Which one??

# Use all!

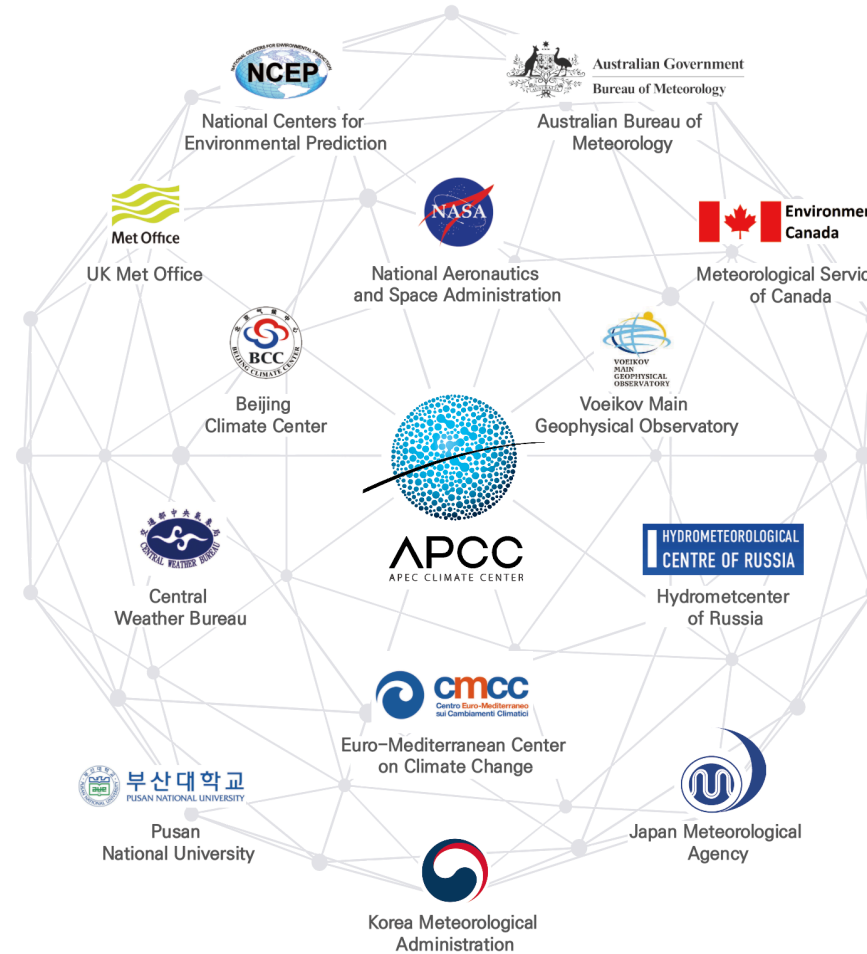
Pattern correlation : summer monsoon precip.



$$P = \sum_i a_i F_i$$

A way to **reduce prediction uncertainties** generated when any single model is selected (to avoid extremely wrong forecast), in the end, to **improve overall prediction skill!**

# APCC MME Climate Prediction



Collection of Dynamic ensemble seasonal prediction data from NMHS and research institutes (14 operations/institutions from 10 countries)

# List of available models

(as of March 2018)

Nation	Organization	Acronym
<b>Australia</b>	Bureau of Meteorology	BoM
<b>Canada</b>	Meteorological Service of Canada	MSC
<b>China</b>	Beijing Climate Center, China Meteorological Administration	BCC
<b>Chinese Taipei</b>	Central Weather Bureau	CWB
<b>Italy</b>	Centro Euro-Mediterraneo sui Cambiamenti Climatici	CMCC
<b>Japan</b>	Japan Meteorological Agency	JMA
<b>Korea</b>	APEC (Asia-Pacific Economic Cooperation) Climate Center	APCC
	Korea Meteorological Administration	KMA
	Pusan National University	PNU
<b>Russia</b>	Hydrometeorological Centre of Russia	HMC
	Main Geophysical Observatory	MGO
<b>United Kingdom</b>	United Kingdom Met Office	UKMO
<b>USA</b>	National Centers for Environmental Prediction, NOAA	NCEP
	National Aeronautics and Space Administration	NASA

# APCC operational forecast

Collecting model data

Preprocessing

(data reconstruction, QC and so forth)

Calculation & visualization

(MME & verification)

Issuing prediction

(& graphics)

Middle of month (-1)

Second half of month (-1)

First half of month (0)

Middle of month (0)

# APCC Climate Information

## Seasonal outlook (global)

## ENSO & IOD prediction

### Climate Outlook for April - September 2019

(Issued: 25 Mar, 2019)

- During February 2019, El Niño conditions were strengthened with positive sea surface temperature anomalies across the equatorial Pacific Ocean.
- The latest APCC ENSO outlook suggests a greater than 55% probability for moderate El Niño during April – June, and a greater than 80% probability for El Niño conditions during July – September 2019.
- Positive temperature anomalies are likely to prevail over the tropical Pacific, subtropical South Pacific, northern North Pacific, maritime continent, tropical Atlantic, western and central Indian Ocean, southern Africa, northern South America for April – September 2019.
- Below normal precipitation anomalies are expected for the central off-equatorial Pacific and the seas off the north coast of Australia, and above normal precipitation anomalies are expected for the equatorial Pacific for April – September 2019.

#### Temperature and Precipitation Outlook:

##### 1. Forecast for April – June 2019

Strongly enhanced probability for above normal temperatures is predicted for the tropical Pacific, northwestern and northern North Pacific, subtropical South Pacific, maritime continent, tropical and subtropical Atlantic, northern South America, southern Africa, and the Indian Ocean (excluding the eastern part). Enhanced probability for above normal temperatures is expected for the Arctic, Canada, Australia, and north Africa. Enhanced probability for below normal temperatures is predicted for the southern Indian Ocean near Australia and the Antarctic Ocean near South America. Strongly enhanced probability for above normal precipitation is expected for the equatorial Pacific. Strongly enhanced probability for below normal precipitation is predicted for the Philippines, Philippine Sea, and the central off-equatorial North Pacific. Enhanced probability for below normal precipitation is expected for the seas off the north coast of Australia, Bay of Bengal, Arabia Sea, Caribbean Sea, and the tropical Atlantic.

### Temperature at 2m for April-June 2019

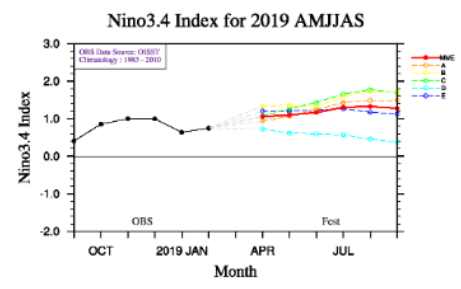
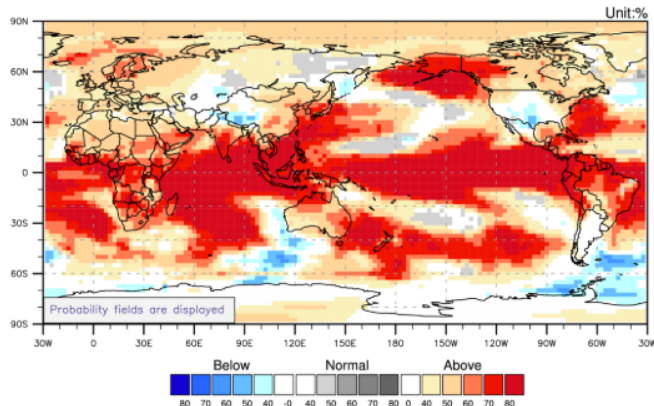


Fig. 1. Predicted Niño 3.4 Index from individual models (A, B, C, D, and E) and the Multi-Model Ensemble (MME).

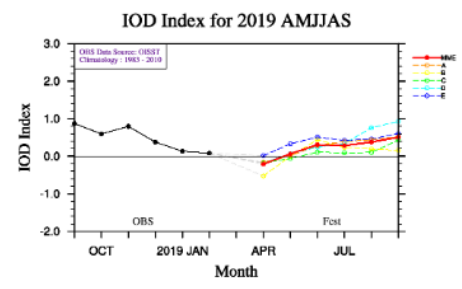


Fig. 2. Predicted Indian Ocean Dipole mode index (IODMI) from individual models (A, B, C, D, and E) and the MME.

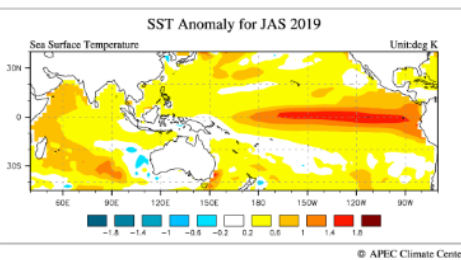
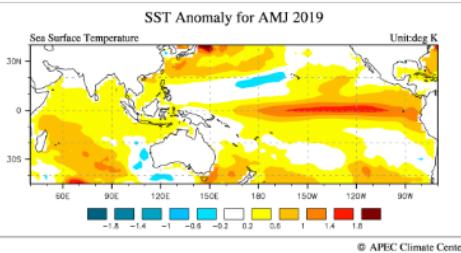
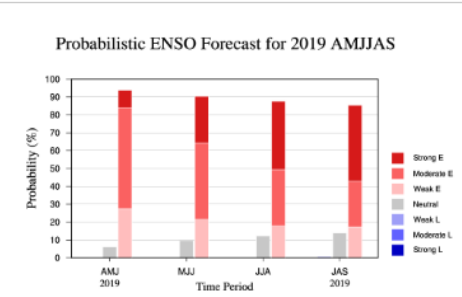


Fig. 3. Multi-model ensemble (MME) forecasts of SST anomalies for April - June 2019 (top) and July - September 2019 (bottom). Anomalies are computed with respect to the common base period of participating models in the APCC MME prediction (1983-2010).



\* ENSO Intensity based on 3M Mean Niño3.4 SST Anomaly (Category Boundries: +/-1.5, 1.0, 0.5°C)  
© APEC Climate Center

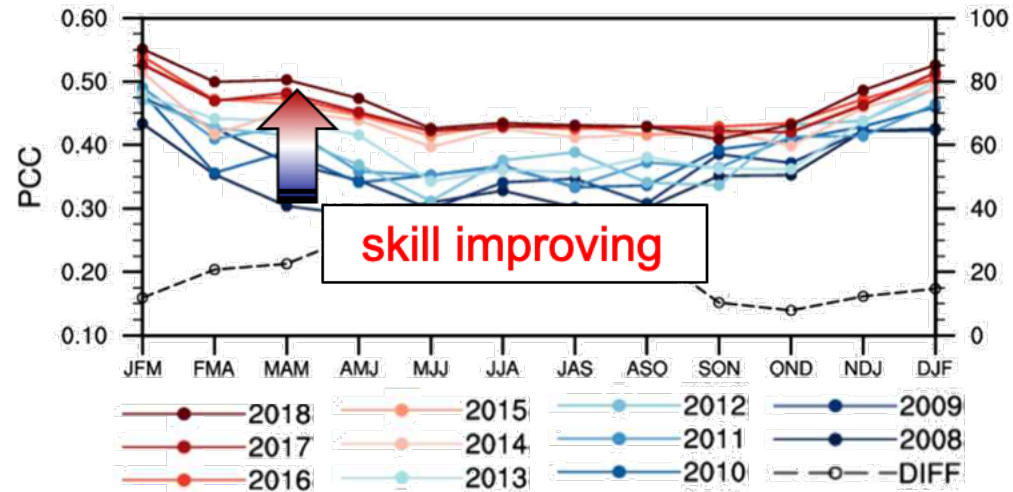
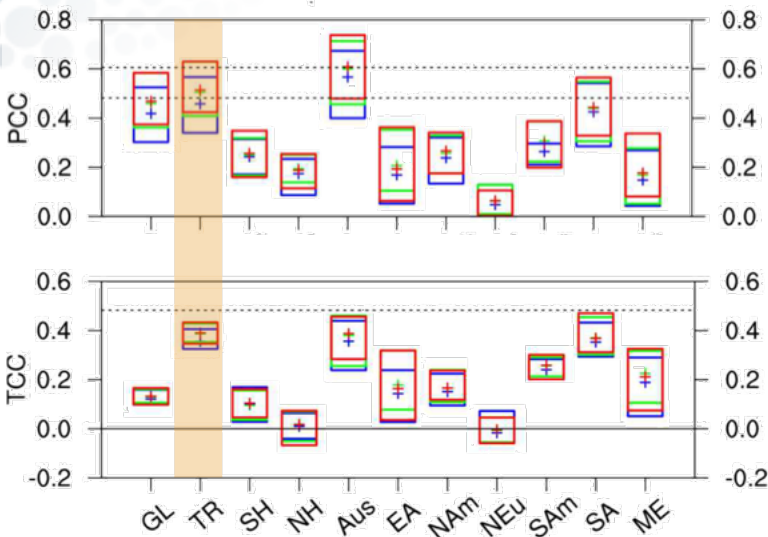
Fig. 4. Probabilistic MME forecasts of the status and intensity based on 3-month mean Niño3.4 index for four overlapping 3-month mean periods. Anomalies are computed with respect to the common base period of participating models in the APCC MME prediction (1983-2010).

# APCC MME skill improvement

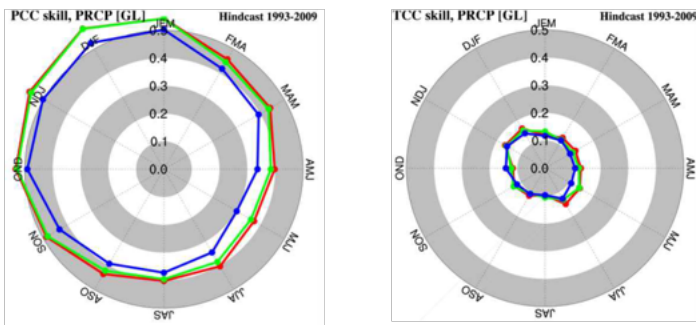
By YM Min (APCC)

More skillful compared to WMO & NMME

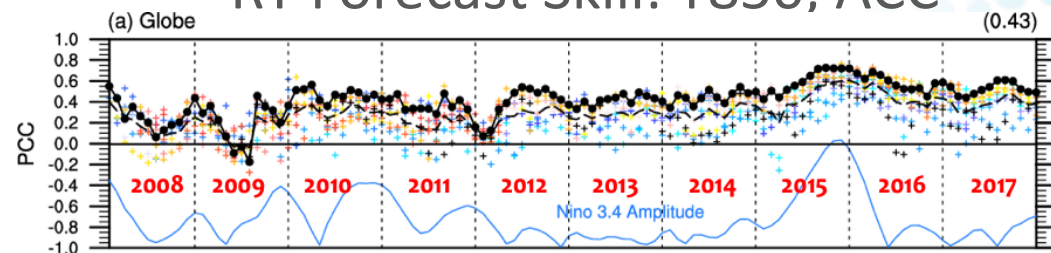
Hindcast Skill: ACC



it keeps improving!



RT Forecast Skill: T850, ACC



● APCC ● benchmarks

# Evaluation of Seasonal Prediction

Yun-Young Lee



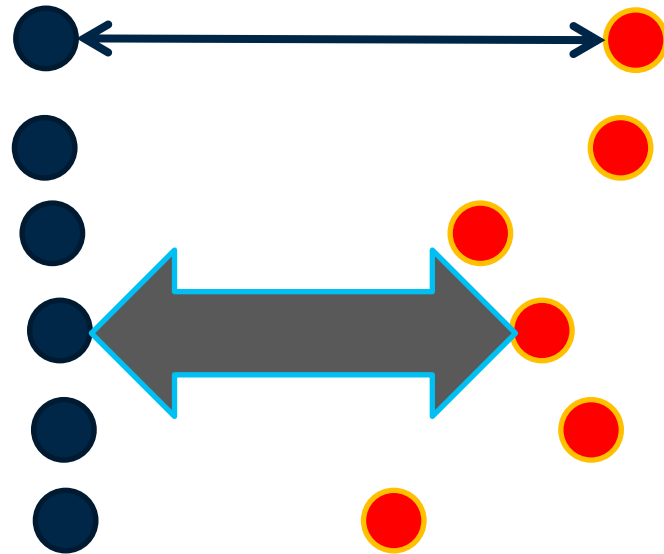
# How GOOD?

- Evaluation of forecast : verification



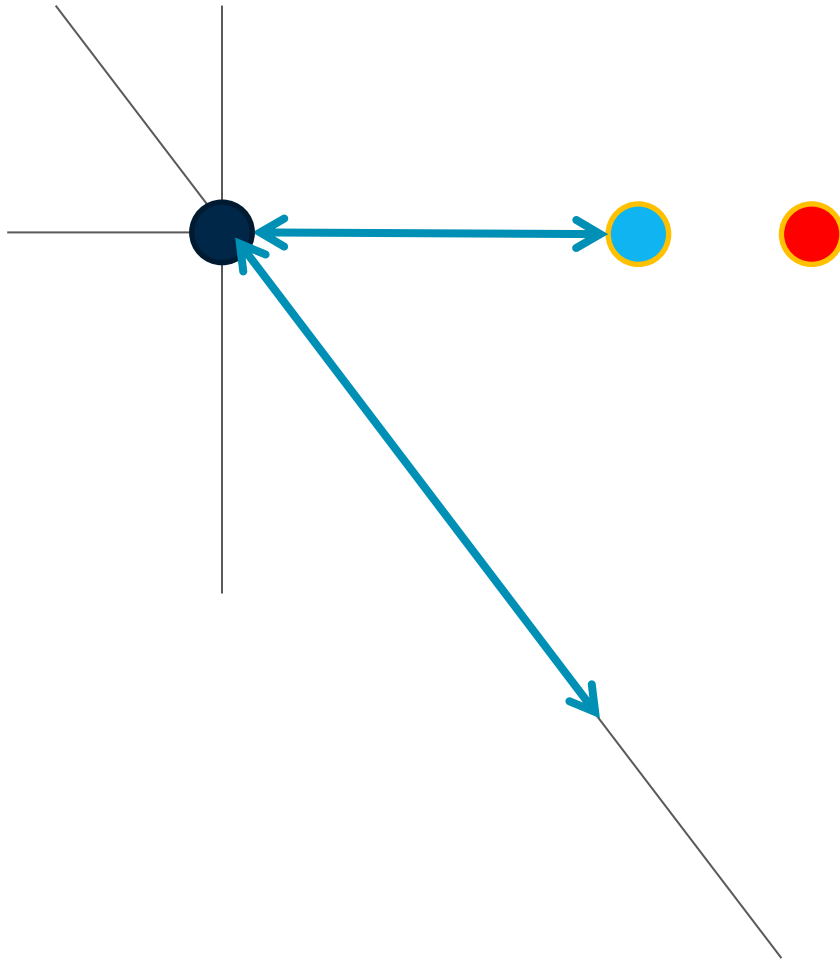
# Verification

- Evaluation : measure of **closeness**



# Verification

- Evaluation : depends on **Dimension/Viewpoint**



# Deterministic continuous forecast

## ▪ Various measures

- **MSE** (Mean Square Error), **RMSE** (Root MSE)

$$MSE = \frac{1}{N} \sum_i (F_i - O_i)^2$$

- **MSSS** (Mean Square Skill Score)

- Conventional form of “skill score”
- $1 - \frac{MSE}{MSE_c}$ , MSE : error/penalty,  $MSE_c$  : error of climatology forecast

- **TCC**(Temporal Correlation Coefficient), **ACC**(Anomaly Correlation Coefficient)

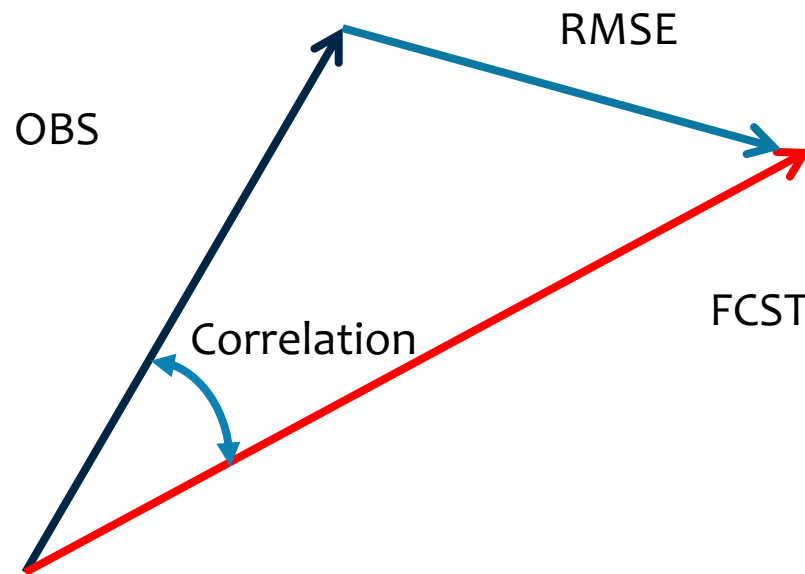
$$ACC = \frac{\sum_{i=1}^N w_i (f_i - \bar{f})(o_i - \bar{o})}{\sqrt{\sum_{i=1}^N w_i (f_i - \bar{f})^2 \sum_{i=1}^N w_i (o_i - \bar{o})^2}}$$

$$\text{skill score} = \frac{SCORE_{forecast} - SCORE_{reference}}{SCORE_{perfect\ forecast} - SCORE_{reference}}$$

,Which is designed to give an answer for the question “What is the relative improvement of the forecast over some reference forecast?”

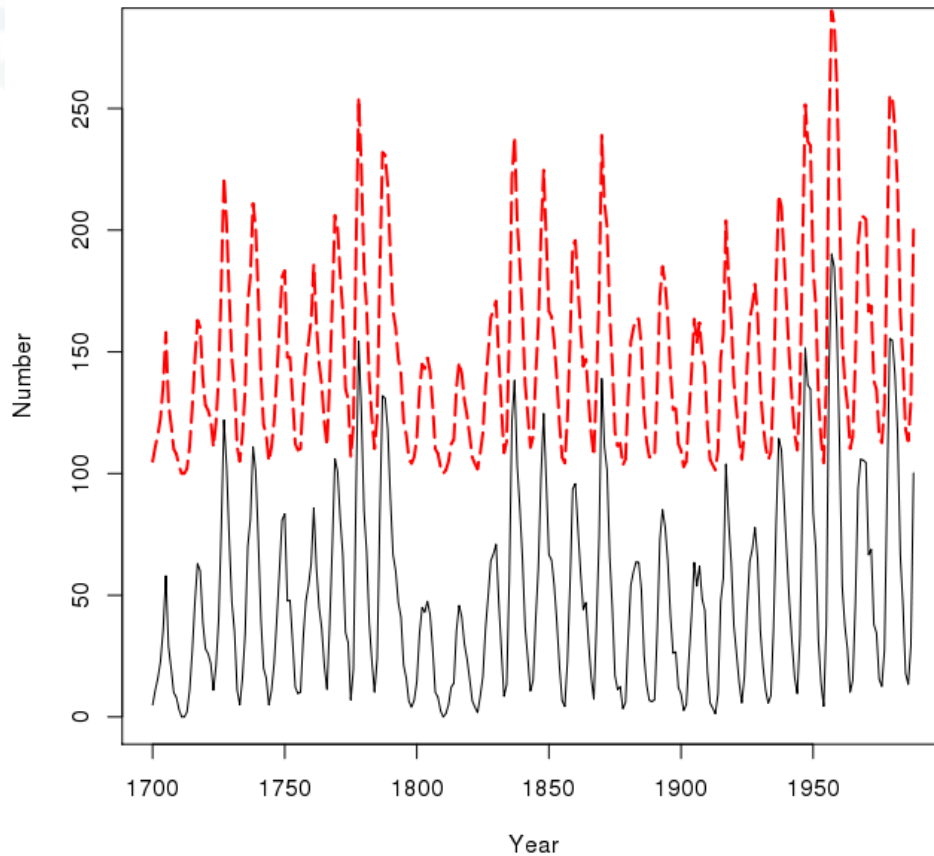
# Verification

- Evaluation : depends on **Dimension/Viewpoint**



# Examples

Sunspot Number



$O(t)$

$$F(t) = O(t) + 100$$

**RMSE?**

**But, Temporal Correlation?**

# Probabilistic forecast

## ■ Brier score (BS)

– MSE of prob. forecast

$$BS = \frac{1}{N} \sum_i (F_i - O_i)^2$$

F=probability(forecast),

O=1/0 (actual outcome of instance)

Eg. Binary events such as “rain” or “no rain”

Range: 0 to 1, Perfect score = 0

**Intuitively**, Higher score = Better skill?

$$\text{skill score} = \frac{SCORE_{forecast} - SCORE_{reference}}{SCORE_{perfect\ forecast} - SCORE_{reference}}$$

,Which is designed to give an answer for the question “What is the relative improvement of the forecast over some reference forecast?”

## ■ Brier Skill Score (BSS)

$$BSS = 1 - \frac{BS}{BS_c}$$

BS : error/penalty,

BS<sub>c</sub>: BS of climatology forecast

Range: -infinity to 1

Perfect score = 1

# Probabilistic forecast (Categorical)

F \ O		“rain”	“no rain”
		Yes	No
Yes	Hit (H)	False Alarm (F)	
No	Miss (M)	Correct Rejection (C)	

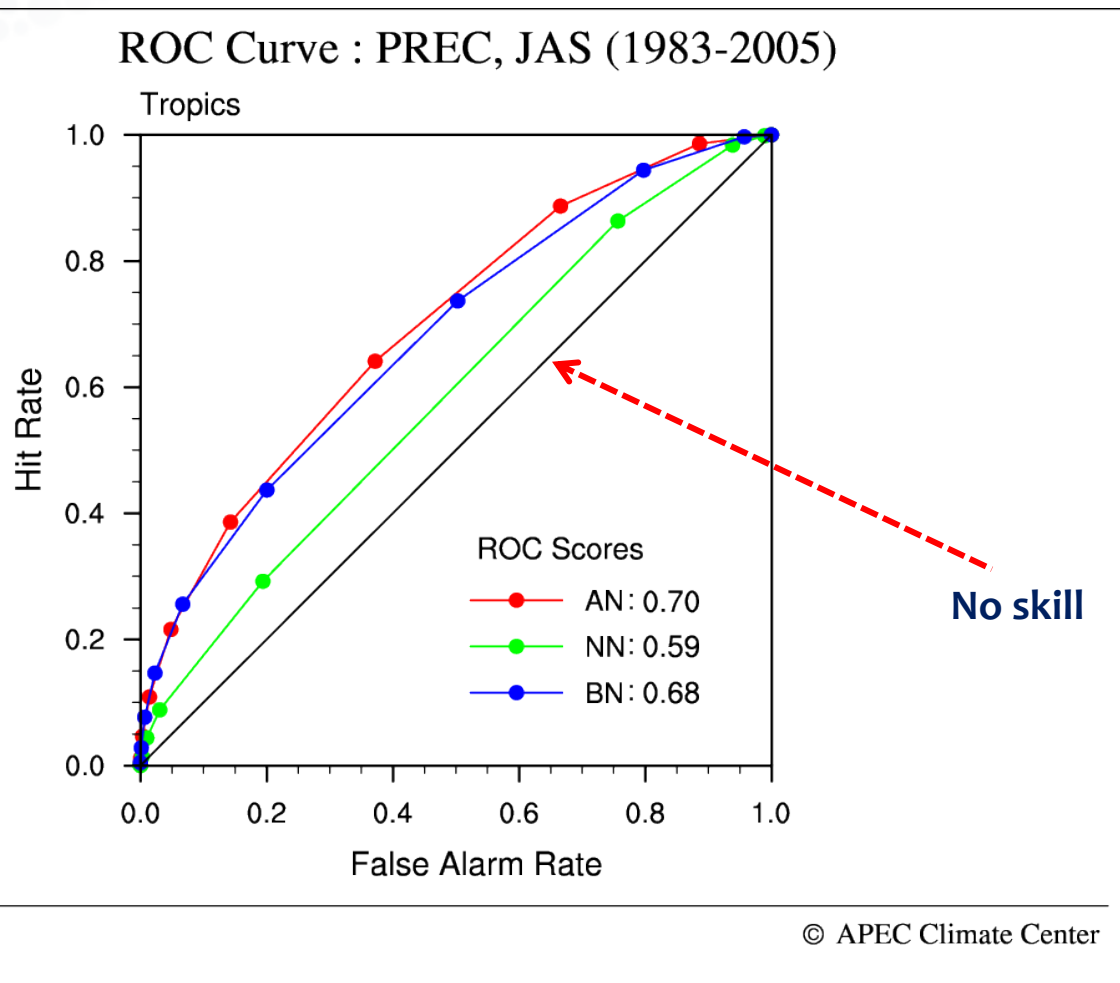
Correct forecast

<b>SR (Success Rate)</b>	$= (H+C)/(H+M+F+C)$	0 to 1	Perfect score = 1
<b>bias</b>	$= (H+F)/(H+M)$	0 to $\infty$	Perfect score = 1
<b>TR (Threat Score)</b>	$= H/(H+M+F)$	0 to 1	Perfect score = 1
<b>HR (Hit Rate)</b>	$= H/(H+M)$	0 to 1	Perfect score = 1
<b>FAR (False Alarm Rate)</b>	$= F/(F+C)$	0 to 1	Perfect score = 0

Good forecast : **HR**↑, **FAR** ↓

# Probabilistic forecast (Categorical)

## ROC (Relative Operating Characteristics)

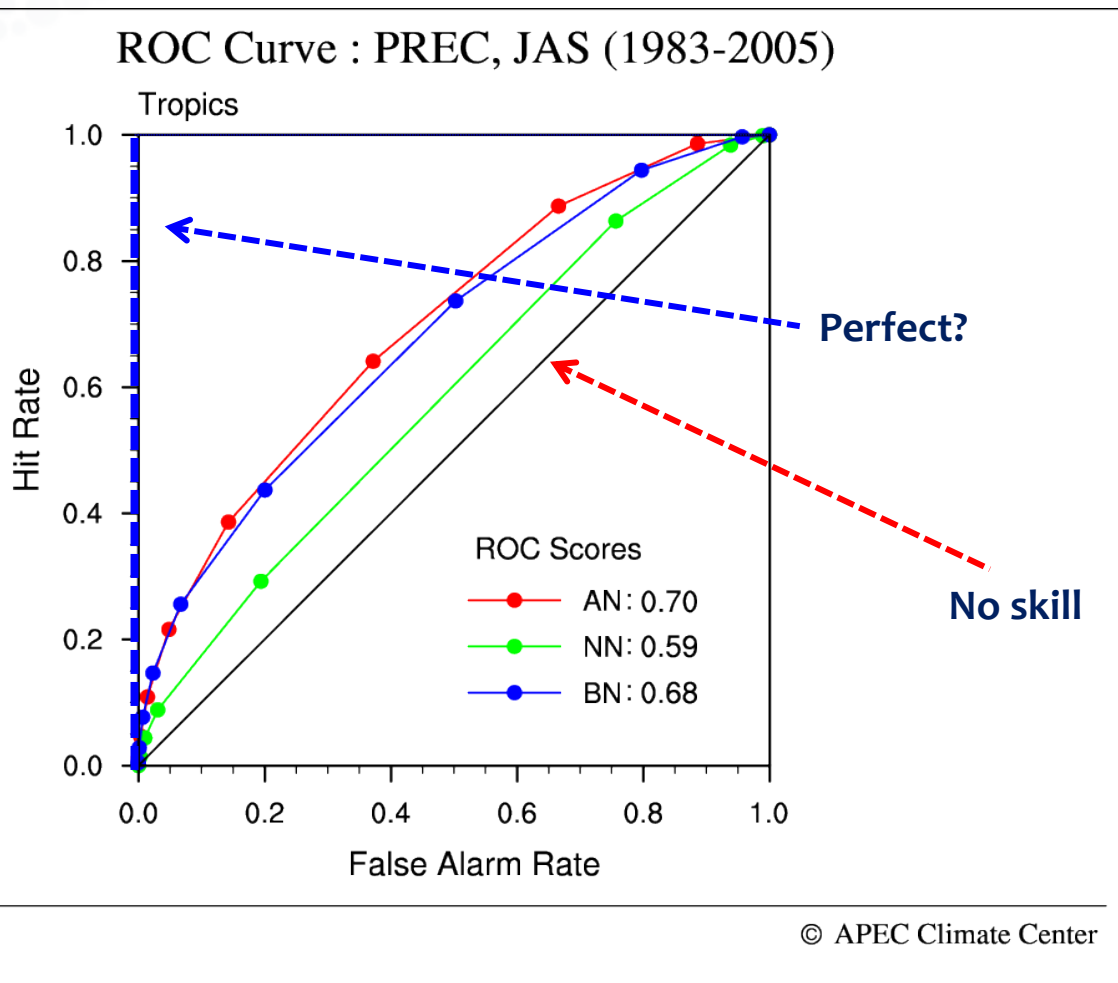


**ROC score**  
=Area Under ROC curve

Range: 0 to 1  
perfect: ROC score = 1  
no skill: ROC score = 0.5  
(no added value)

# Probabilistic forecast (Categorical)

## ROC (Relative Operating Characteristics)

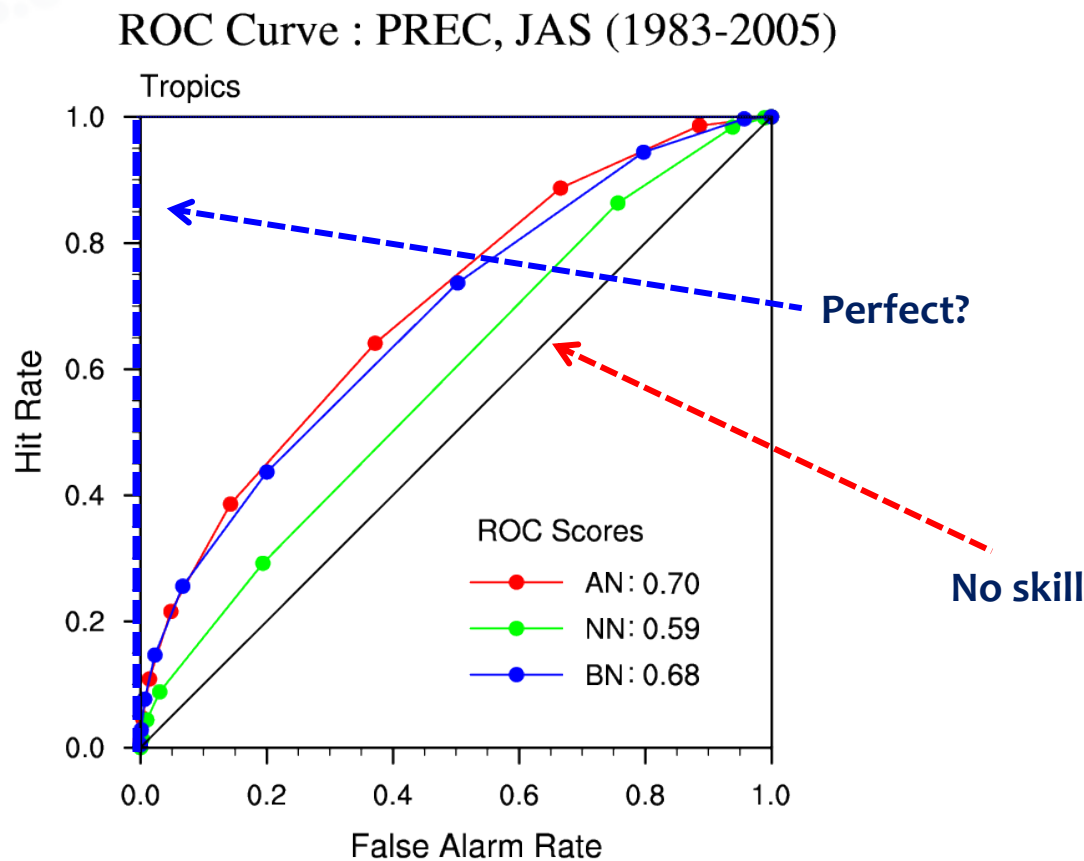


**ROC score**  
=Area of ROC curve

Range: 0 to 1  
perfect: ROC score = 1  
no skill: ROC score = 0.5  
(no added value)

# Probabilistic forecast (Categorical)

## ROC (Relative Operating Characteristics)



- ✓ Biased forecast with high ROC score
- ✓ A measure of *potential usefulness*

**ROC score**  
=Area of ROC curve

Range: 0 to 1  
perfect: ROC score = 1  
no skill: ROC score = 0.5  
(no added value)

# Probabilistic forecast (Categorical)

## ■ HSS (Heidke Skill Score)

Giving the answer for the question “What was the accuracy of the forecast in predicting the correct category, relative to that of random chance?”

<b>F</b> \ <b>O</b>	<b>Yes</b>	<b>No</b>
<b>Yes</b>	Hit (H)	False Alarm (F)
<b>No</b>	Miss (M)	Correct Rejection (C)

$$\begin{aligned} HSS &= \frac{SCORE_{forecast} - SCORE_{by\ chance}}{SCORE_{perfect\ forecast} - SCORE_{by\ chance}} \\ &= \frac{\left\{ \frac{(H + C)}{n} - \frac{[(H + F)(H + M) + (F + C)(M + C)]}{n^2} \right\}}{\left\{ 1 - \frac{[(H + F)(H + M) + (F + C)(M + C)]}{n^2} \right\}} \end{aligned}$$

Range: - infinity to 1, **0=no skill**, **1=perfect skill**

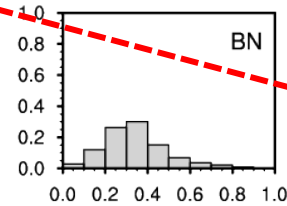
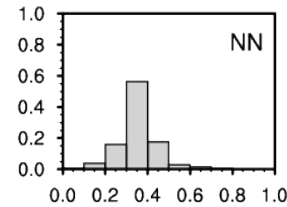
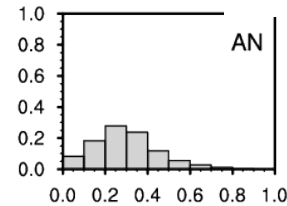
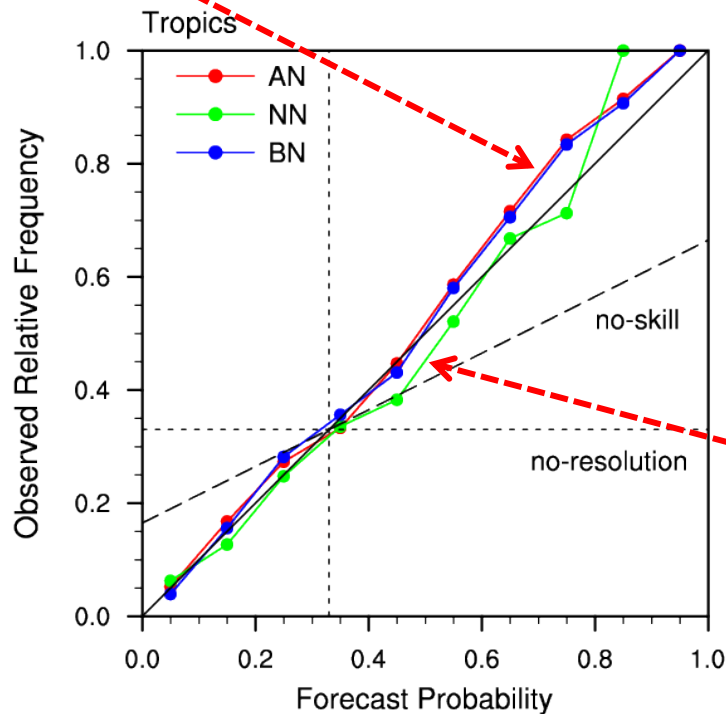
# Probabilistic forecast (Categorical)

## Reliability curve

Accurate probability forecast system

- ✓ Reliability
- ✓ Sharpness
- ✓ Resolution

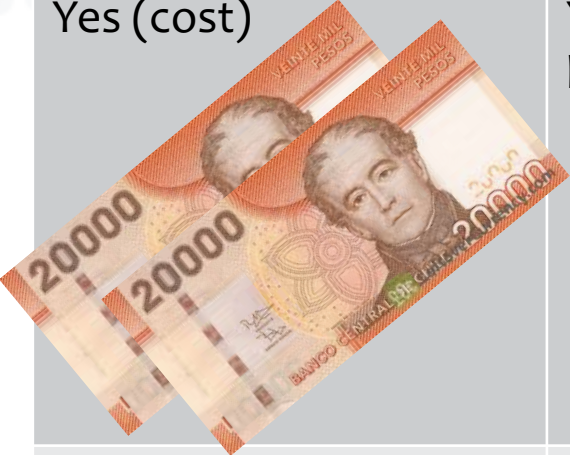
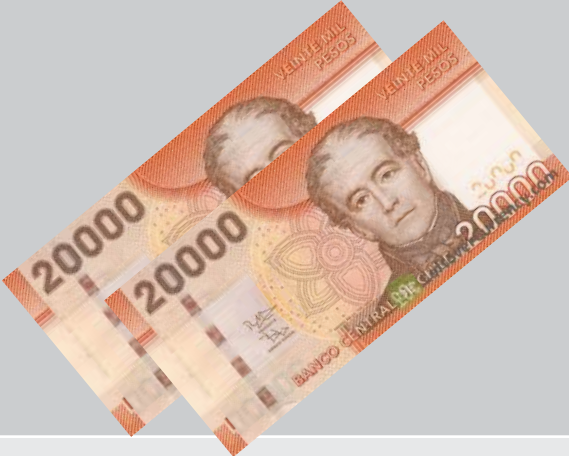


Underforecasting Reliability Diagram : PREC, JAS (1983-200)



Frequency Histogram

# Money Problem!

**Drought expected!**

Preparing (reservoir)	Drought happens?	Net cost
Yes (cost) 	Yes or No (No money loss because of drought)	
No (no cost)	Yes (money loss) 	

# Forecast Economic Value

$$V = \frac{E_{cli} - E_{fore}}{E_{cli} - E_{per}}$$

**V=1** : perfect forecast

**V=0** : climatological forecast

$E_{fore}$  : Expected expense of forecast

$E_{per}$  : Expected expense of perfect forecast

$E_{cli}$  : Expected expense of climatological forecast

		Observation (real event)	
		Yes	No
Forecast (action)	Yes	Hit (h) Cost (C)	False alarm (f) Cost (C)
	No	Miss (m) Loss (L)	Correct rejection (c) 0

$$E_{fore} = (h + f)C + mL$$

- When the forecast is **perfect**,  $f = m = 0$ . and  $h = \bar{o}$ . Then,  $E_{per} = hC = \bar{o}C$

- When the forecast is **climatology**. The only one kind of action will be kept.

If we do act :  $E \rightarrow C$ , otherwise  $E \rightarrow \bar{o}L$ .

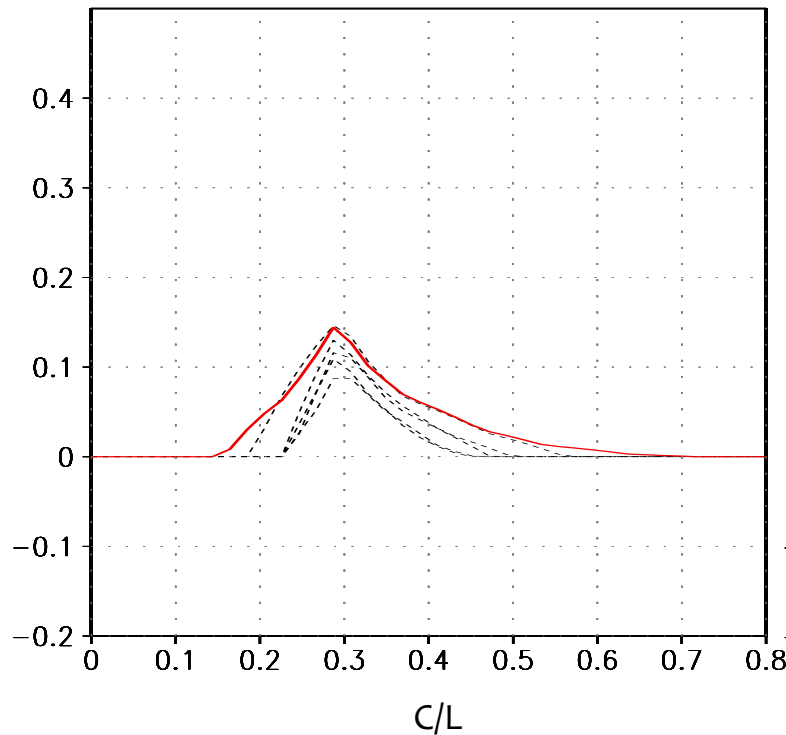
**Decision: action of low expense.** Thus,  $E_{cli} = \min(C, \bar{o}L)$

$$V = \frac{\min(C, \bar{o}L) - (h + f)C - mL}{\min(C, \bar{o}L) - \bar{o}C} = \frac{\min\left(\frac{C}{L}, \bar{o}\right) - (h + f)\frac{C}{L} - m}{\min\left(\frac{C}{L}, \bar{o}\right) - \bar{o}\frac{C}{L}}$$

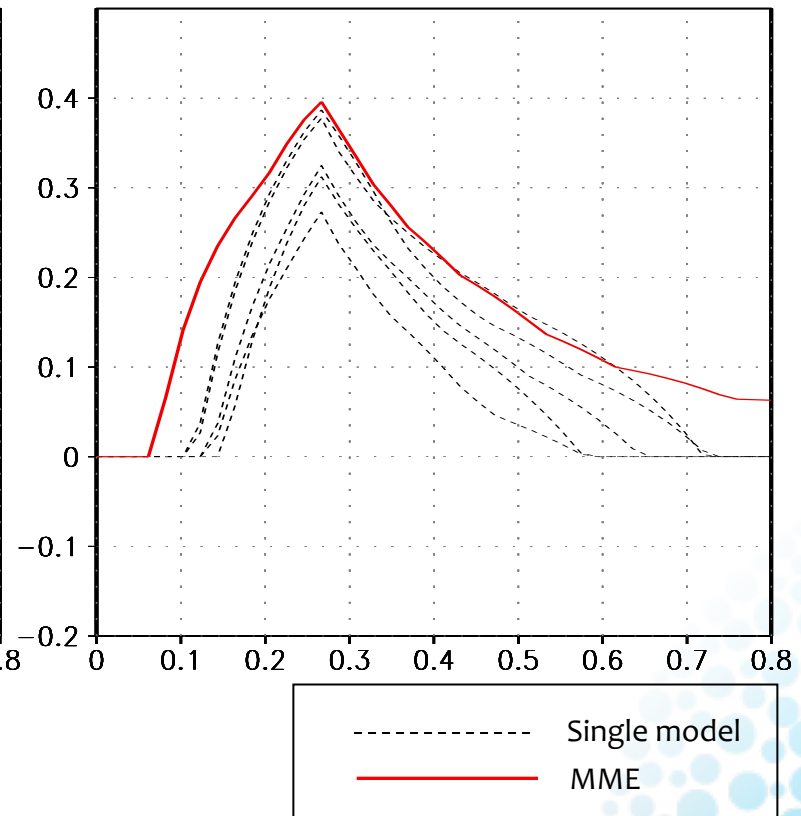
# Economic Value of Probabilistic Forecast (Above normal) : GCMs

$$V = \frac{\min\left(\frac{C}{L}, \bar{o}\right) - (h + f)\frac{C}{L} - m}{\min\left(\frac{C}{L}, \bar{o}\right) - \frac{C}{L}\bar{o}} = \frac{\min\left(\frac{C}{L}, \bar{o}\right) - f(1 - \bar{o})\frac{C}{L} + h\bar{o}\left(1 - \frac{C}{L}\right) - \bar{o}}{\min\left(\frac{C}{L}, \bar{o}\right) - \frac{C}{L}\bar{o}}$$

(a) Monsoon(40E-160E,20S~40N)



(b) ENSO (160E-280E,20S~20N)



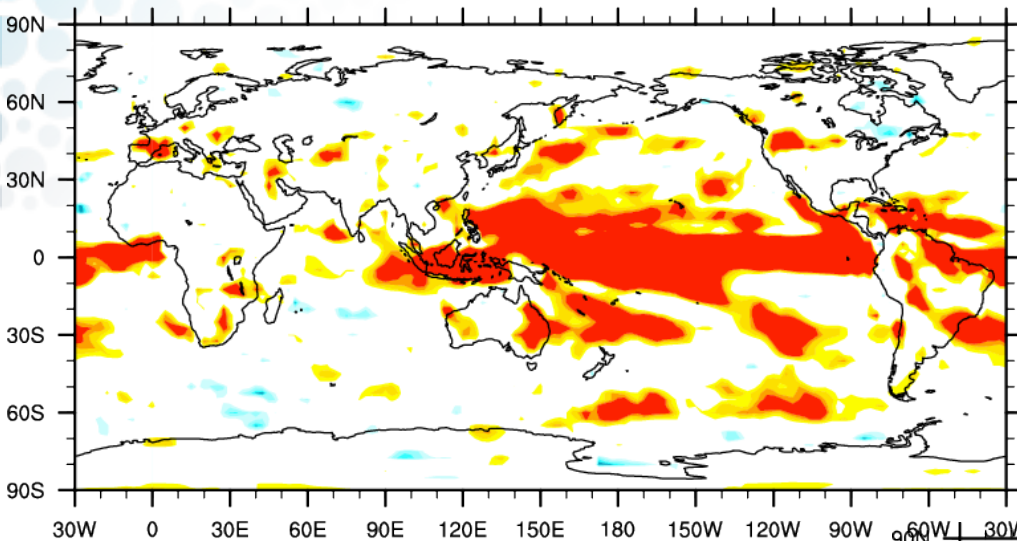
**Cost-Loss ratio**

----- Single model  
 ———— MME

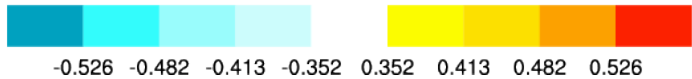
# Forecast Verification

- Multi aspect evaluation is preferred.
- A single verification score (e.g.  $R=0.5$ , explaining 25% variance) cannot tell everything.
- User oriented verification would be useful.
- If not clear, use popular one.
- Difficulties in “translating” meteorological skill score into Public wording.
- Let’s see some results!!!

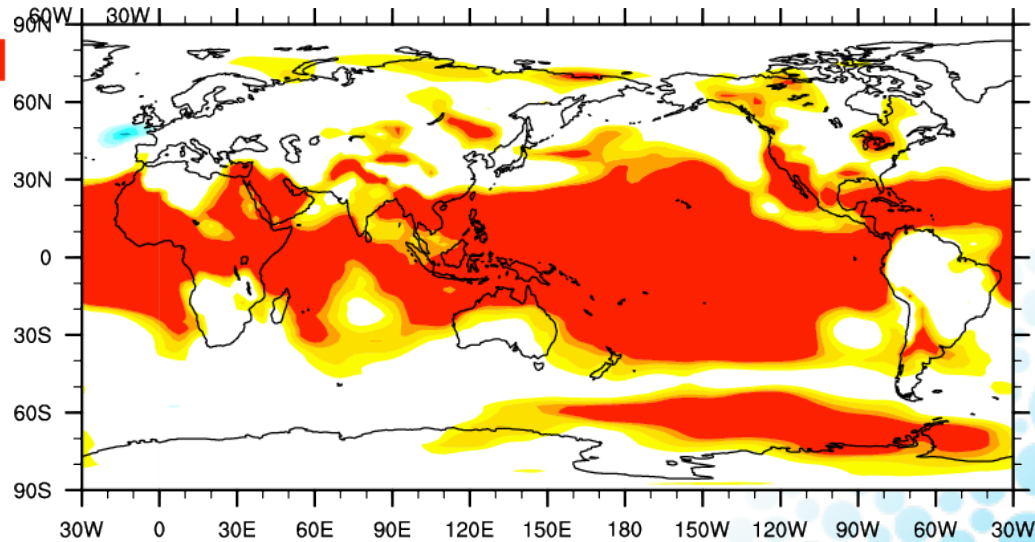
# APCC continuous DMME (TCC)



Rainfall (JJA)



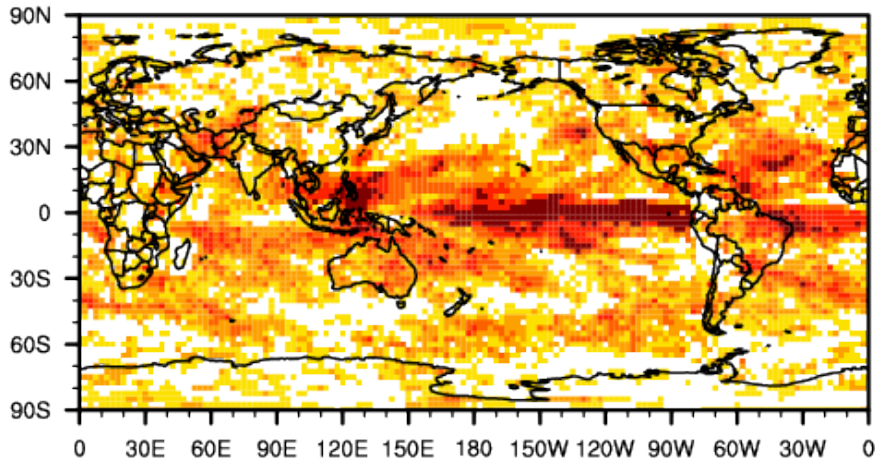
SLP (JJA)



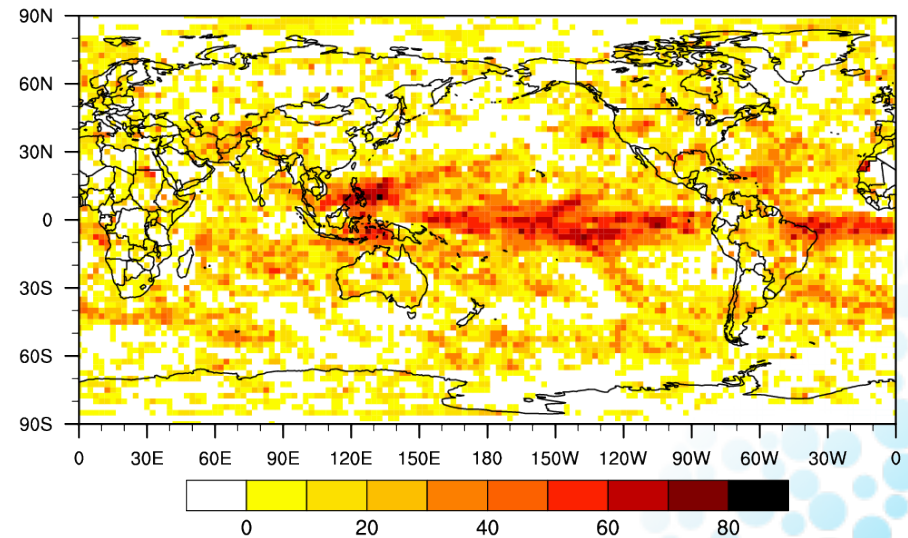
# APCC categorical PMME

ROC Score : PREC, AMJ (1983-2010)

Above-Normal



Heidke Skill Score : PREC, AMJ (1983-2010)





Thank you.