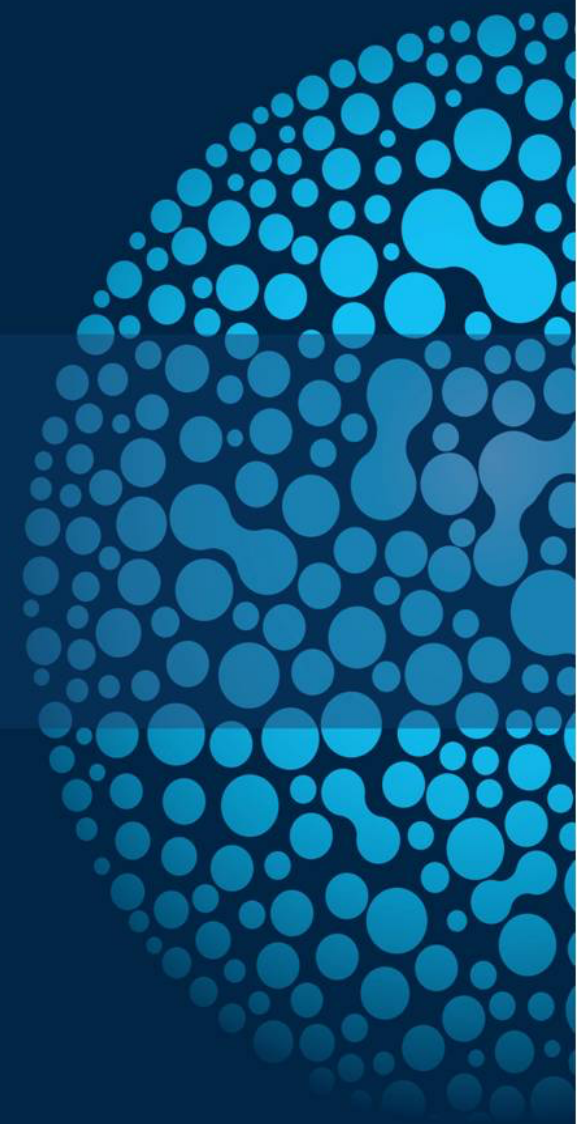


Lecture 4-1

Downscaling of seasonal prediction

Yun-Young Lee





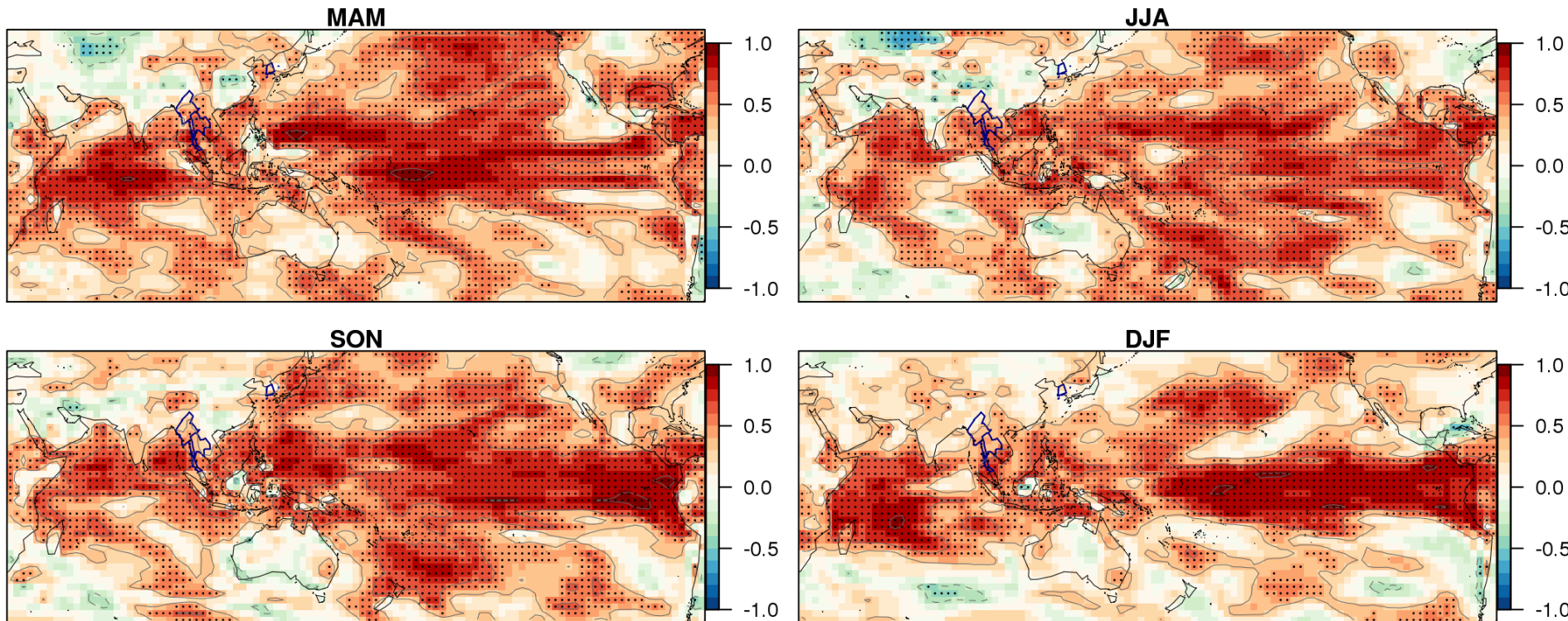
Why downscaling is required?



1. Low skill of dynamical seasonal forecast...

- near surface temperature...

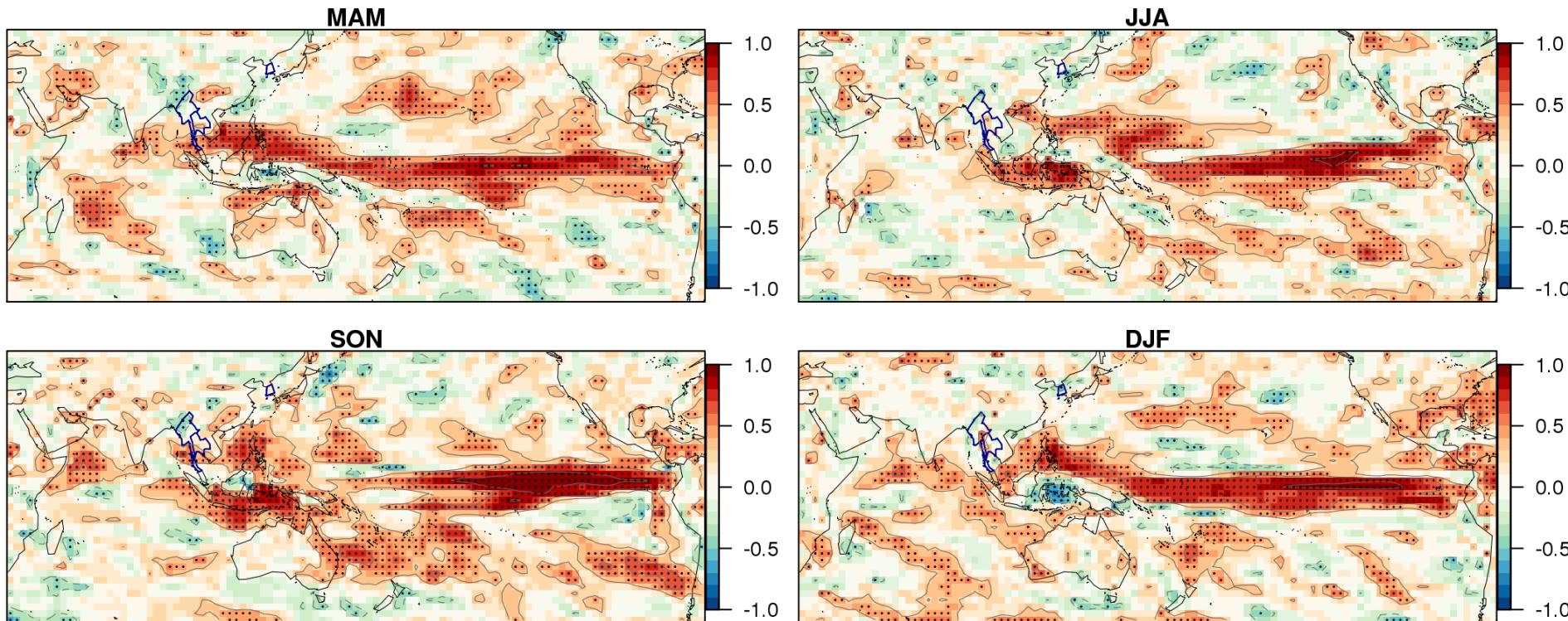
TCC (NNR2 vs SCM), t2m



1. Low skill of dynamical seasonal forecast...

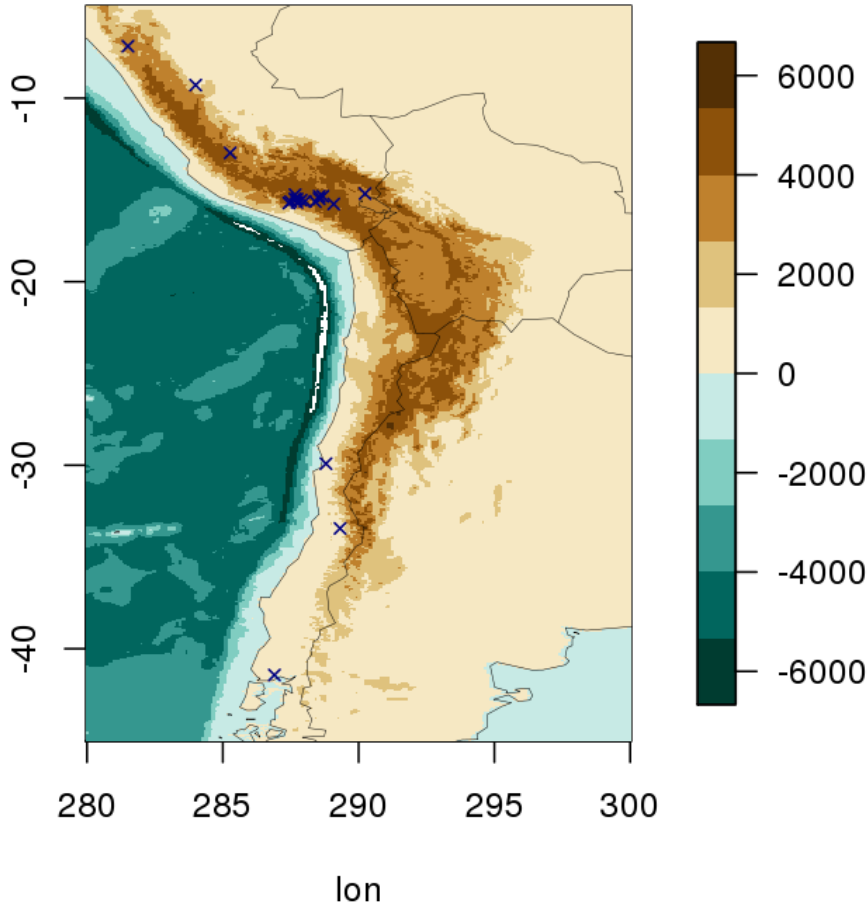
- *Rainfall ?*
- *tropical Pacific only?*
- *Southeast Asia?*

TCC (NRR2 vs SCM), prec



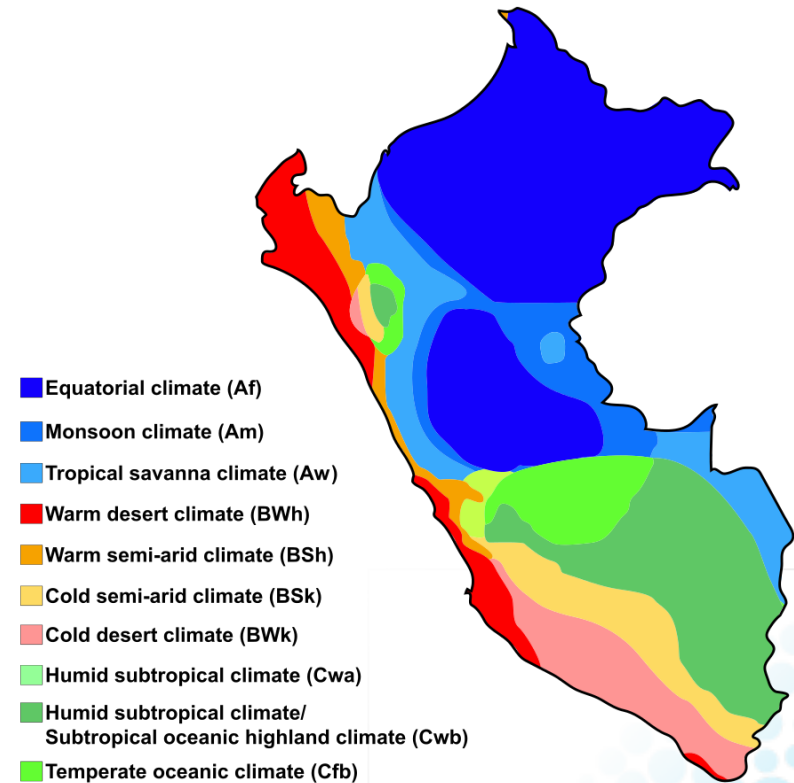
2. Climate Locality

20 stations (Peru + Chile)



- Complicate climate of Peru

Peru map of Köppen climate classification

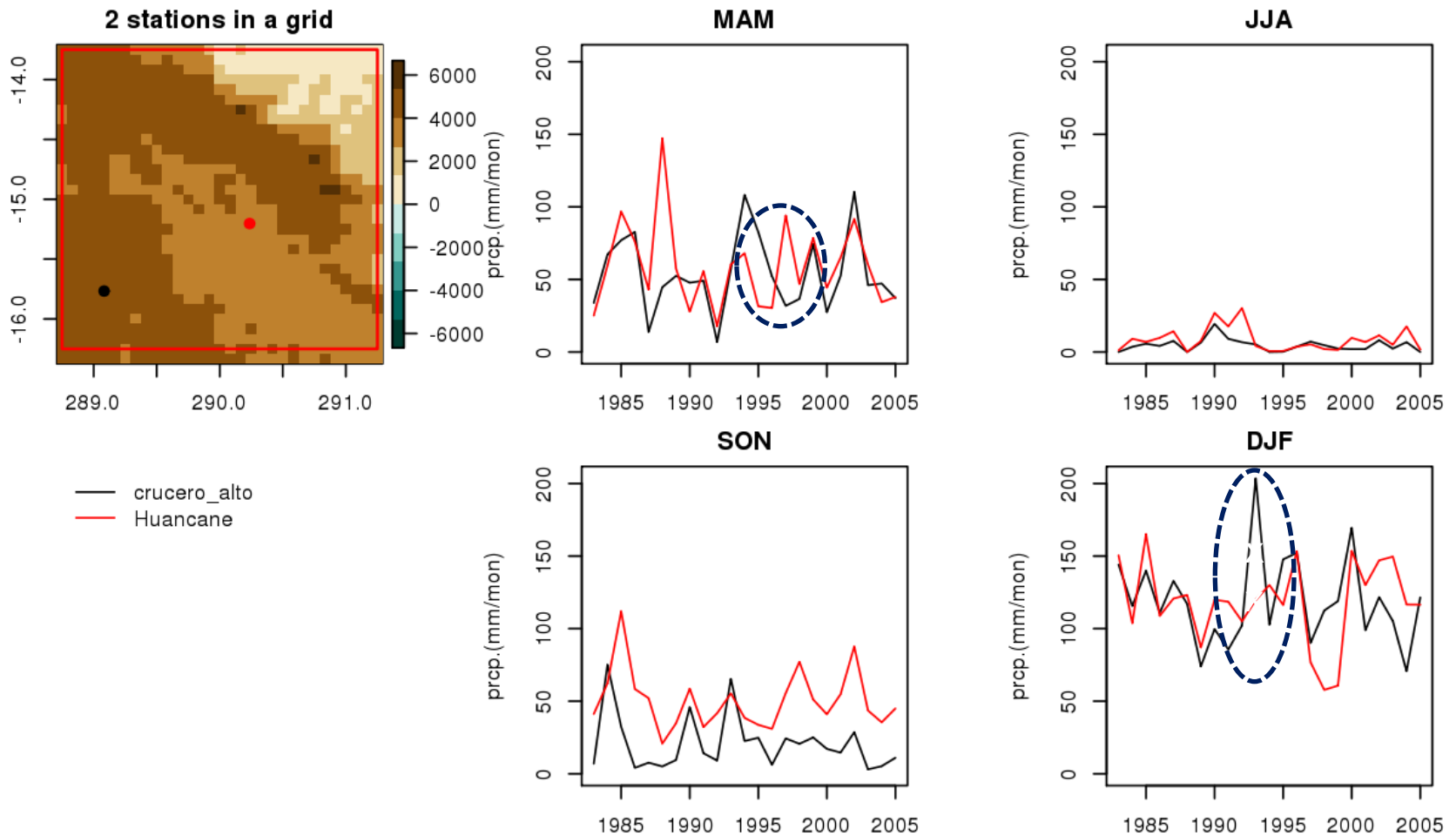


✓ Can 2.5 by 2.5 grid pixel simulate *steep terrain* effect therefore *locality of station climate*? Not really.

2. Climate Locality

How different is the climate between 2 adjacent stations **in the east of Arequipa?**
But, they are in one grid! OMG!!!

East of Arequipa [290, -15]





What is downscaling?

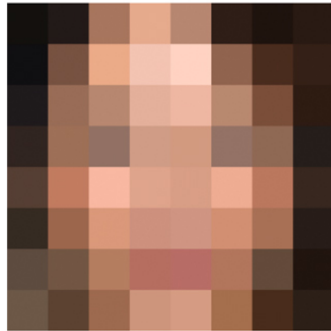


Who are you?



Google uses AI to sharpen low-res images

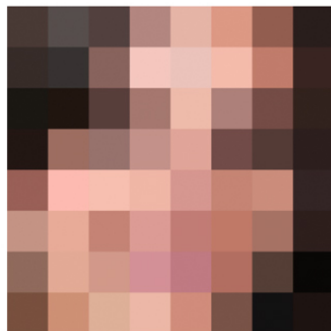
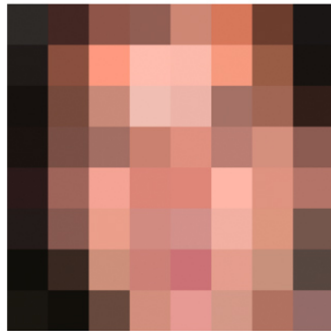
8×8 input



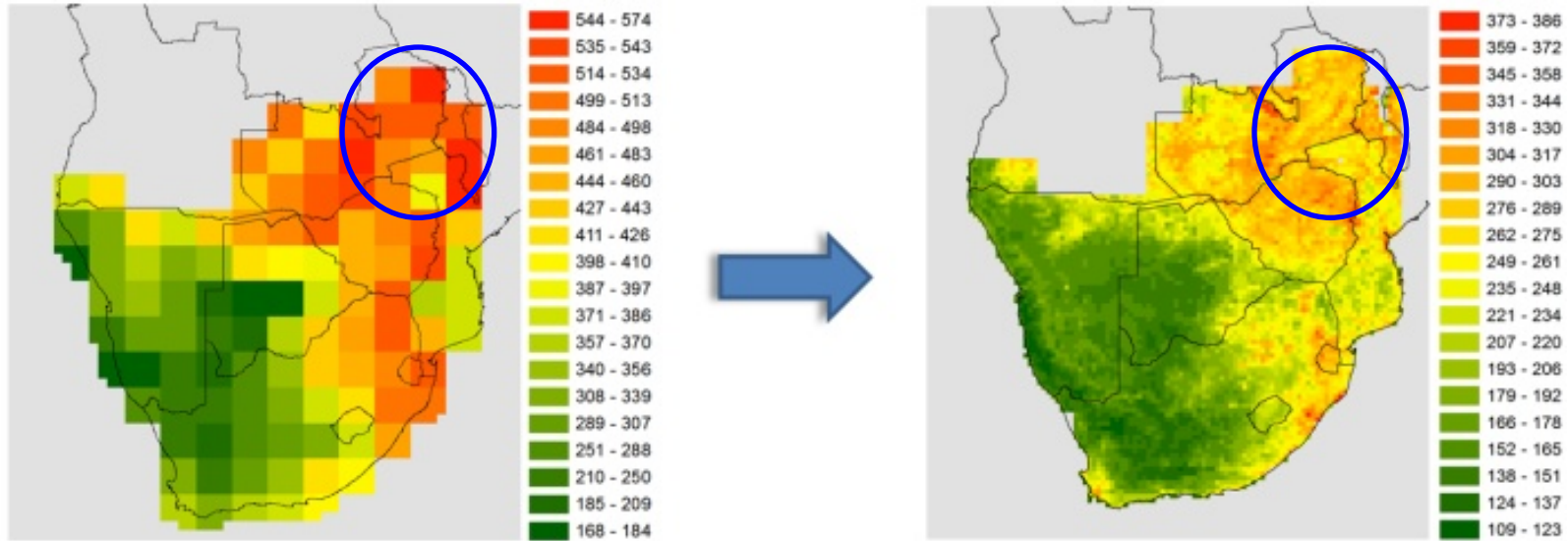
32×32 samples



ground truth



Downscaling/tailoring



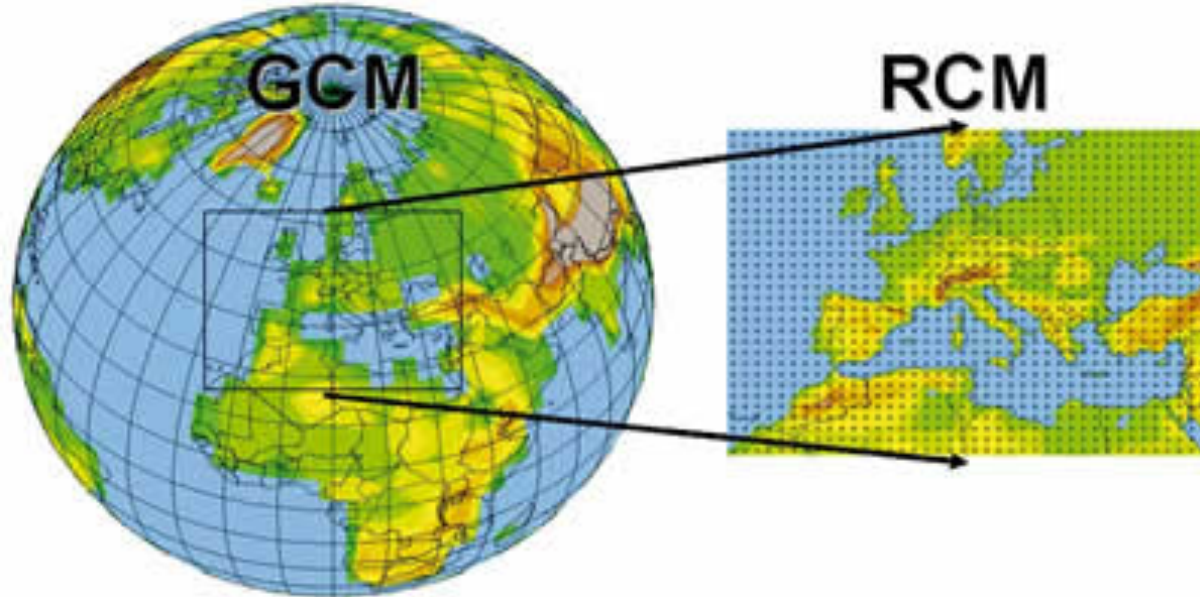
In seasonal prediction,
how to draw the **information of a particular “point”** from **COARSE grid model data** ?

We need *extra information* to downscale!

How to overcome?

- Resolve the (dynamical/physical) process determining sub-grid scale point value
- Find a ***relationship between the point and large scale pattern***

What is dynamical downscaling?



- Simply, it is running a regional climate model (RCM).

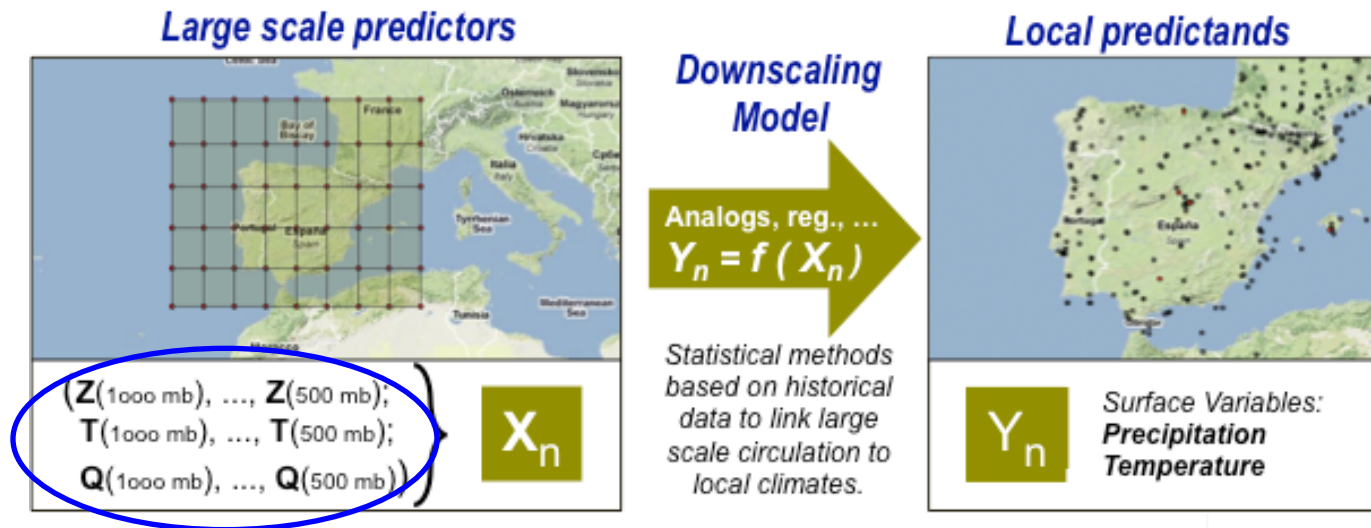
- BC from GCM, IC \rightarrow solving dynamic equations!

- 1 month computing time for 1 month prediction ?

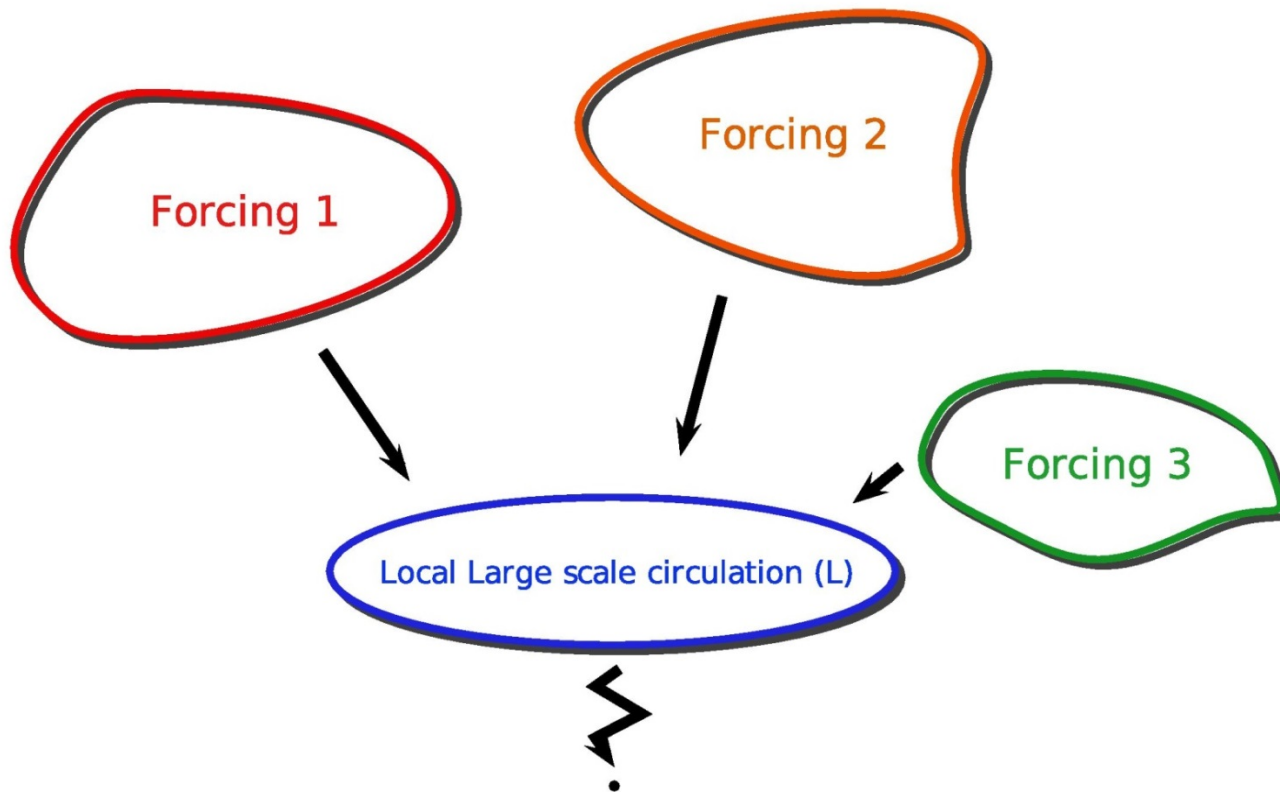


Empirical-statistical downscaling

- Based on empirical relationship between **precipitation/temperature** at particular stations and **in-situ/remote large scale Atmospheric/Oceanic condition**
- Developing simple downscaling model (regression)



Local large scale circulation



Local weather statistics (Korean summer rainfall)

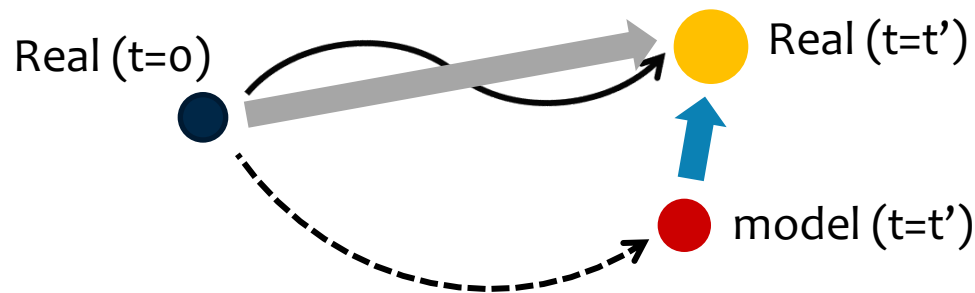
Approach

- Statistical downscaling forecast 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 & $j = 1$: Linear regression
 $i > 1, j = 1$: Multiple regression
 i & $j > 1$: CCA, SVD, etc

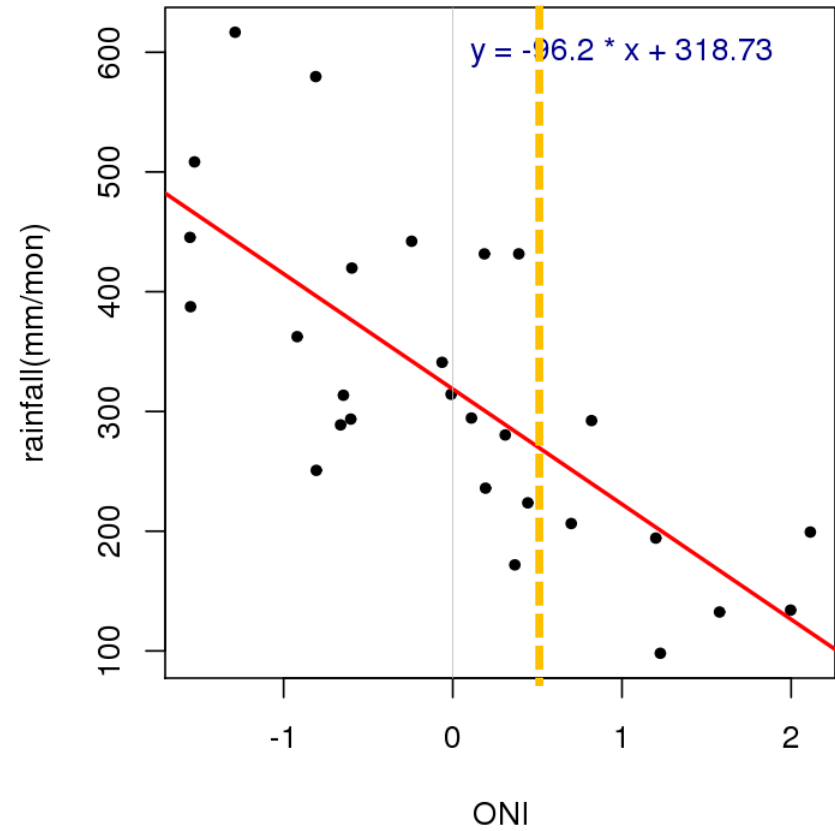
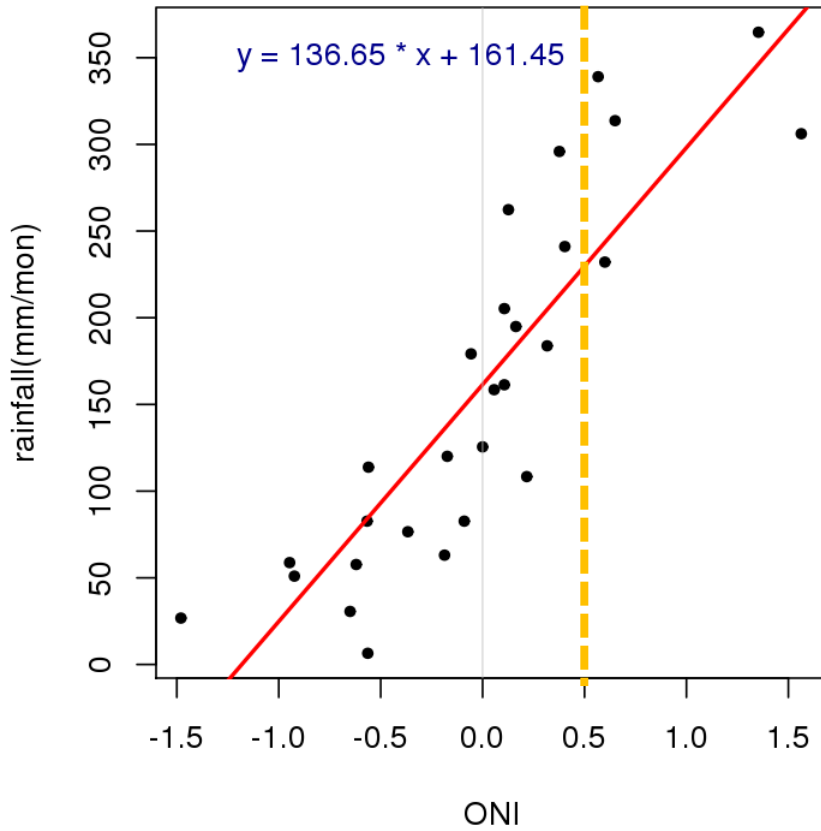
Regression concept!

Scatter plot & least square fitting!

$$Y = a * x + b$$

x: predictor (ONI)

y: predictand (rainfall)

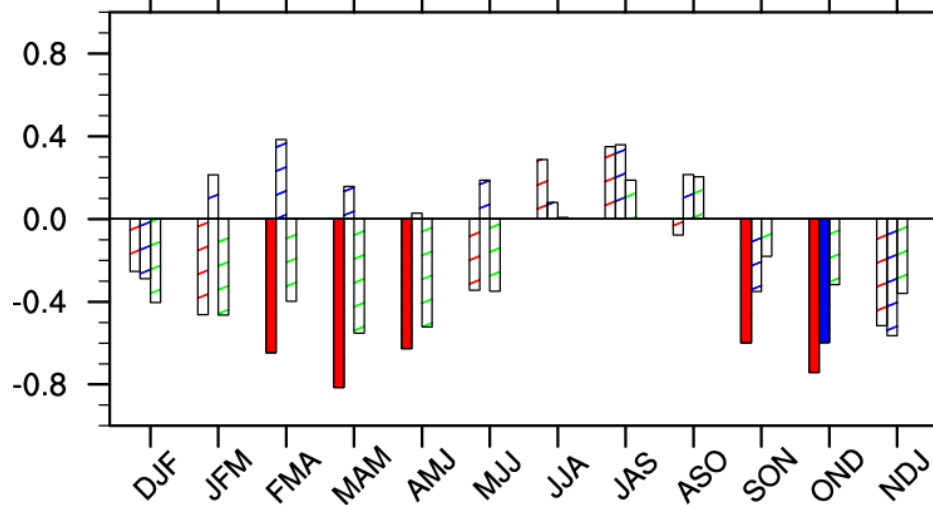


e.g. simply utilizing Climate Indices

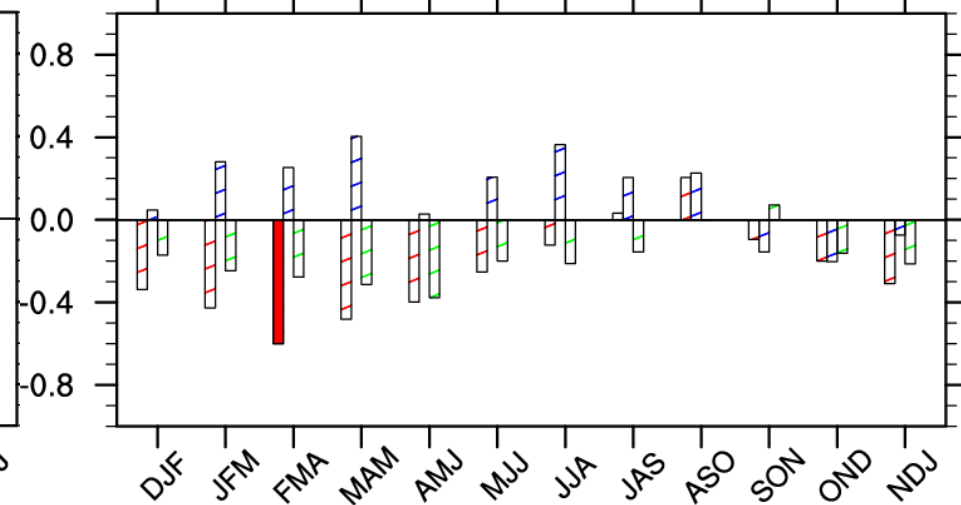
- TCC for 1987-2000

Climate indices vs. prec over Thai

Ranong



Songkhla



— ONI — IOD — IOBW

Pros and Cons

Advantages	Disadvantages
Statistical Downscaling is relatively easy to produce.	There are assumptions of stationarity between the large and small scale dynamics when using statistical downscaling.
Impact-relevant variables not simulated by climate models can be downscaled using statistical downscaling.	Small scale dynamics and climate feedback are not reflected when statistical downscaling is used.

<http://www.glisacclimate.org>



How downscaling is formulated in CLIK?

:Based on **large scale pattern** associated with local temperature/rainfall



CLIK downscaling

➡ A way to **localize** existing coarse climate information

CLIK downscaling is mainly based on station to Large Scale Meteorological Field (LSMF) relationship. ($Y = a \cdot X + b$) By utilizing the simulated LSMF (X, predictor), CLIK estimates seasonal mean precipitation/temperature (Y, predictand) at specific station.

Dynamical fcst.

Simulated LSMF from
Individual models

- Hypothesis: The station to LSMF relationship is well replicated in individual models

Statistical dwncsc.

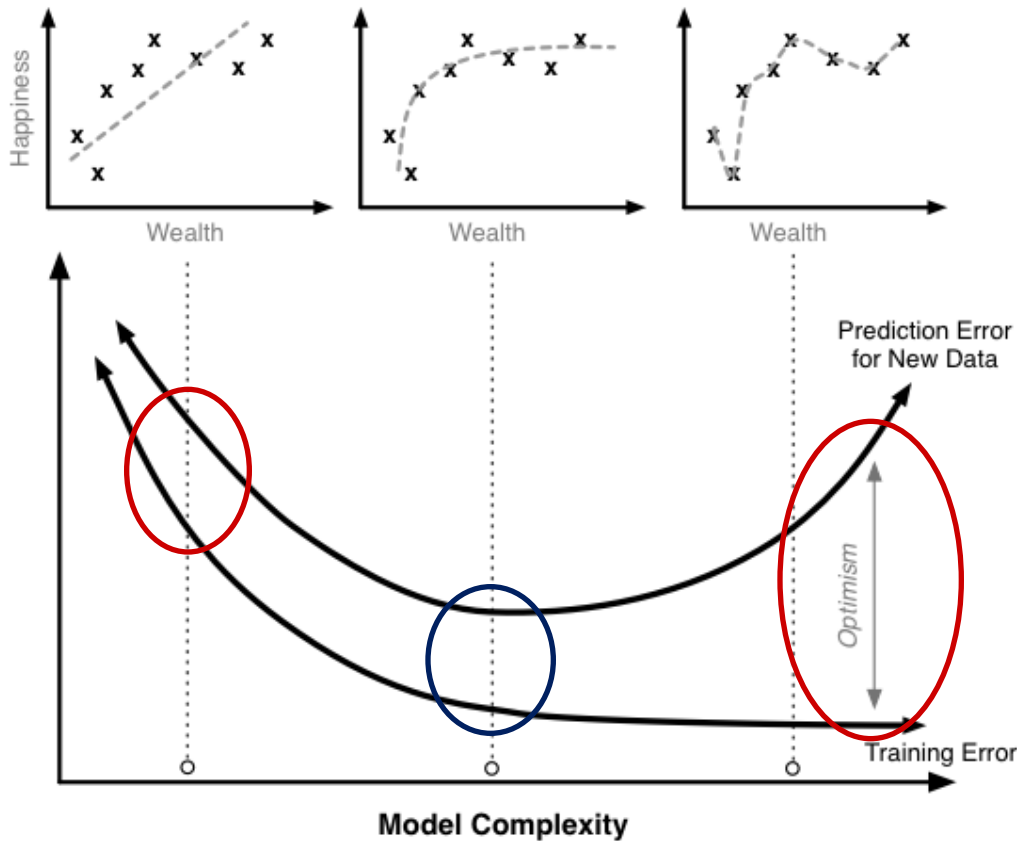
Station to LSMF
regression
relationship

- Predictor: LSMF
- Predictand: Prec. at specific station

A kind of hybrid system
for point-wise seasonal forecast

Weakness : **overfitting**

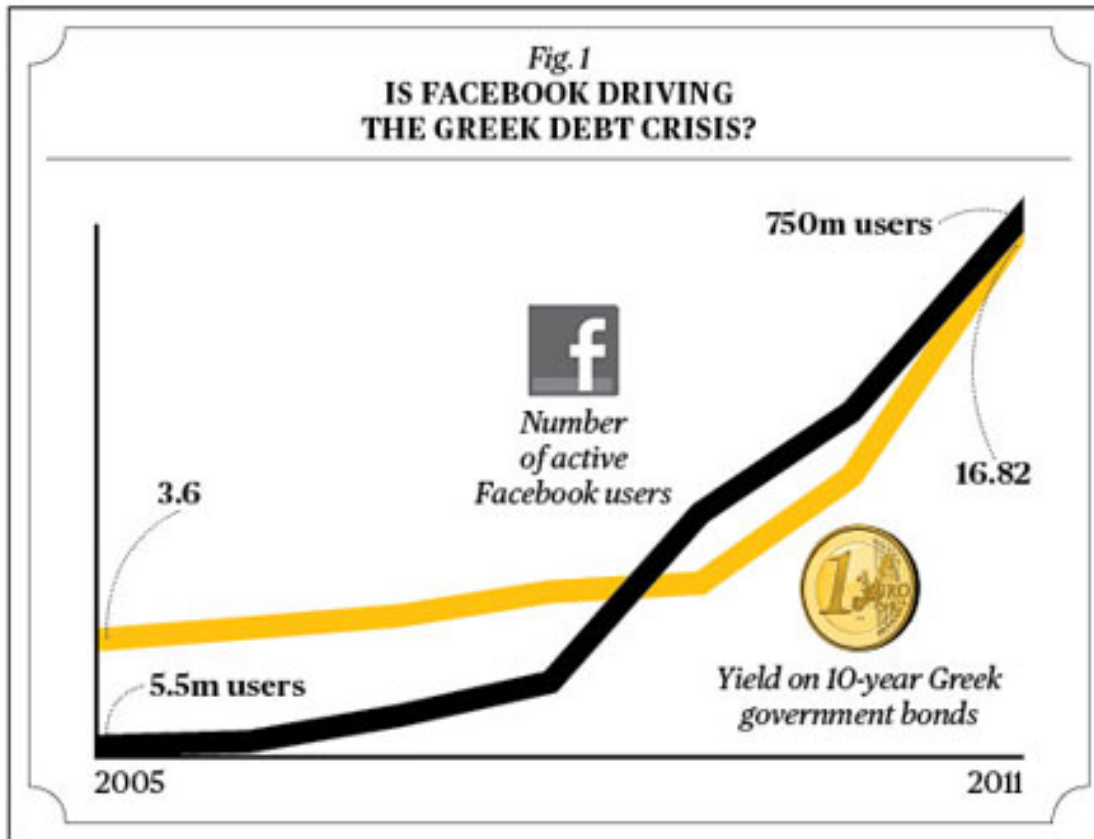
■ Consider potential predictability



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

Predict yield of Greek bonds with number of Facebook users

Is it appropriate?



If yes, why?

If not, why?

From *business week*

Predict global average temperature with Carbon dioxide concentration

Is it appropriate?

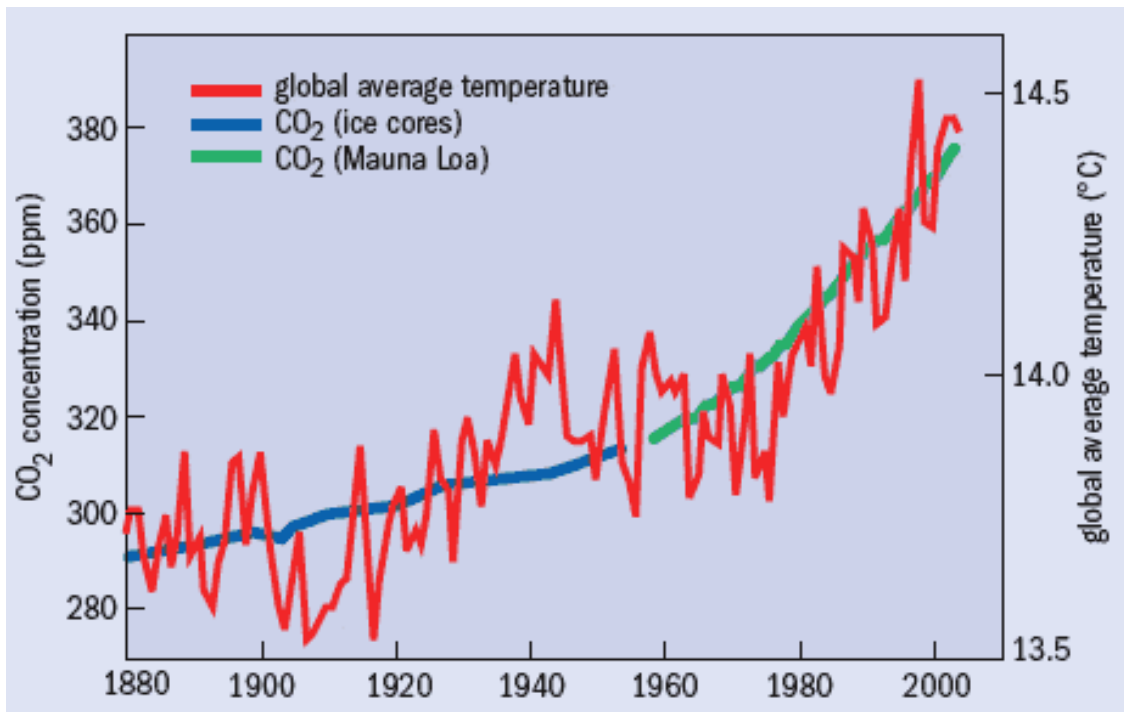


Image Source: images.iop.org

If yes, why?

If not, why?

The most important things...

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

→ Finding **predictors** (large scale meteorological patterns (circulations) associated with local prcp/temp of your station)
2. whether GCM (MME) is able to reproduce those patterns/relationship?

→ **Applicability** of downscaling



Example of Domain Selection

:should be based on **large scale pattern** associated with local temperature/rainfall

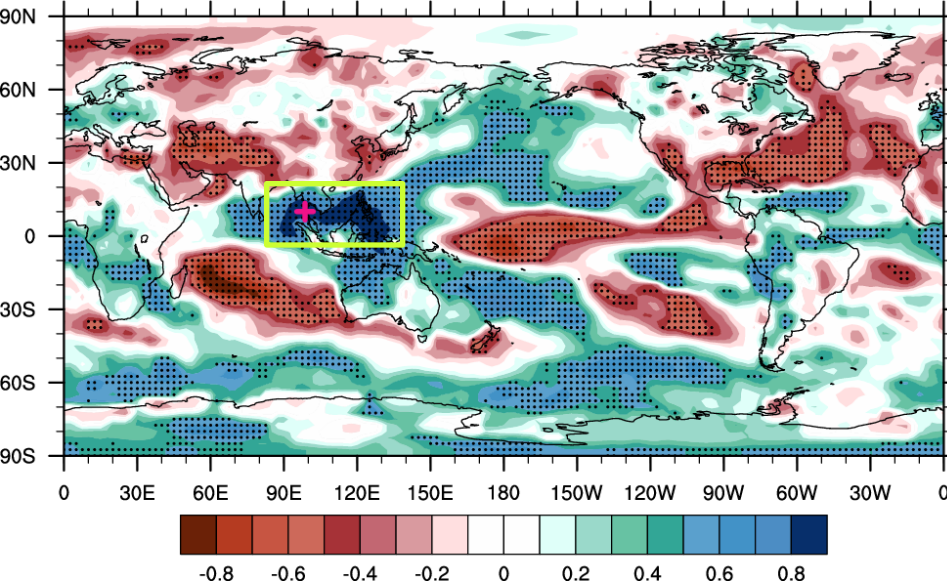


Station to LSMP relationship

OBS (Reanalysis)

prec vs. prec over Ranong

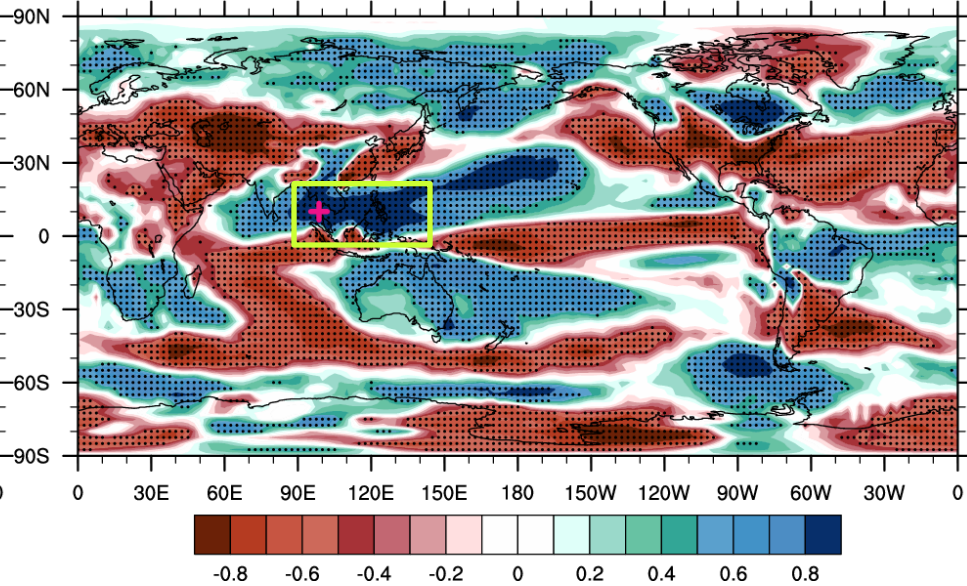
MAM



Model (SCM)

prec (scm) vs. prec over Ranong

MAM



Large-scale rainfall system over Maritime Continent:

LR \uparrow \rightarrow Ranong rain \uparrow

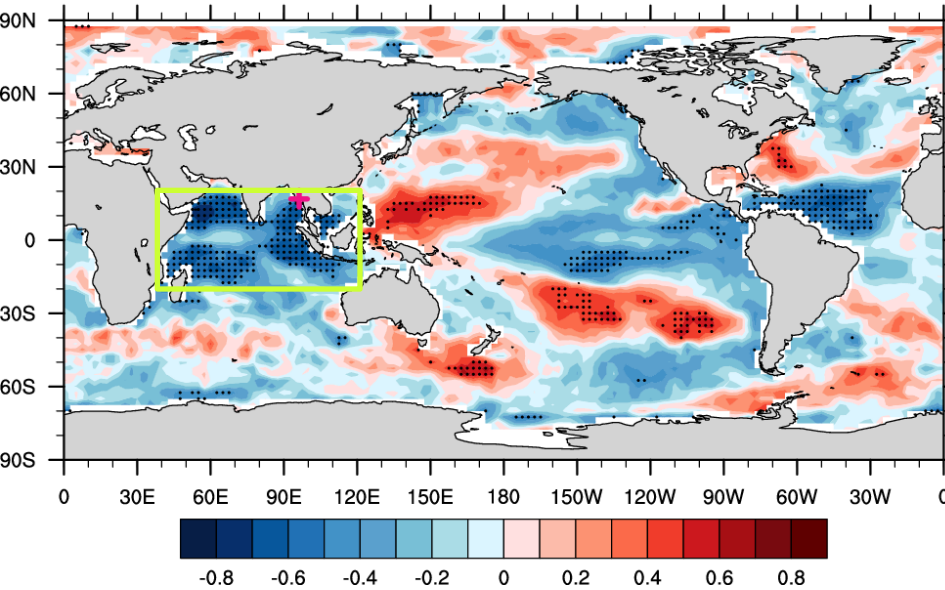
LR \downarrow \rightarrow Ranong rain \downarrow

Station to LSMP relationship

OBS (Reanalysis)

sst vs. prec over Yangon

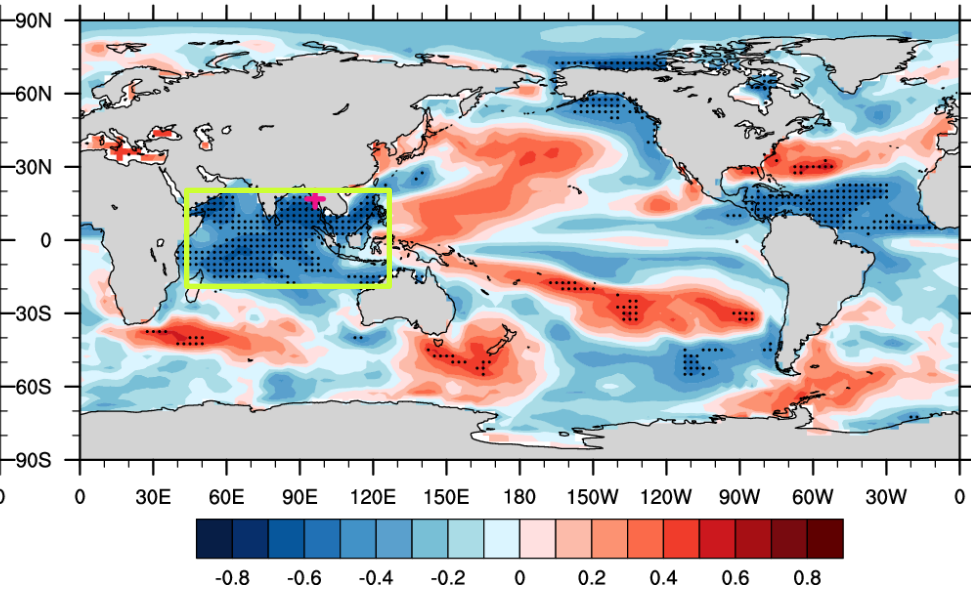
MJJ



Model (SCM)

sst (scm) vs. prec over Yangon

MJJ



Indian Ocean Basin-wide Cooling:

SST ↓ → Yangon rain ↑

SST ↑ → Yangon rain ↓

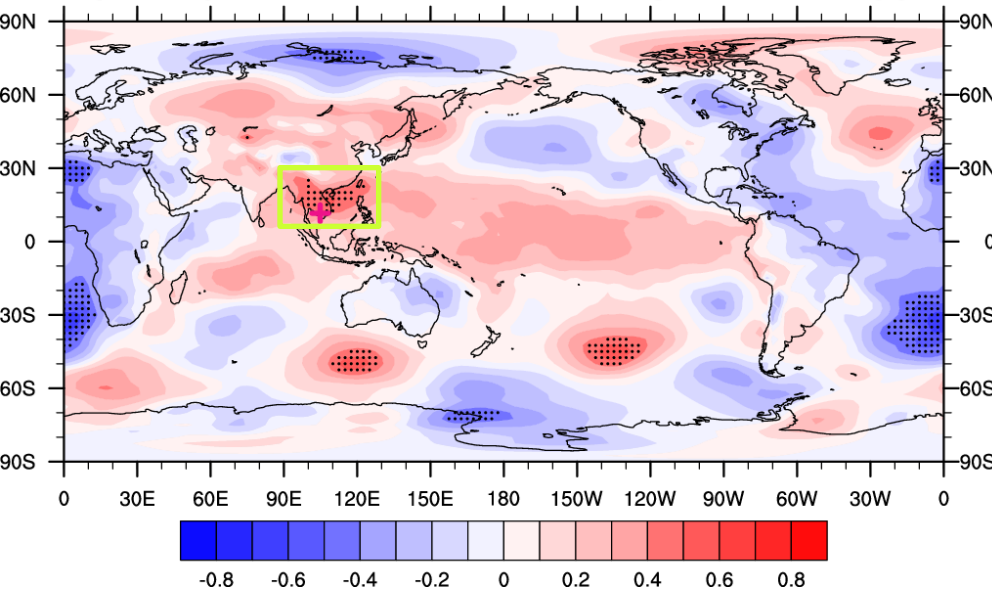
Station to LSMP relationship

OBS (Reanalysis)

Model (SCM)

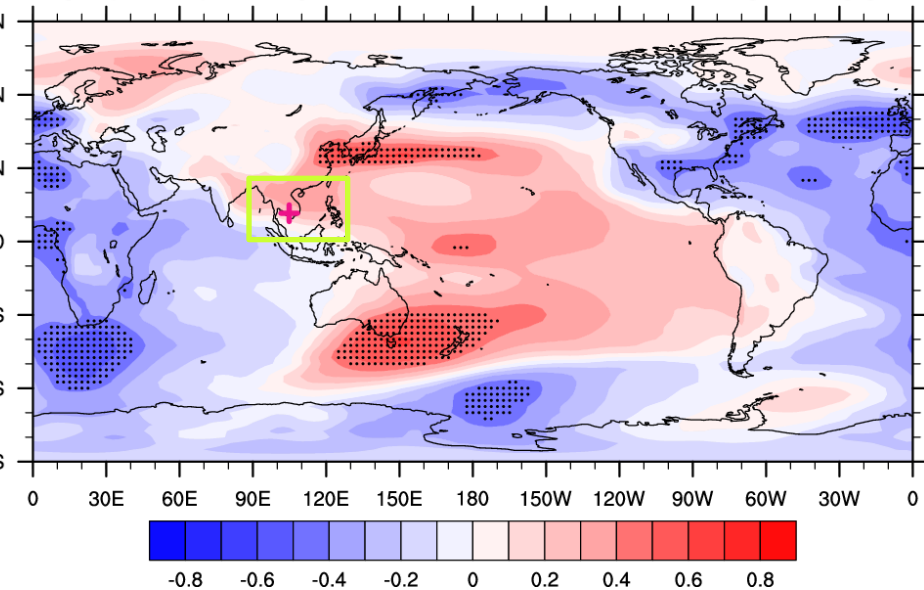
slp vs. prec over Phochentong

JJA



slp (scm) vs. prec over Phochentong

JJA



Low pressure system:

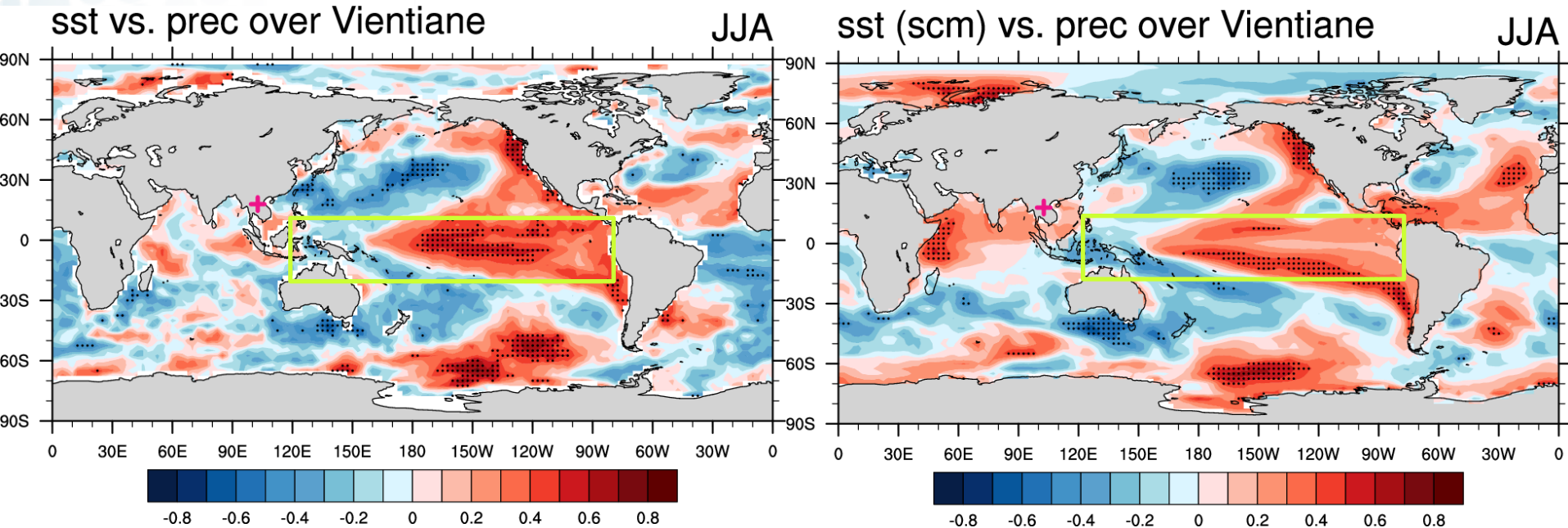
Pressure ↓ → Phochentong rain ↑

Pressure ↑ → Phochentong rain ↓

Station to LSMP relationship

OBS (Reanalysis)

Model (SCM)



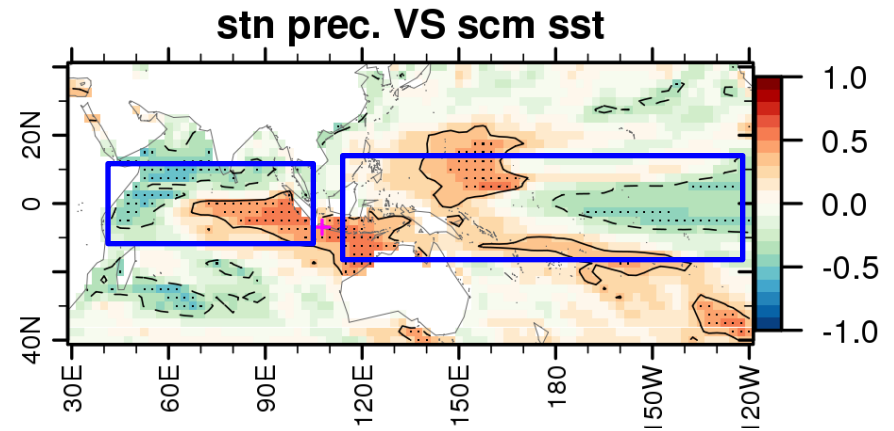
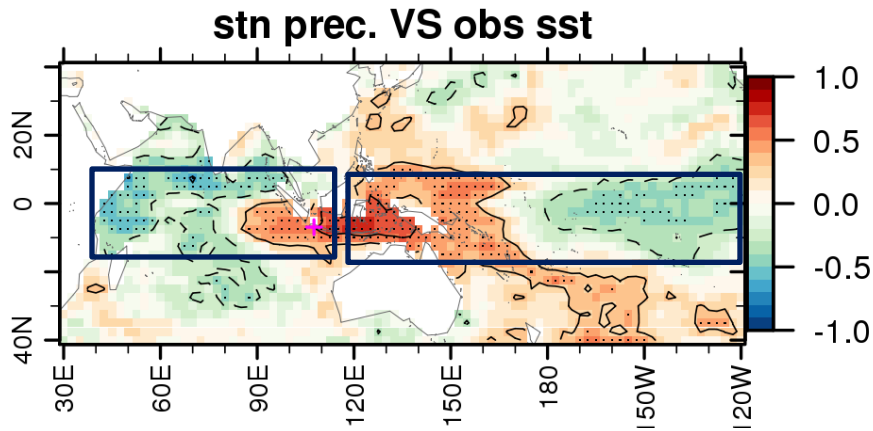
ENSO system:

El Nino → Vientiane rain ↑

La Nina → Vientiane rain ↓

Maritime Continent: Indonesia

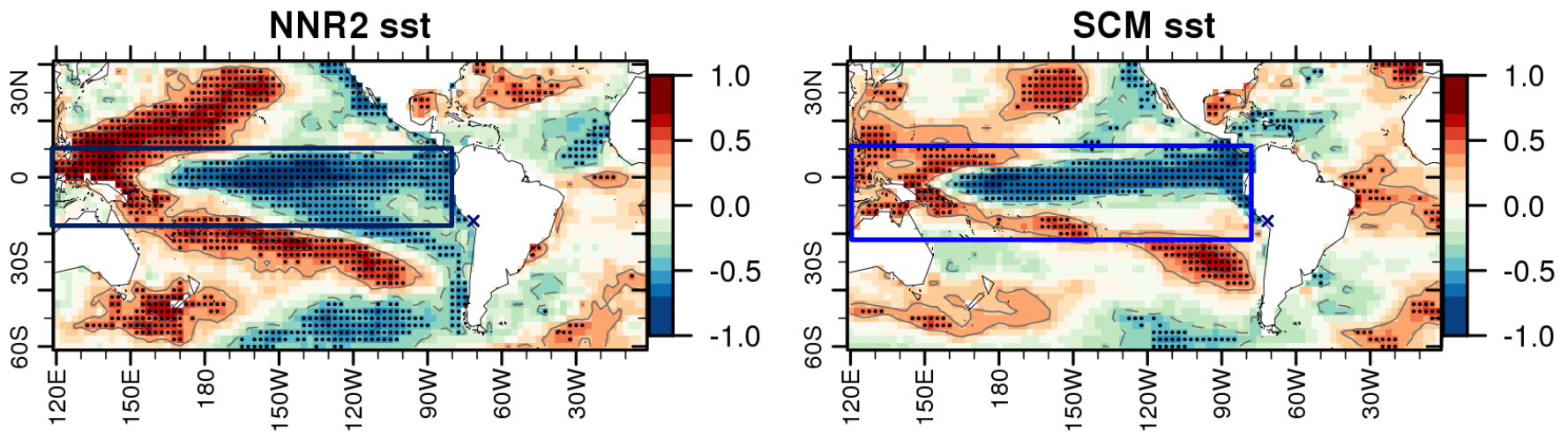
SON [Jakarta]



La Nina (and negative IOD) signature

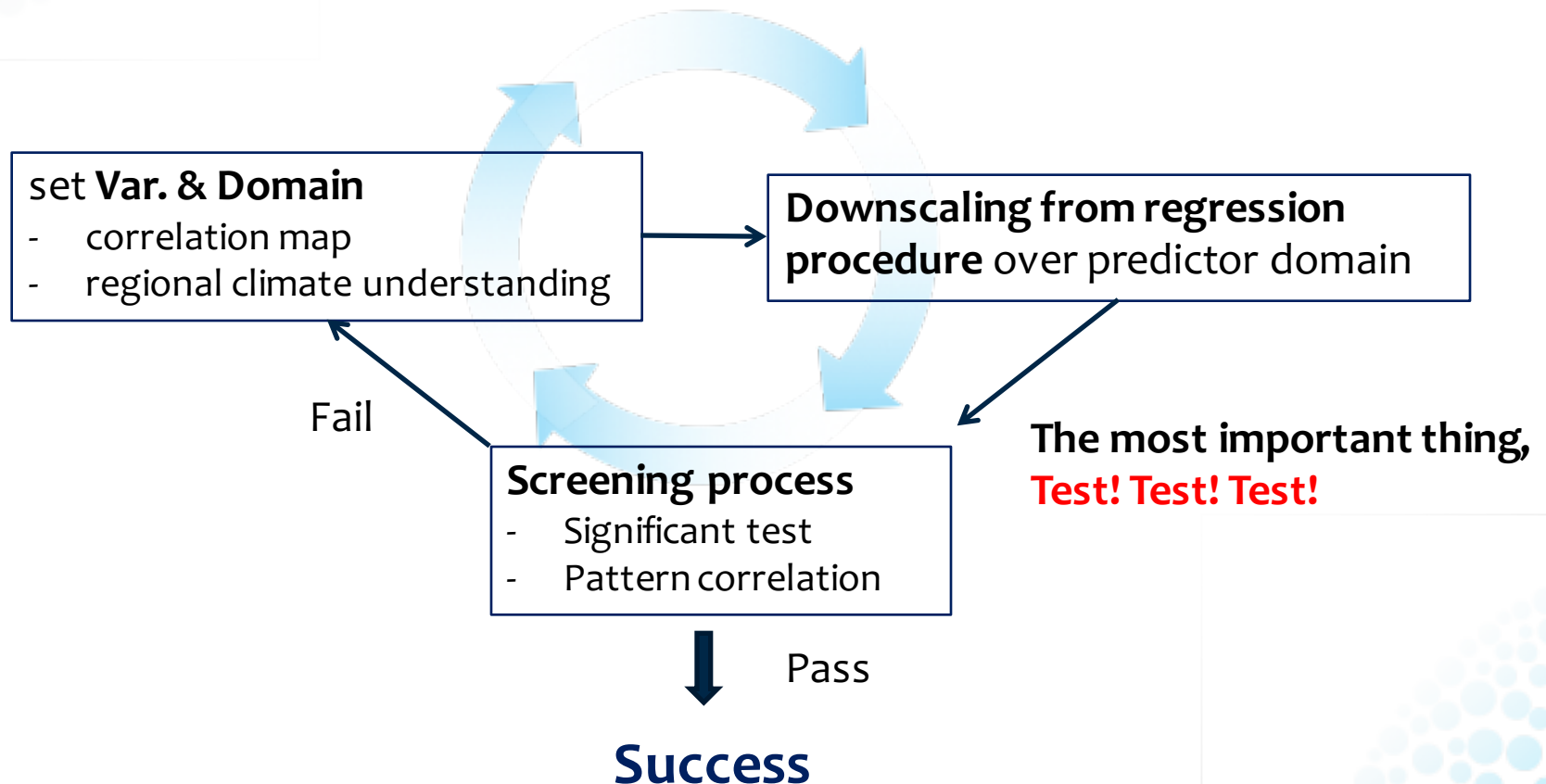
West South America: Sibayo

sibayo [FMA]



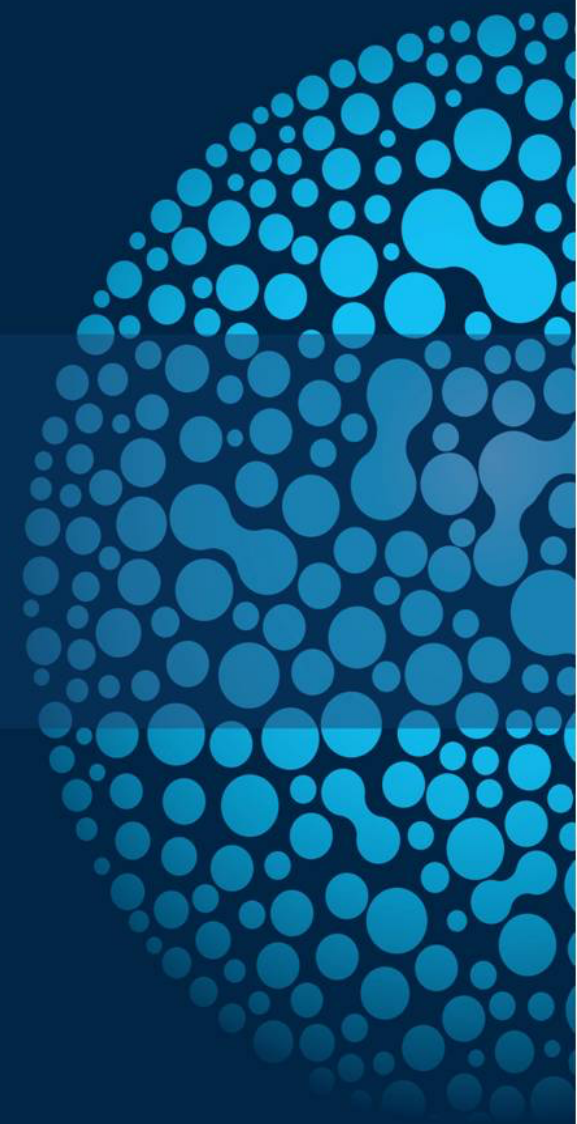
La Nina signature

CLIK downscaling procedure



Lecture 4-2
**Evaluation of
seasonal prediction**

Yun-Young Lee



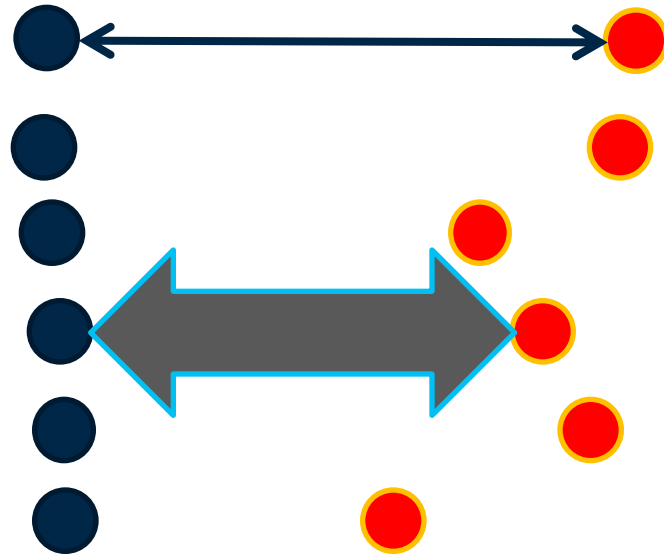
How GOOD?

- Evaluation of forecast : verification



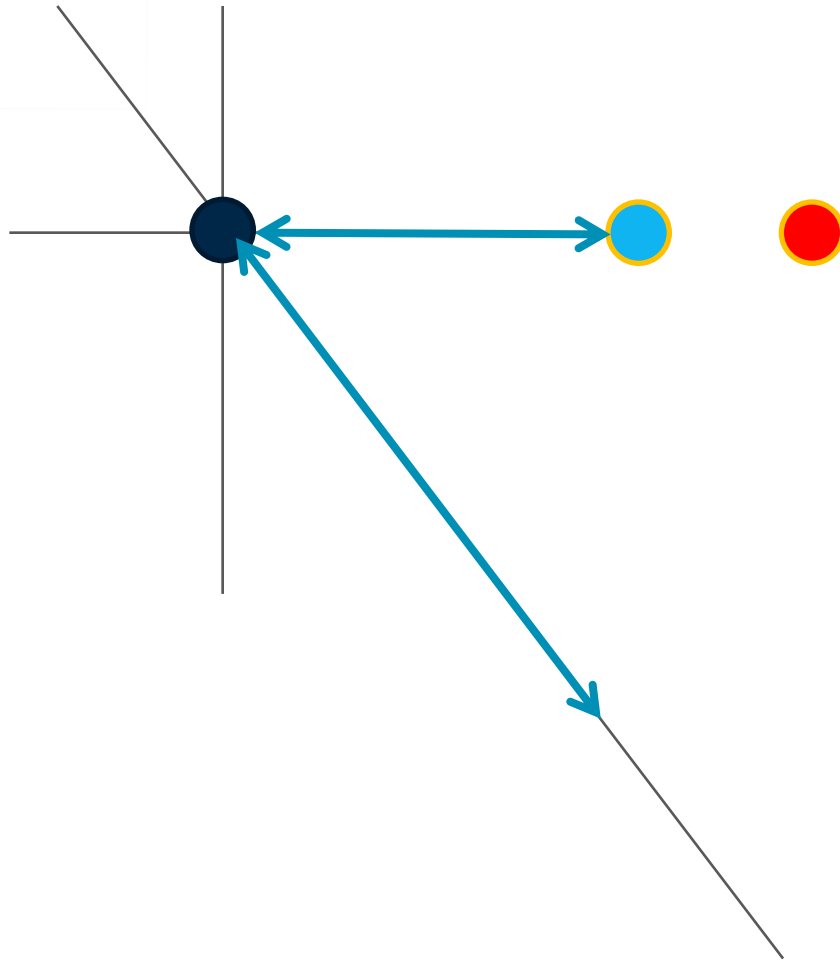
Verification

- Evaluation : measure of closeness



Verification

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



Deterministic 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

- ACC (Anomaly correlation, Pattern), TCC (Temporal correlation)

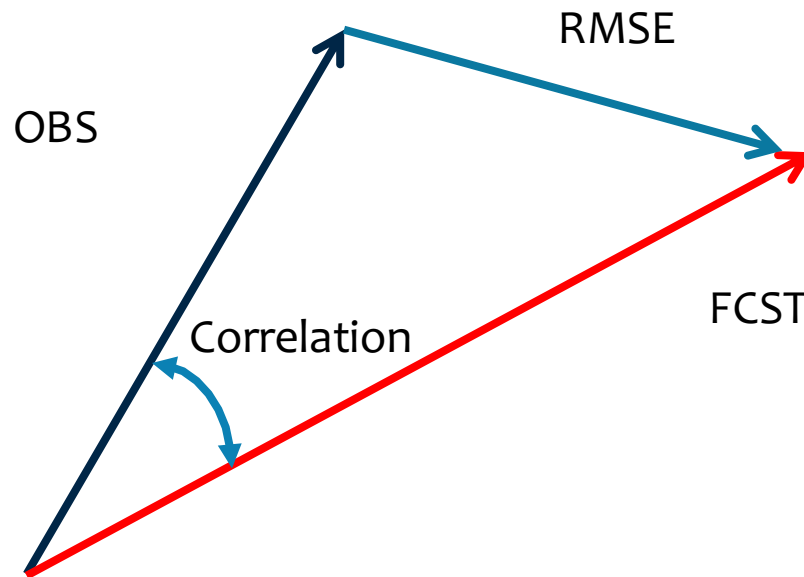
$$ACC = \frac{\sum_{i=1}^N w_i (f_i - \bar{f})(o_i - \bar{o})}{\sqrt{\sum_{i=1}^N w_i (f_i - \bar{f})^2 \sum_{i=1}^N w_i (o_i - \bar{o})^2}}$$

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

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

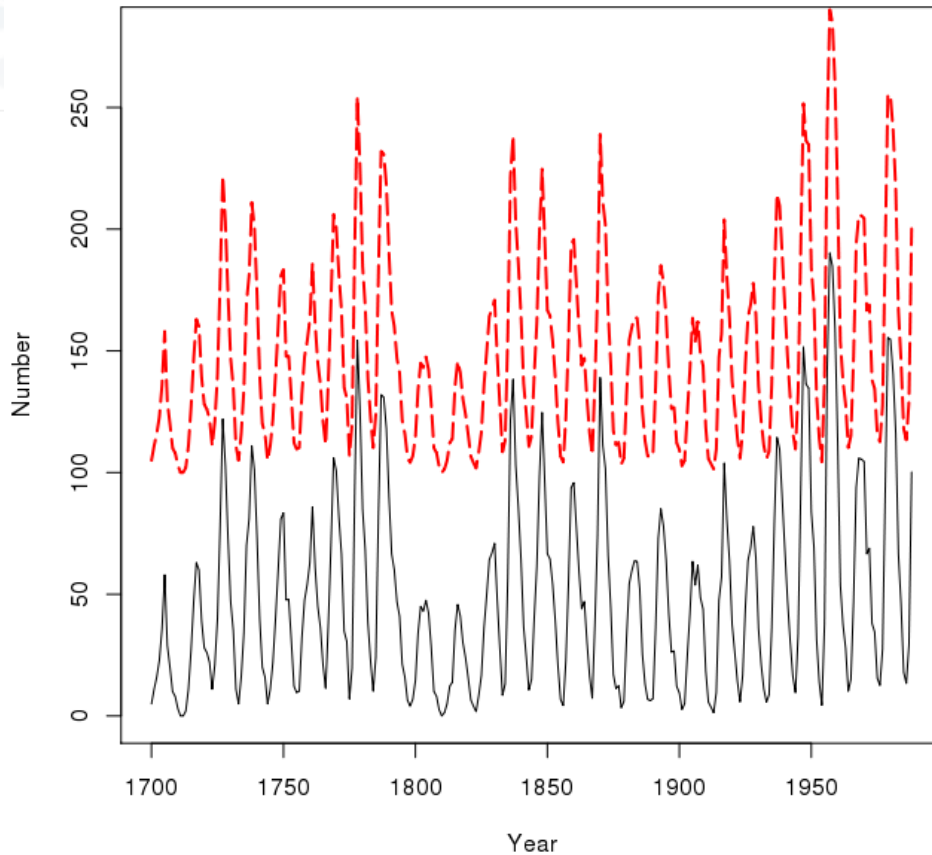
Verification

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



Examples

Sunspot Number



$F(t)$

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

RMSE?

But, 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, High value = High Score?

■ Brier Skill Score (BSS)

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

BS : error/penalty,

BS_c: BS of climatology forecast

Range: -infinity to 1

Perfect score = 1

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

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

Probabilistic forecast (Categorical)

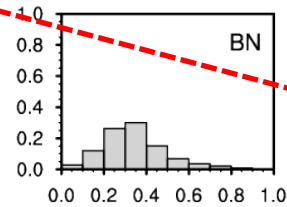
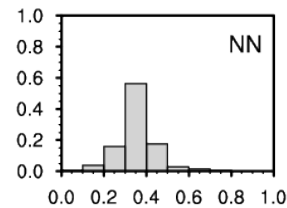
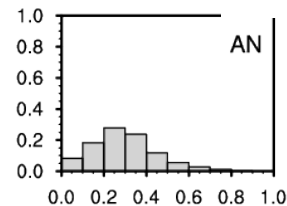
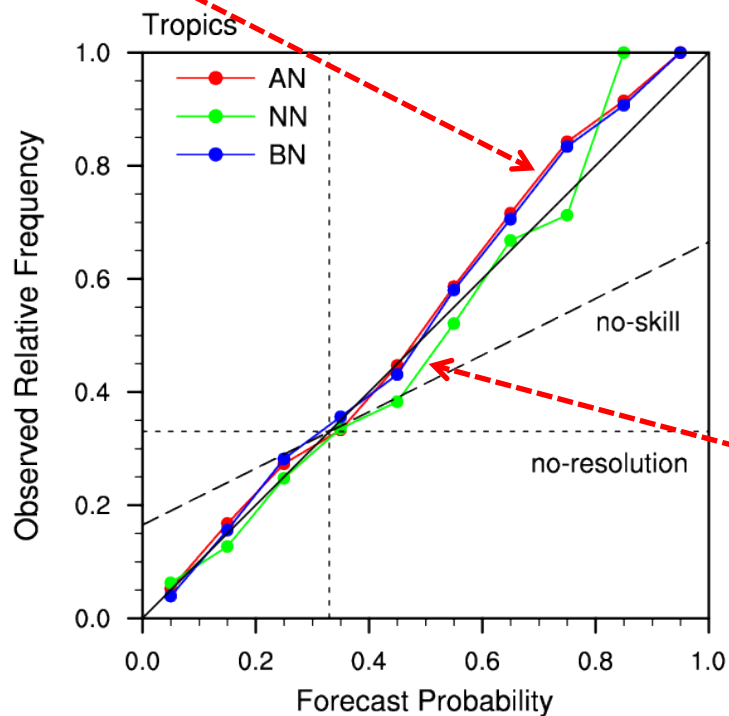
Reliability curve

Accurate probability forecast system

- ✓ Reliability
- ✓ Sharpness
- ✓ Resolution

Underforecasting

Reliability Diagram : PREC, JAS (1983-200)



Frequency Histogram

overforecasting

Probabilistic forecast (Categorical)

		O	
		Yes	No
F	Yes	Hit (H)	False Alarm (F)
	No	Miss (M)	Correct Rejection (C)

“rain” “no rain”

Correct forecast

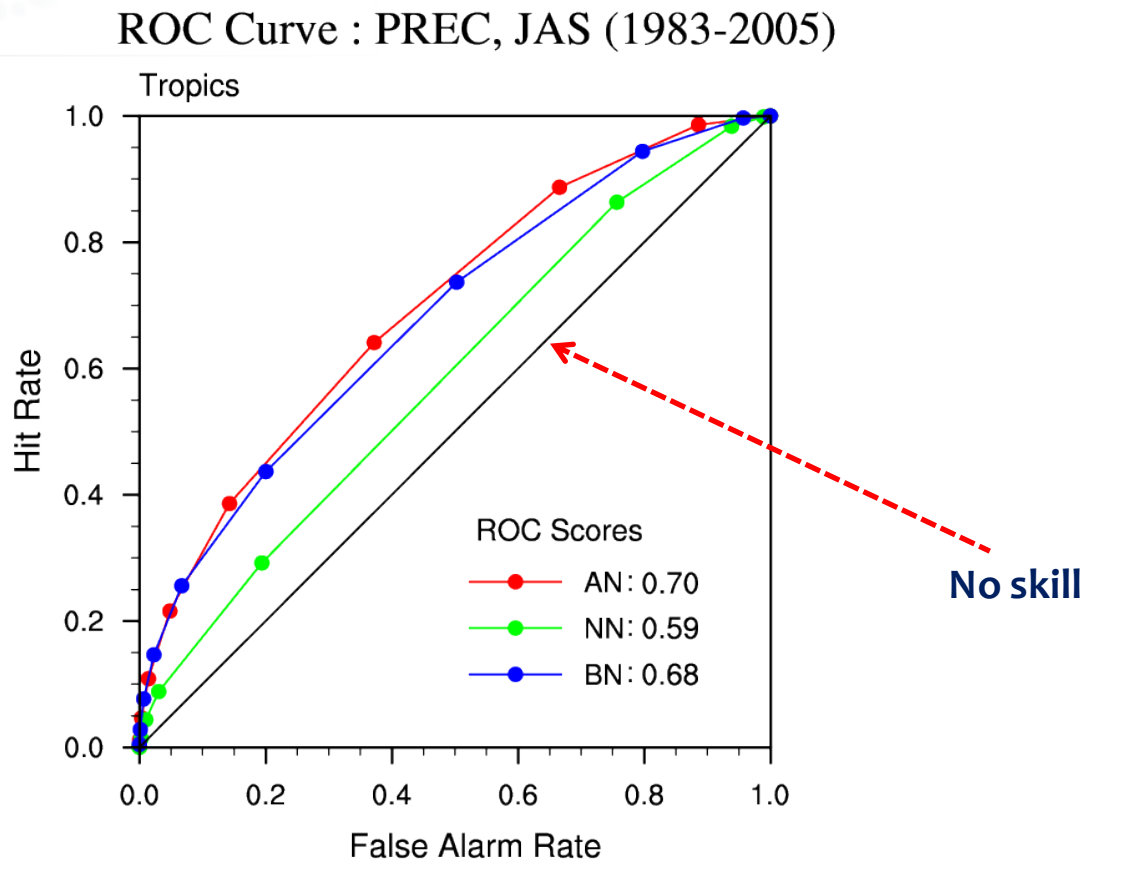
- HR (Hit rate) = $H/(H+M)$
0 to 1, perfect score = 1

- FAR (False Alarm rate) = $F/(F+C)$
0 to 1, perfect score = 0

Good forecast: HR \uparrow , FAR \downarrow

Probabilistic forecast (Categorical)

ROC (Relative Operating Characteristics)

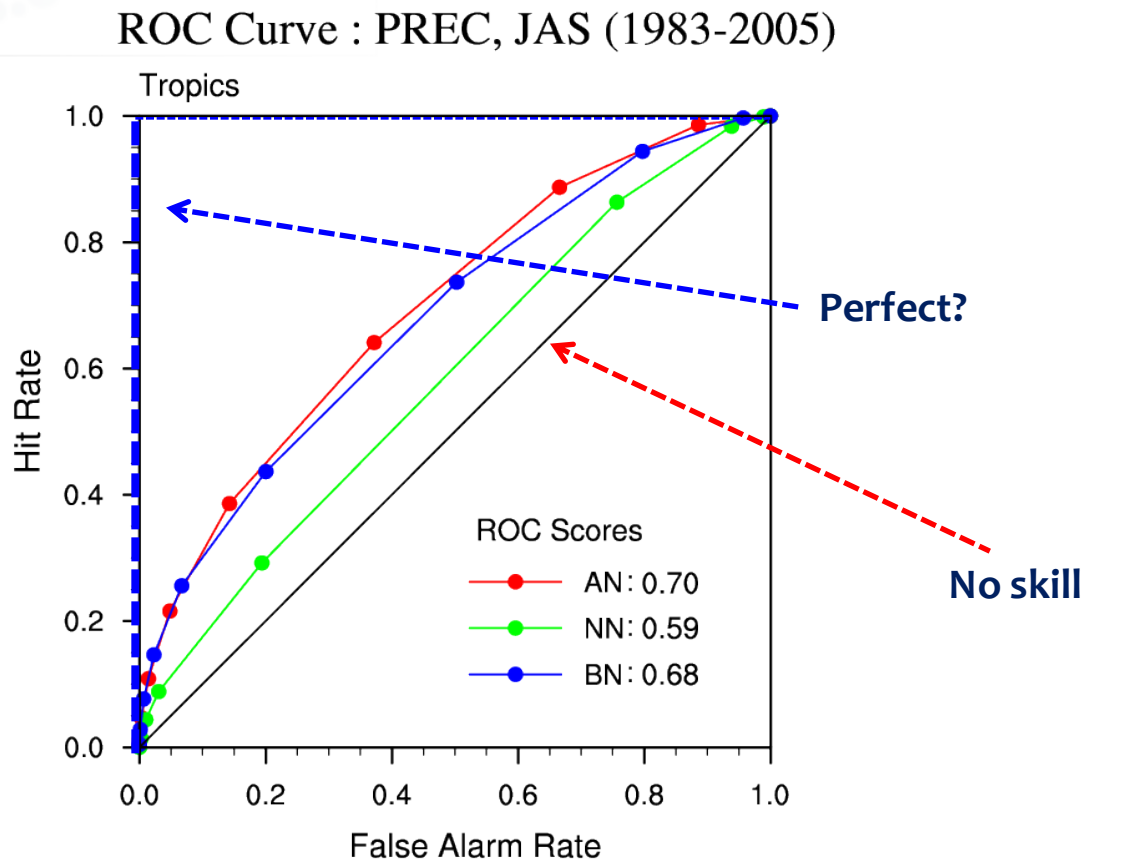


ROC score
=Area of ROC curve

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

Probabilistic forecast (Categorical)

ROC (Relative Operating Characteristics)

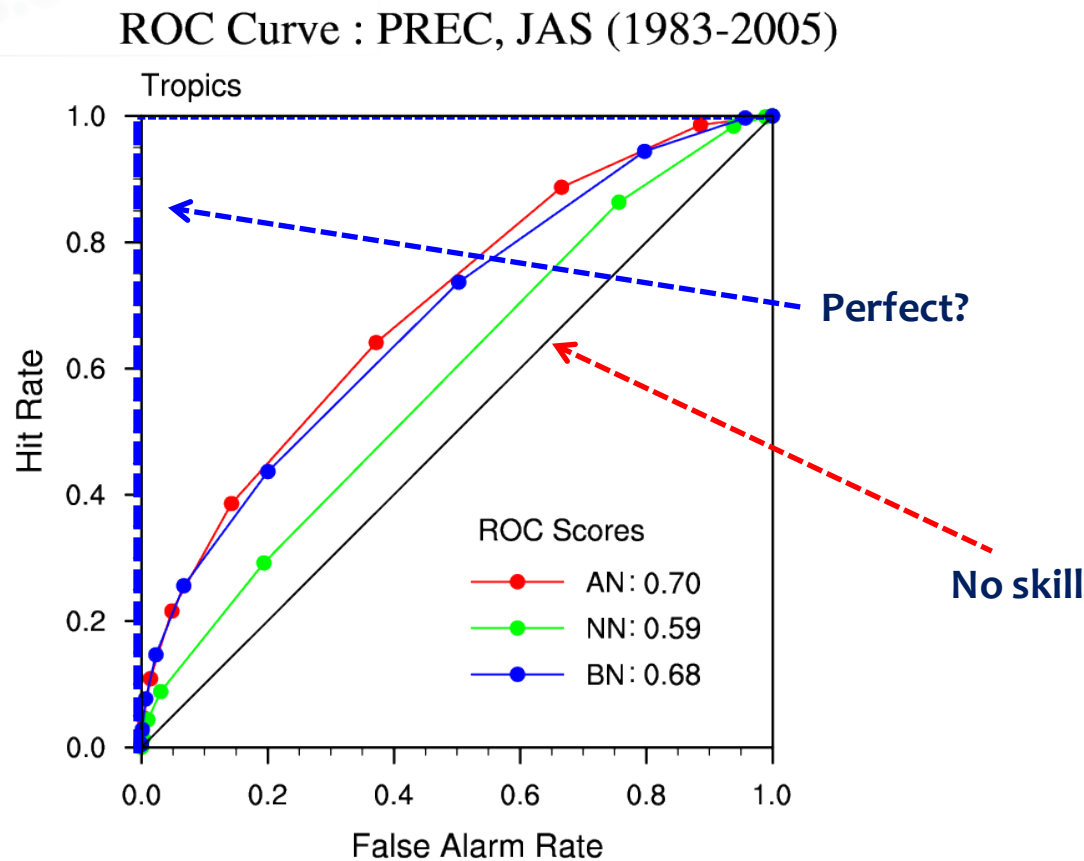


ROC score
=Area of ROC curve

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?**”

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

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

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

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 Yes : $E = (h+f)C = C$, otherwise $E = mL = \bar{o}L$.

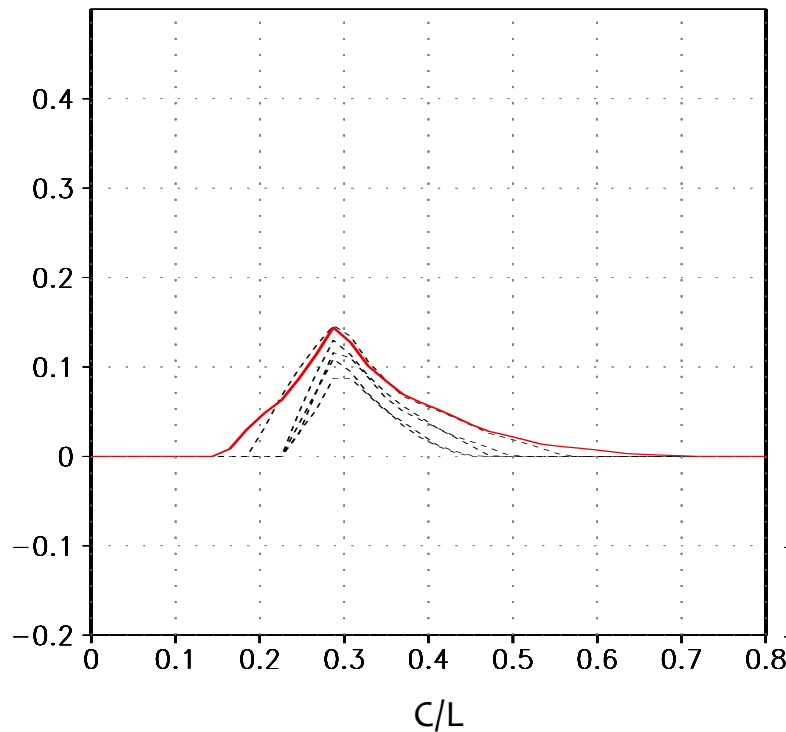
Decision: action of low expense. Thus, $E_{cli} = \min(C, \bar{o}L)$

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

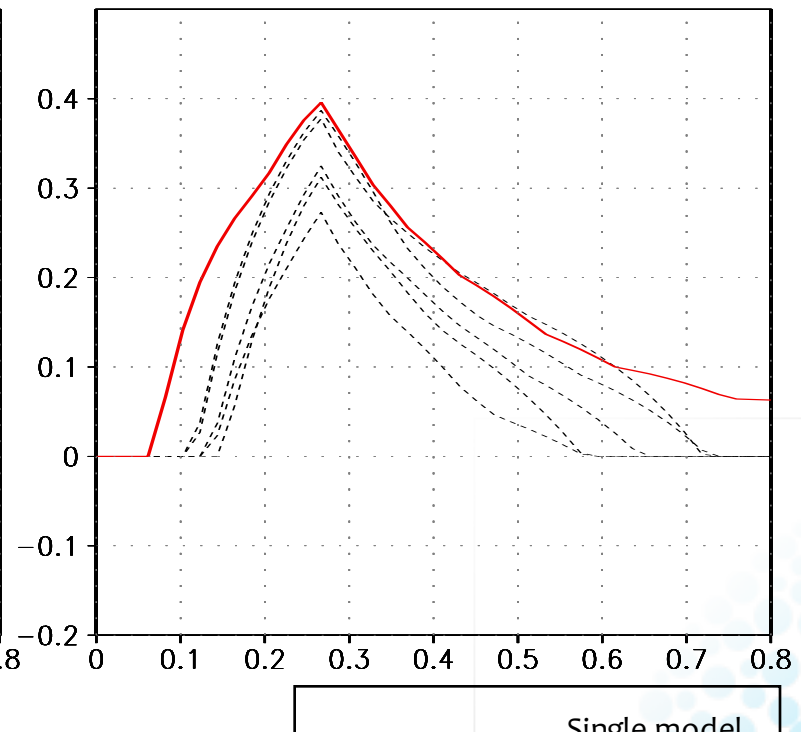
Value of Probabilistic forecast (Above normal) : GCMs

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

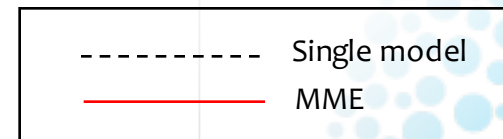
(a) Monsoon(40E-160E,20S~40N)



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



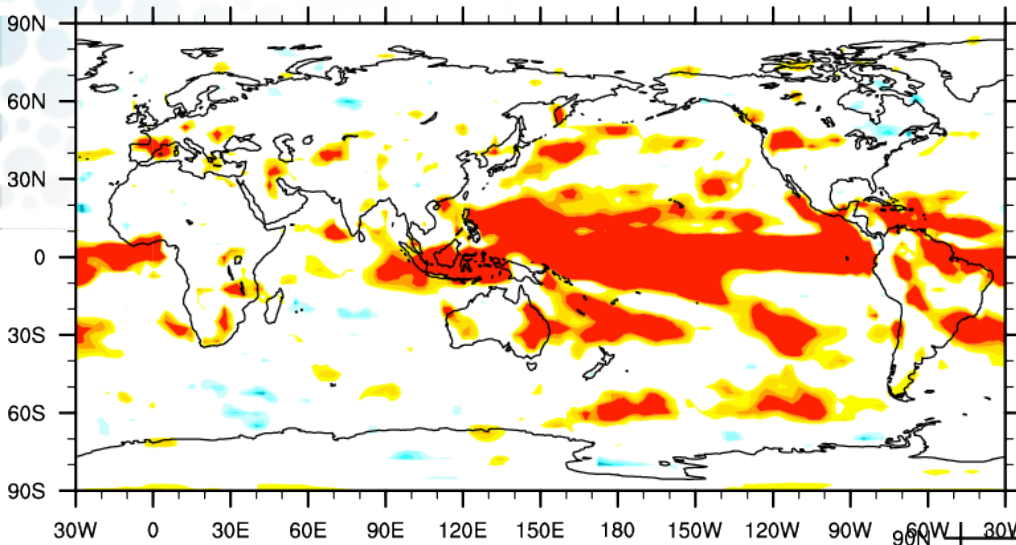
Cost-Loss ratio



Forecast Verification

- Multi aspect evaluation is necessary.
- 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!!!

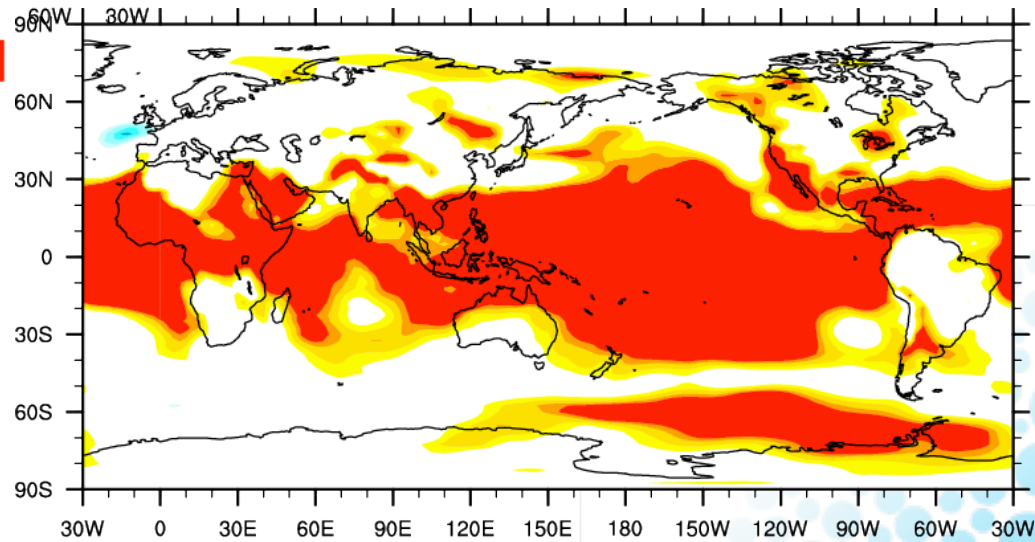
APCC MME (TCC)



Rainfall (JJA)

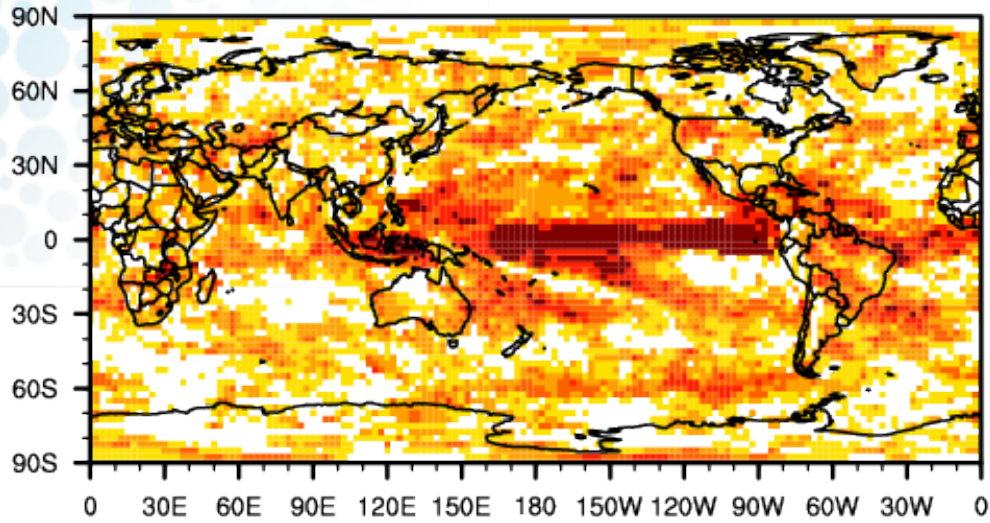


SLP (JJA)

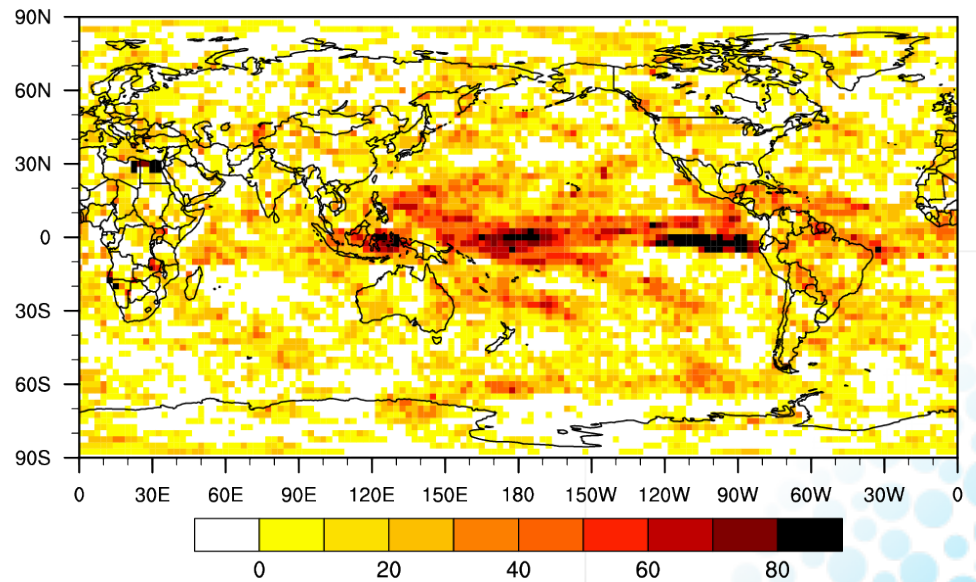


ROC Score : PREC, JJA (1983-2005)

Above-Normal



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





Thank you