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 (NNR2 vs SCM), prec](image_url)
2. Climate Locality

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]**

```
crucebro Alto
Huancane
```
What is downscaling?
Who are you?
Google uses AI to sharpen low-res images

https://www.engadget.com/2017/02/07/google-ai-image-enhancement/
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 → 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 Large scale circulation (L)

Forcing 1

Forcing 2

Forcing 3

Local weather statistics (Korean summer rainfall)
Statistical downscaling forecast based on past forecast

\[ y(s, t) : \text{observation} \]
\[ x(s, t) : \text{forecast} \]

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

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!

\[ Y = a \cdot x + b \]

\( x \): predictor (ONI)
\( y \): predictand (rainfall)
e.g. simply utilizing Climate Indices

- TCC for 1987-2000
# Pros and Cons

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

[http://www.glisaclimate.org](http://www.glisaclimate.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. 

\[ Y = a \times X + b \]

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 dwnc.**
  - 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?

---

from Scott Fortmann-Roe 2012
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?

If yes, why?
If not, why?

Image Source: images.iop.org
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
Model (SCM)
prec (scm) vs. prec over Ranong

Large-scale rainfall system over Maritime Continent:
LR↑ → Ranong rain ↑
LR↓ → Ranong rain ↓
Station to LSMP relationship

Indian Ocean Basin-wide Cooling:
SST ↓ → Yangon rain ↑
SST ↑ → Yangon rain ↓
Station to LSMP relationship

Low pressure system:
Pressure↓ → Phochentong rain ↑
Pressure↑ → Phochentong rain ↓
Station to LSMP relationship

**ENSO system:**
- El Nino $\rightarrow$ Vientiane rain $\uparrow$
- La Nina $\rightarrow$ Vientiane rain $\downarrow$
Maritime Continent: Indonesia

La Nina (and negative IOD) signature
West South America: Sibayo

sibayo [FMA]

La Nina signature
**CLIK downscaling procedure**

- **set Var. & Domain**
  - correlation map
  - regional climate understanding

- **Screening process**
  - Significant test
  - Pattern correlation

- **Downscaling from regression procedure** over predictor domain

- **The most important thing, Test! Test! Test!**

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

Yun-Young Lee
How GOOD?

- Evaluation of forecast: verification

- Excellent
- Good
- Satisfactory
- Poor
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)
    \[ ACC = \frac{\sum_{i=1}^{N} w_i (f_i - \bar{f})(o_i - \bar{o})}{\sqrt{\sum_{i=1}^{N} w_i (f_i - \bar{f})^2 \sum_{i=1}^{N} w_i (o_i - \bar{o})^2}} \]

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

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

\[ F(t) \]
\[ G(t) = F(t) + 100 \]

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

\[
\begin{align*}
\text{skill score} &= \frac{\text{SCORE}_{\text{forecast}} - \text{SCORE}_{\text{reference}}}{\text{SCORE}_{\text{perfect forecast}} - \text{SCORE}_{\text{reference}}} \\
\end{align*}
\]

, 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

Observed Relative Frequency

Forecast Probability

Frequency Histogram

© APEC Climate Center
Probabilistic forecast (Categorical)

<table>
<thead>
<tr>
<th></th>
<th>“rain”</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>“no rain”</td>
<td></td>
</tr>
<tr>
<td>F</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>O</td>
<td>Hit (H)</td>
<td>False Alarm (F)</td>
</tr>
<tr>
<td>Yes</td>
<td>Miss (M)</td>
<td>Correct Rejection (C)</td>
</tr>
<tr>
<td>No</td>
<td></td>
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- **HR** (Hit rate) = \( \frac{H}{H+M} \)
  
  0 to 1, perfect score = 1

- **FAR** (False Alarm rate) = \( \frac{F}{F+C} \)
  
  0 to 1, perfect score = 0

Good forecast: HR↑, FAR ↓
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)

**ROC score**
- \[ \text{ROC score} = \text{Area of ROC curve} \]
- Range: 0 to 1
  - **Perfect**: ROC score = 1
  - **No skill**: ROC score = 0.5 (no added value)

- Biased forecast with high ROC score
- A measure of potential usefulness
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?”

<table>
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\[
HSS = \frac{\text{SCORE}_{\text{forecast}} - \text{SCORE}_{\text{by chance}}}{\text{SCORE}_{\text{perfect forecast}} - \text{SCORE}_{\text{by chance}}}
\]

\[
= \frac{\left\{ \frac{(H + C)}{n} - \left[ \frac{(H + F)(H + M) + (F + C)(M + C)}{n^2} \right] \right\}}{\left\{ 1 - \left[ \frac{(H + F)(H + M) + (F + C)(M + C)}{n^2} \right] \right\}}
\]

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

\[ E_{fore} : \text{Expected expense of forecast} \]
\[ E_{per} : \text{Expected expense of perfect forecast} \]
\[ E_{cli} : \text{Expected expense of climatological forecast} \]

\[ E_{fore} = (h + f)C + mL \]

- 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

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

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

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

Above-Normal

Thank you