Use of future climate information

Framework and Methodology

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Outline

1 Background

- Introduction of climate change impacts
- General framework for climate change impact assessment
- Future Climate Information (FCI)

2 Key points in using FCI

- Precautions
- Limitations

3 downscaling

- Signification
- Statistical downscaling
- Dynamical downscaling

4 Bias-correction

- Necessity
- Methodology
- precautions

What are the impacts of climate change on…

Rural community & Agriculture

Increase Climate Variability

Increase in incidence rate of infectious diseases and heat wave

Increase Extreme weather events

Increase in frequency and intensity of flood

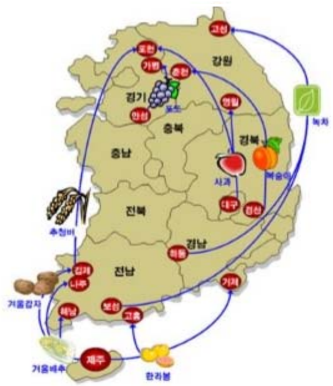
Increase Extreme weather events

Increase in frequency and intensity of drought

Change in precipitation pattern

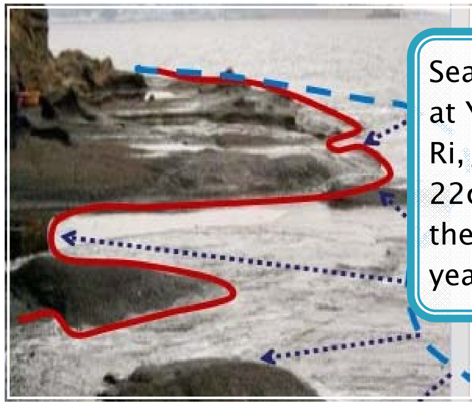
Frequent landslides due to heavy rainfalls

Increase Temperature



A shift in cultivation area

Increase Temperature



Sea level rise at Yong-Mu-Ri, Jeju: 22cm over the past 43 years

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What are the impacts of climate change on…

Projected Impacts of Climate Change in Korea

+3°C

- 30% loss of arable land in coastal swamp and lowland
- Partial desertification of arable land

+2° C

- Decreased production of 15~60% rice due to high sterilizing percentage
- Decreasing temperate zone fruit /vegetable and increasing subtropical zone fruit/vegetable
- Increase in damage due to flood and storm
- Rising concern over coastal infrastructure collapse due to sea level rise
- Rising concern over collapse of reservoir water facility due to increasing precipitation

+1°C

- Continuous shifts of the fittest arable land due to changes of the fittest land for rice, fruit, and vegetable
- Decrease in reproduction, weight gain, and livestock products due to high heat
- Increase in high-temperature disease and insect pest and increase of pests reproduction pace
- Increasing chances of soil erosion during the summer & reducing fertilizer components

+.5°C

- Rising chances of livestock disease and infectious diseases
- Decrease in water resources available for inland & mountainous area increasing draught damages due to rising amount of evaporation

Source: IPCC 2014

What we are doing… e.g.,

APCC, KRC, and others collaborate to adapt to climate change!

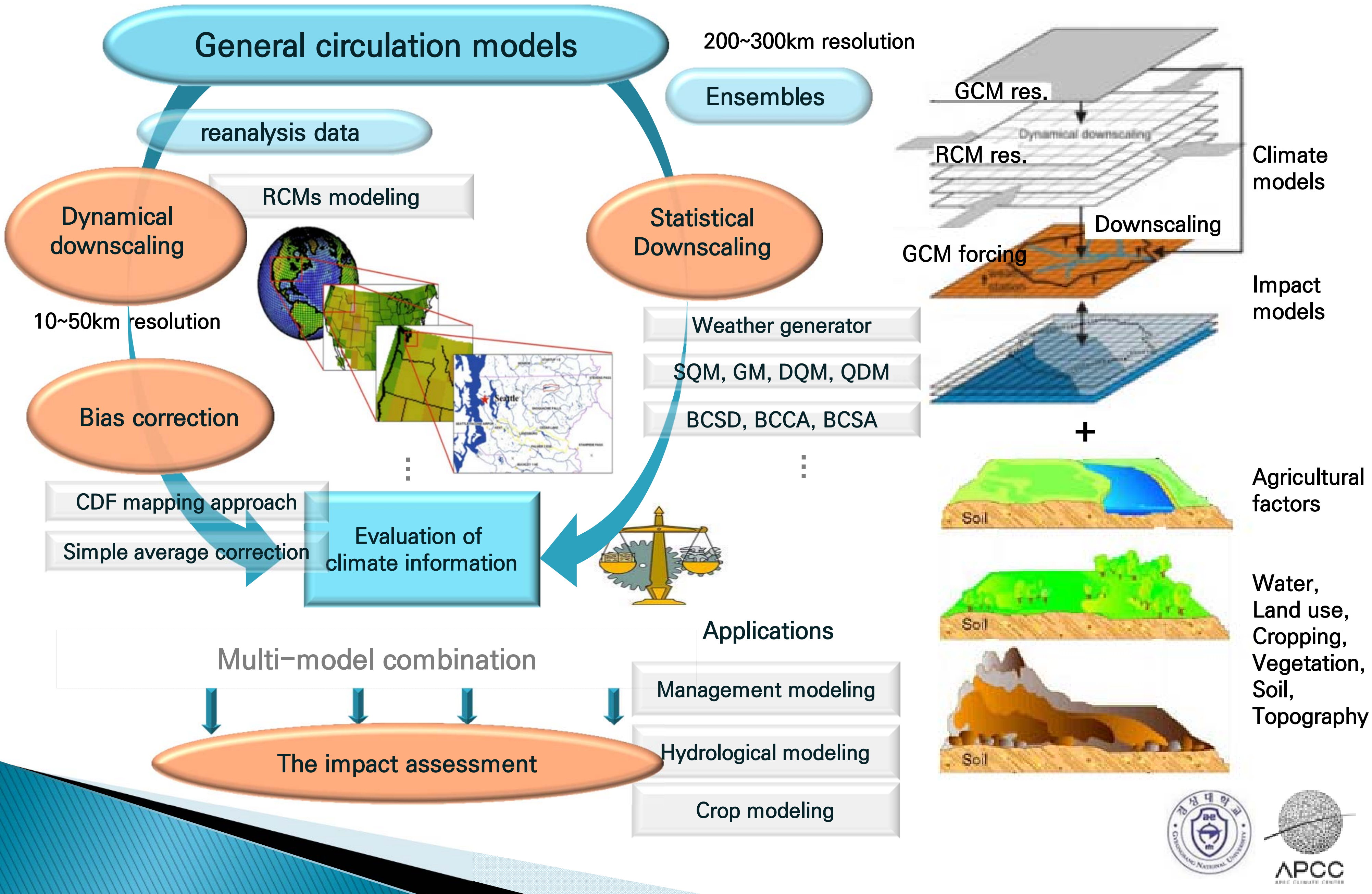
Dr. Jung, CEO of KRC is talking about
Advanced Reaction & Adaption to climate change!

- **Project planning office: Climate Change Counterpart**
  - Diversification of the ways for Water supply
  - Irrigation facility enhancement
  - Water management automation system (ICT)
  - Scientific Investigation of actual conditions, impacts, and vulnerabilities of climate change

- **Suggested Slogan:**

"For Stable, Safe, Sustainable water supply for agricultural system"

General framework of climate change impact assessments



Terms

- Time Scales:
  - Seasonal-to-Interannual (1-12 Months): Predictions
  - Decadal (1-10 Years): Predictions
  - Near-Term (Mid-Century): Projection

- Forcing*:
  - CO_2, Aerosols (Natural and Anthropogenic), and other gases
  - Secondary Importance for Season, but Increasing with Decadal and Longer Time Scale

- Boundary Conditions*:
  - Are Often Also Predicted, i.e., Sea Surface Temperatures, Snow Cover, Soil Moisture, Sea-Ice
  - Evolve Slowly Relative to Weather

- Initial Conditions*:
  - Critical for Seasonal-to-Decadal Predictions, but Secondary for Projections

- Projection vs. Prediction
  - Projection: Forcing is Critical – Initial Condition of Secondary Importance
  - Prediction: Initial Condition is Critical – Forcing of Secondary Importance

- Climate vs. Weather

Hardness of cliamte simulation

$$\frac{\partial u}{\partial t}+\vec{V}\cdot\nabla u+\omega\frac{\partial u}{\partial p}-fv+\frac{\partial\phi}{\partial x}=F_x$$

$$\frac{\partial v}{\partial t}+\vec{V}\cdot\nabla v+\omega\frac{\partial v}{\partial p}+fu+\frac{\partial\phi}{\partial y}=F_y$$

$$\frac{\partial\phi}{\partial p}=-\alpha$$

$$\frac{\partial T}{\partial t}+\vec{V}\cdot\nabla T+\omega\frac{\partial T}{\partial p}-\alpha\omega/Cp=Q/Cp$$

$$\nabla\cdot\vec{V}+\frac{\partial\omega}{\partial p}=0$$

$$p\alpha=RT$$

$$\frac{\partial q}{\partial t}+\vec{V}\cdot\nabla q\cdot+\omega\frac{\partial q}{\partial p}=S_q$$

- Navier-stokes equations
- Thermodynamic Energy equation
- Continuity equation
- Idea Gas Law
- Moisture conservation

7 EQUATIONS, 7 UNKNOWNS: u, v, ω, T, α, Φ, and q

+ error terms

Source of Uncertainty!

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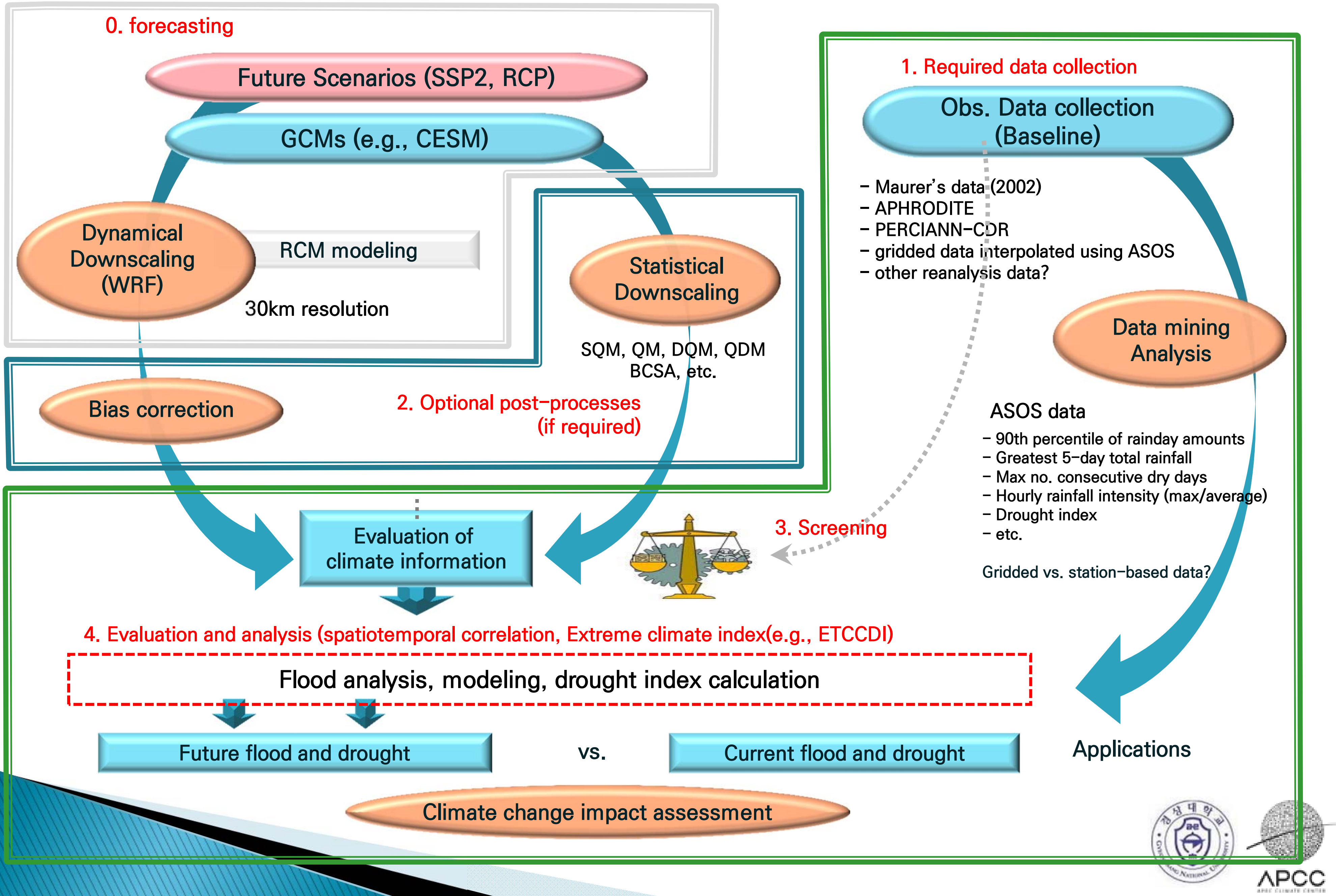
Climate Change Impact Assessment using future climate information



Point #1

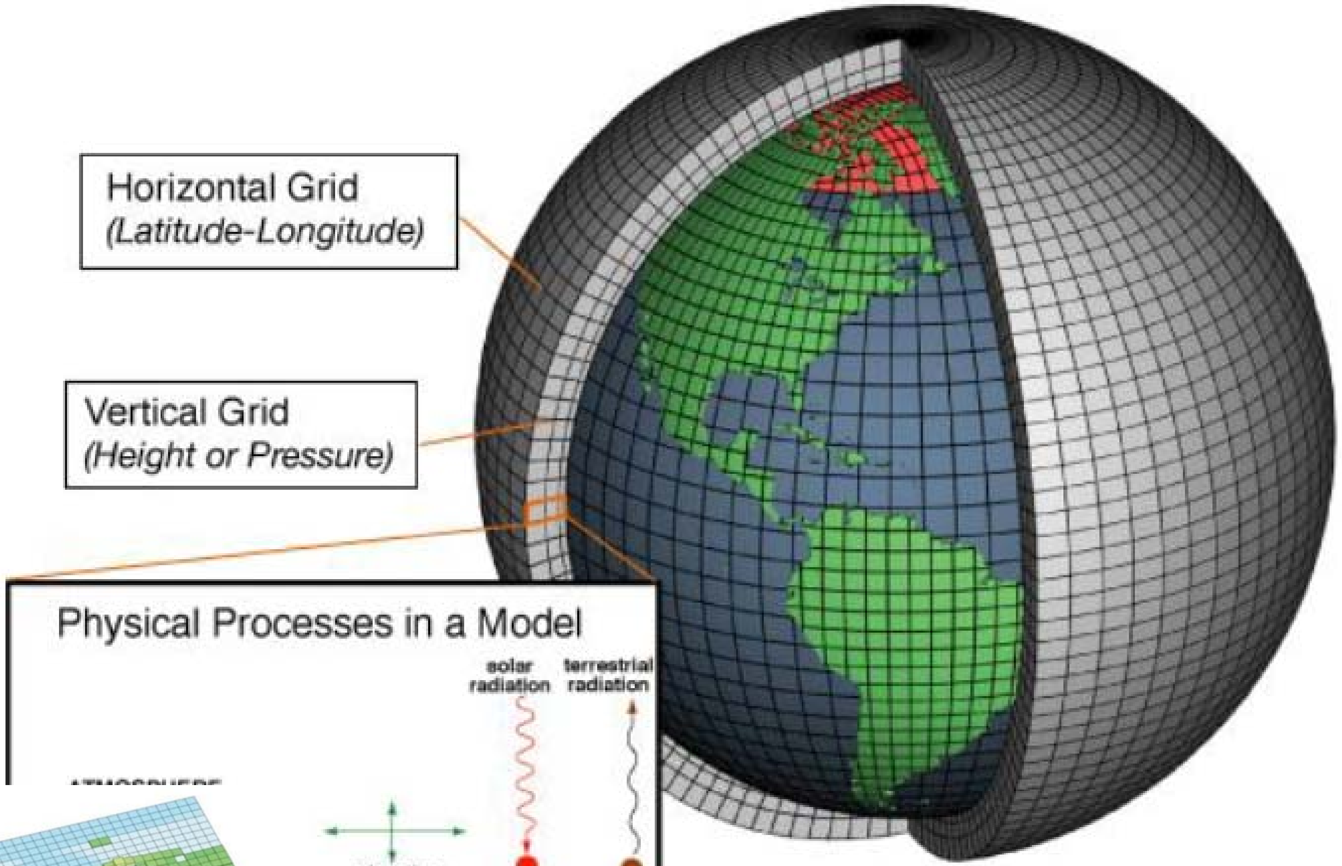
What GCMs look like?

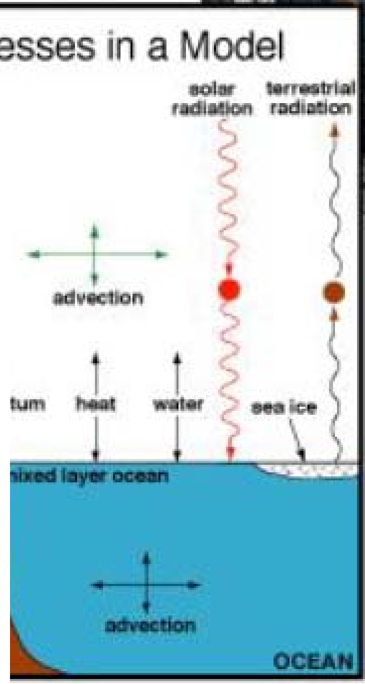
Constraints of resolution

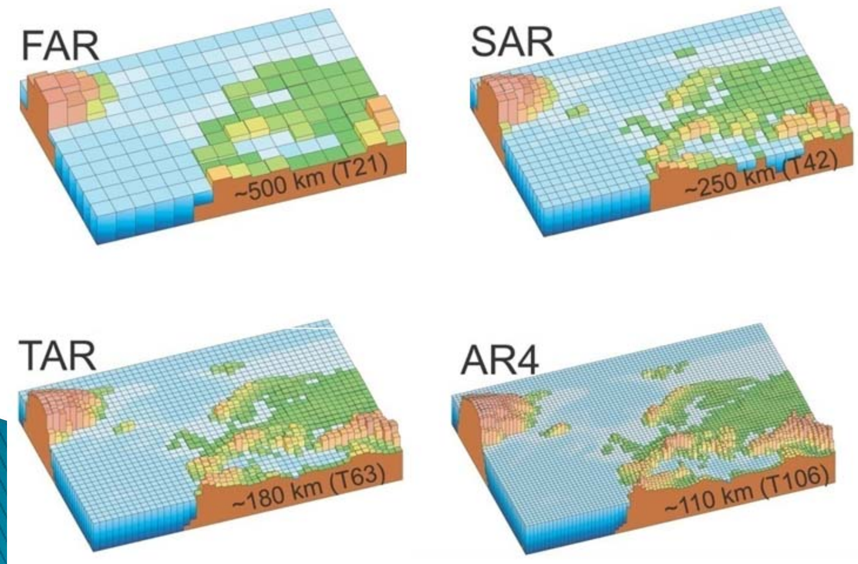
General circulation model (GCM)

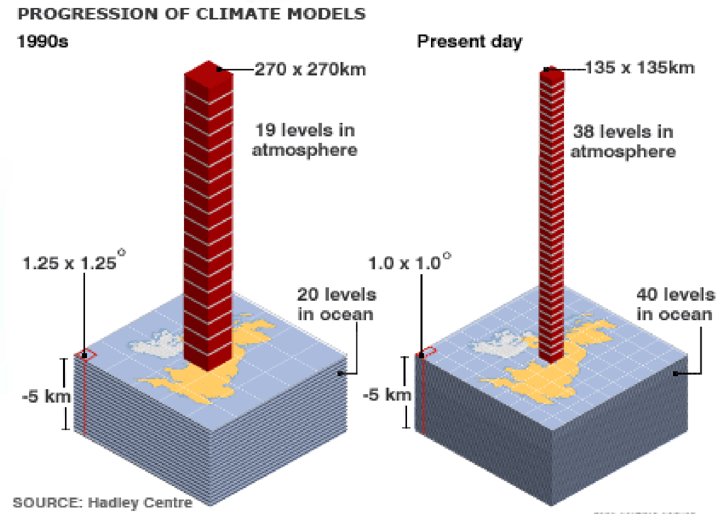
Grid configuration

Typical grid size is 100km, many processes (e. g., clouds) cannot be simulated explicitly







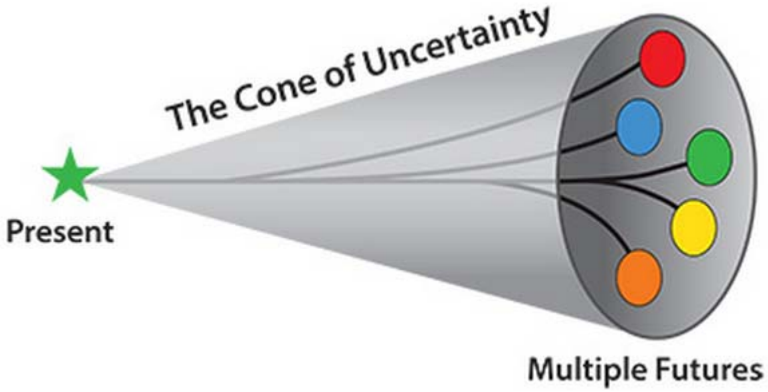


Point #2.1

Constraints of Uncertainty

How to make it useful?

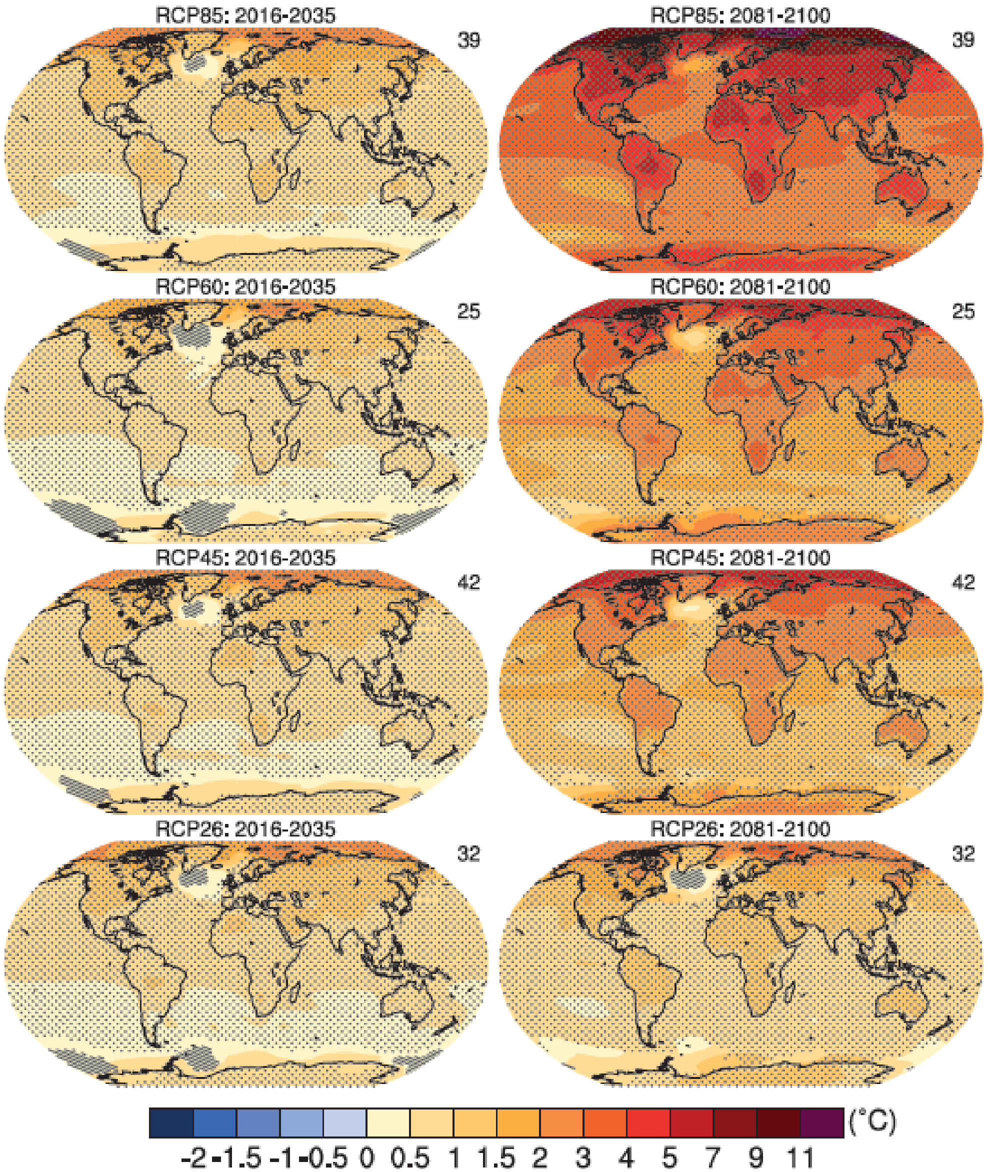
For actionable science in practice
Need to Embrace Uncertainty!!



http://www.wucaonline.org/html/

What is the role of downscaling in uncertainty of future information?

Change in average surface temperature



* Stippling (dots) indicates regions where the projected change is large compared to natural internal variability (i.e., greater than two standard deviations of internal variability in 20-year means) and where 90% of the models agree on the sign of change.

*Source: IPCC, 2014, Climate Change –Synthesis report –
Korea Meteorological Administration, 2013, Climate Change –Scientific Basis –

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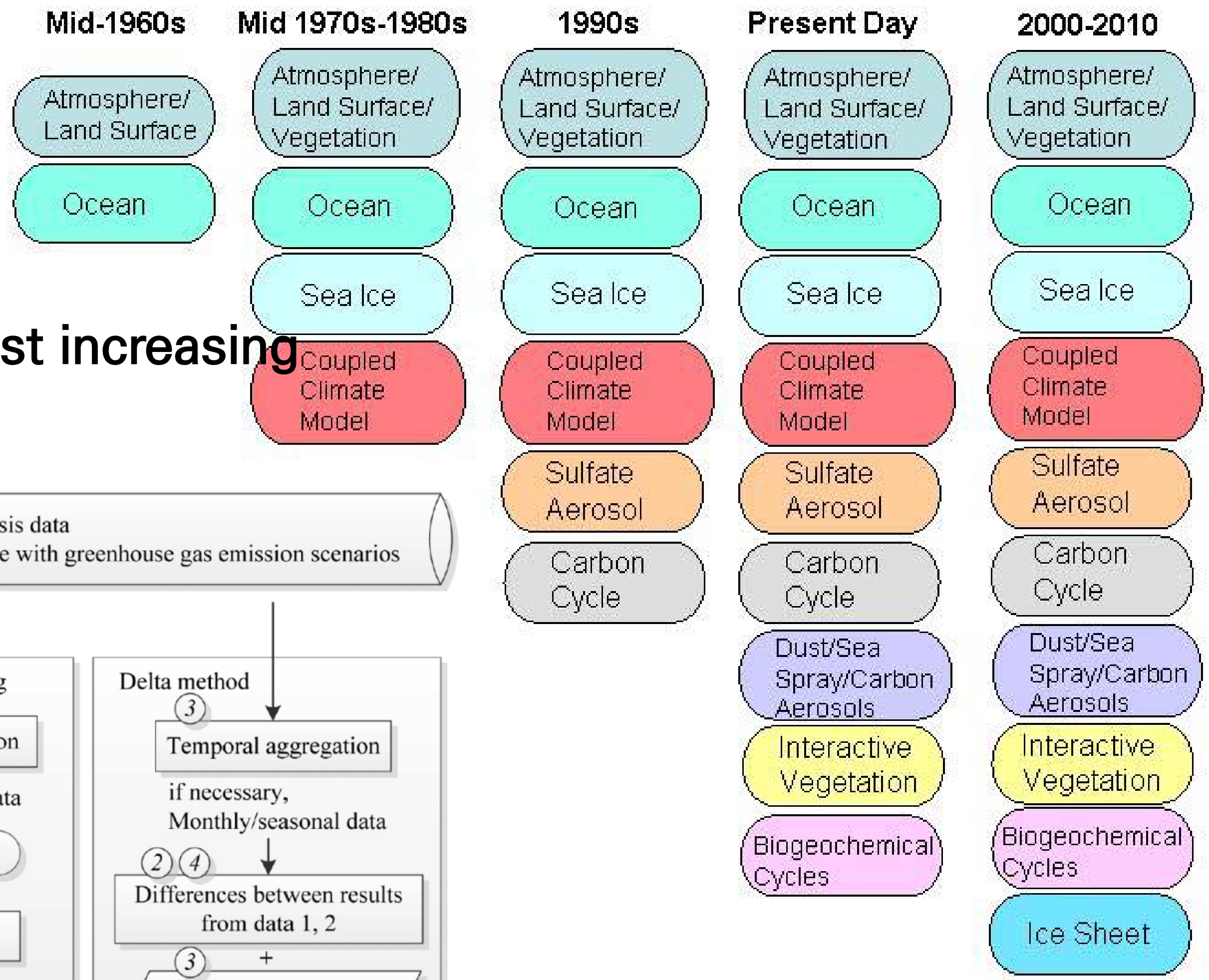
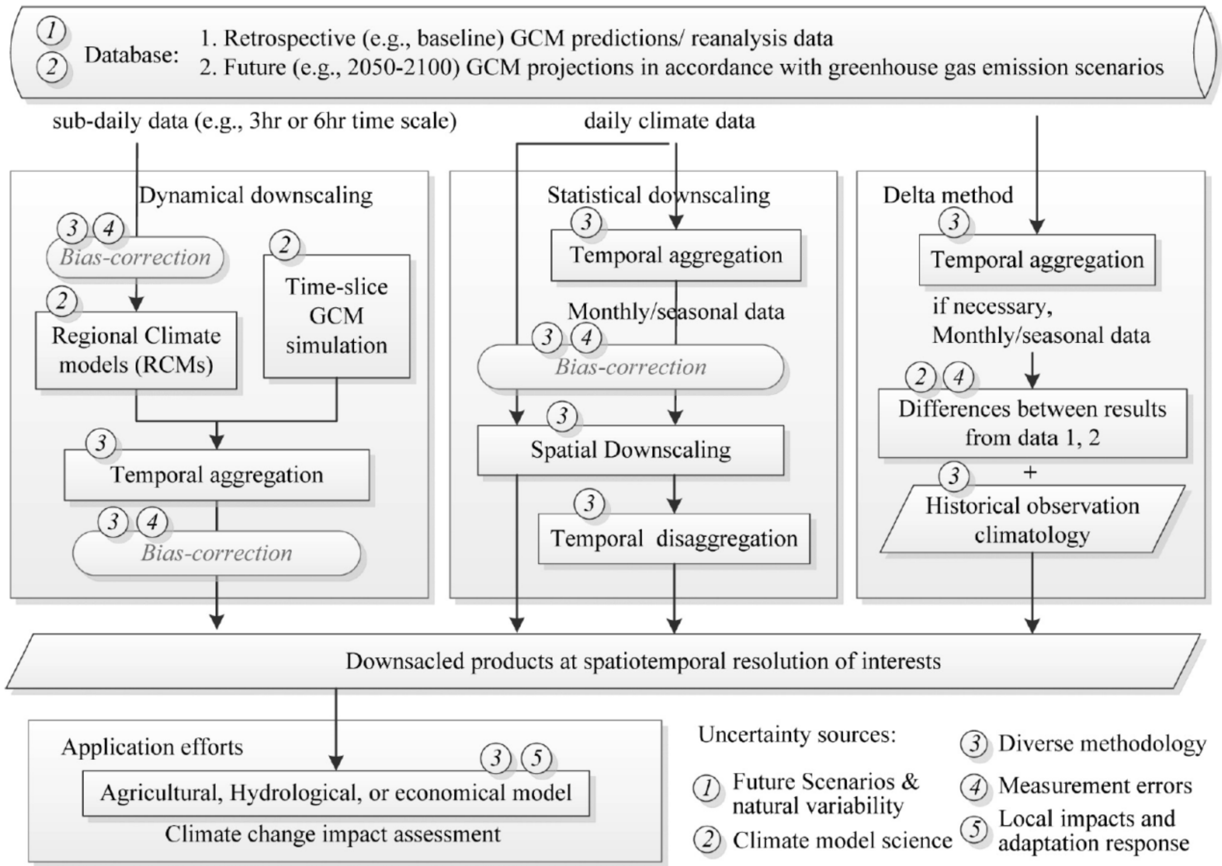
Point #2.2

Potential uncertainty by each process

Constraints of Uncertainty

Are we making progress or just increasing the uncertainty?





(Hwang and Kang, 2013)

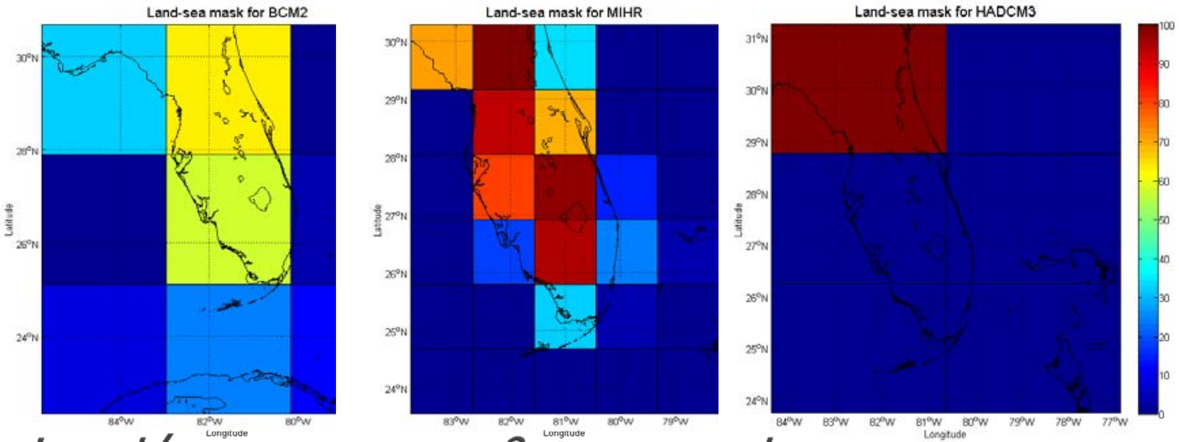
Point #3

What GCMs look like?

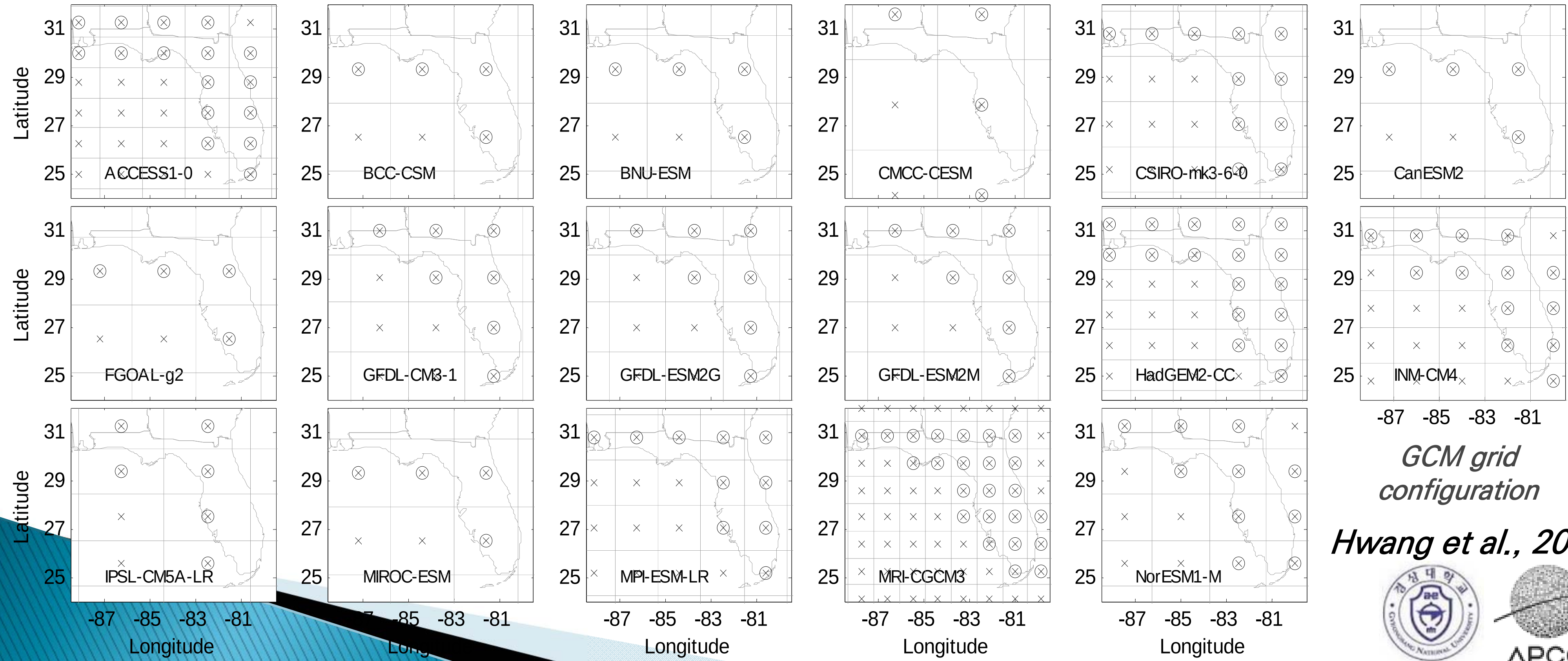
Differences of GCMs

At the local scale additional uncertainties in GCM predictions due to:

- Poor resolution – Korea may not even be modeled in some GCMs; greater errors at smaller scales
- Alternative downscaling methodologies produce additional uncertainty



Land/sea coverage & topography



GCM grid configuration

Hwang et al., 2014

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Point #4

Different methodologies

A variety of methods to use for application

GCMs — Future climate info. (AR5, RCP scenario)

– PCMDI (CMIP5)

GCM evaluation → not OK → **Screening**

↓ OK

Screening GCM → **Model weighting**

- Physical probability
- Global scale
- Climatology
- Purpose:

Downscaling methodologies — Spatially detailed climate info.

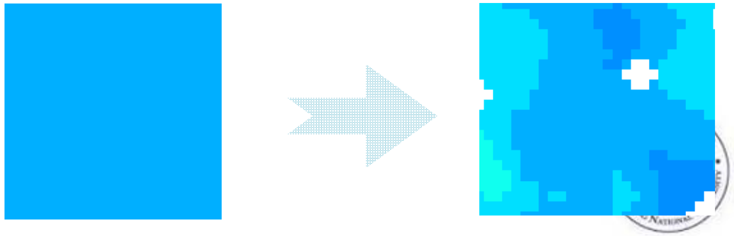
– BCSD, BCCA, SDBC, BCSA, etc.

Method evaluation → not OK → **Selecting**

↓ OK

Method selection → **intercomparison**

- Statistical estimation
- Regional/local scale
- Extreme, diurnal cycle
- Purpose:



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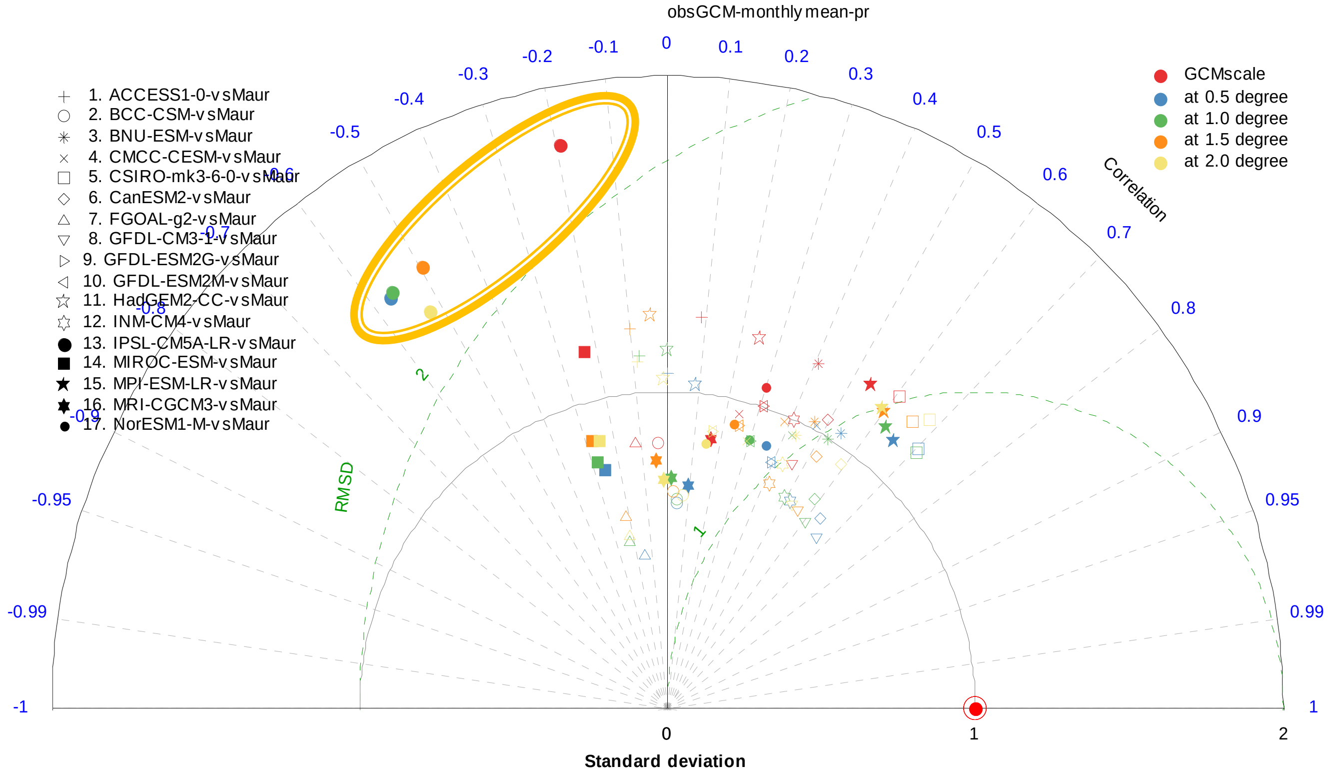
Point #4.1

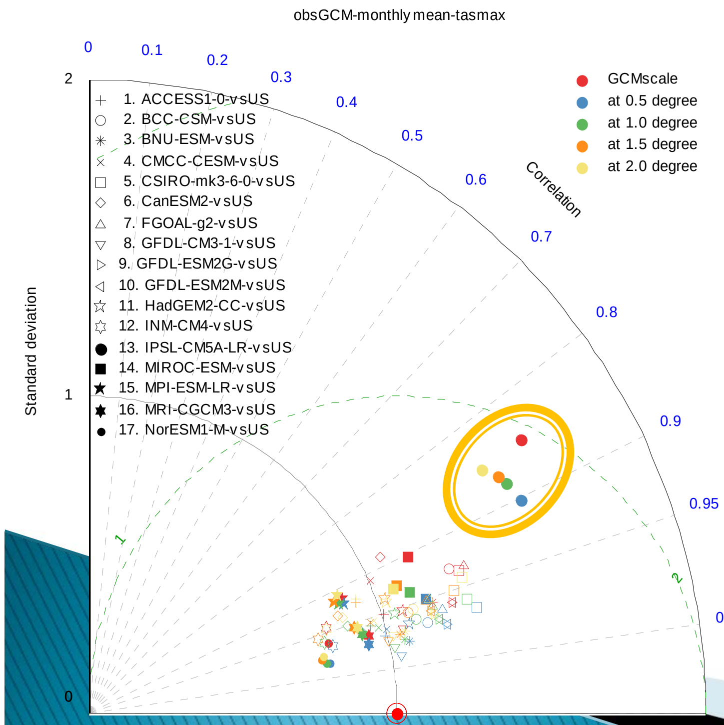
Different methodologies

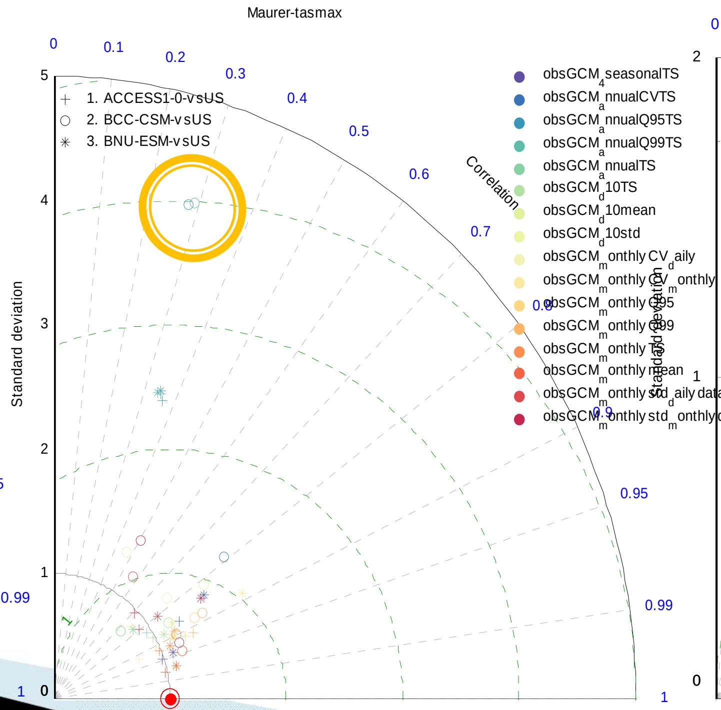
How GCMs work?

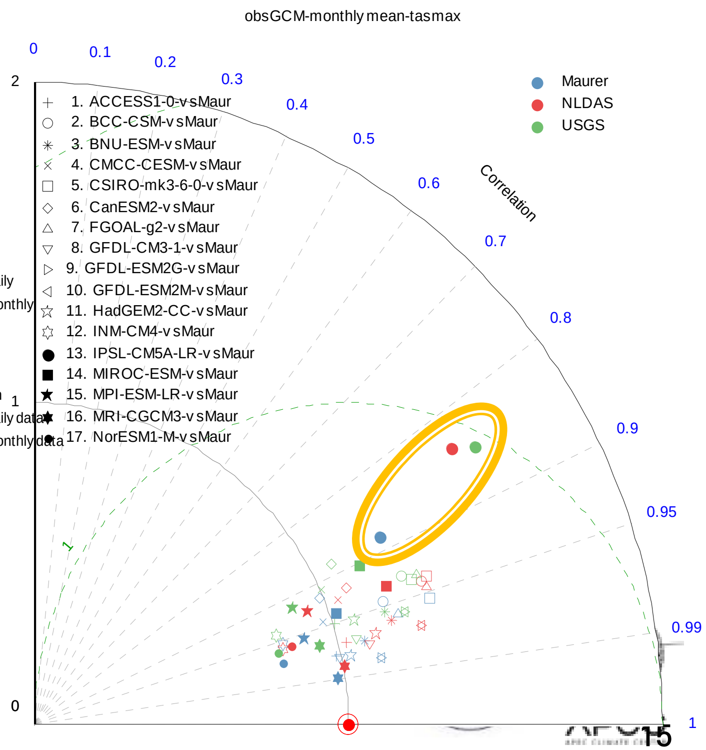
Performance evaluation

at different resolution
with different observation
For different criteria





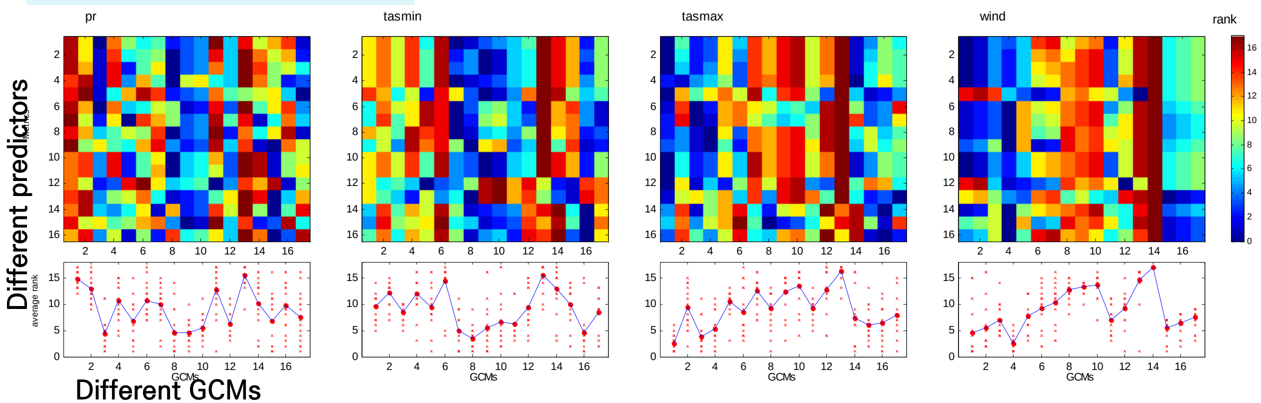




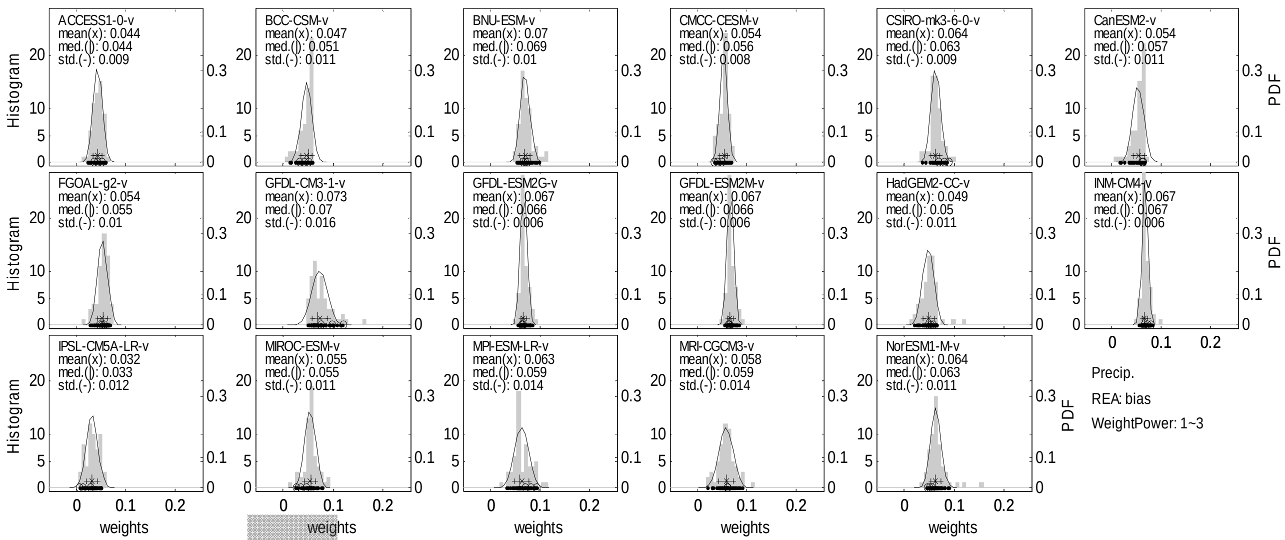
Point #4.2

GCM skill evaluation

Tmax Tmin Wind spped



Distribution of weights for each GCM (precipitation)



Different observations

1 Maurer's data (Maurer et al., 2002)
2 NLDAS data
3 USGS data
4 Reanalysis data?

Different resolutions

1 each GCM scale
2. 0.5'X0.5'
3. 1.0'X1.0'
4. etc.

Different metrics

1 RMSE
2. Correlation
3. Others?

Different indicators

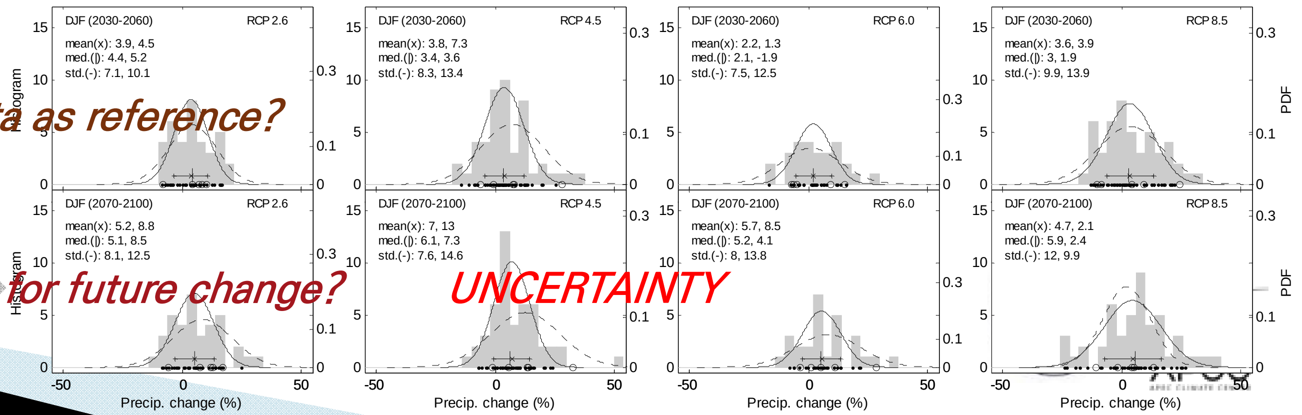
1 d10TS';
2 monthlyTS';
3 4seasonalTS';
4 annualTS';
5 annualCVTS';
6 annualQ95TS';
7 annualQ99TS';
8 monthlyQ95';
9 monthlyQ99';
10 d10mean';
11 monthlymean';
12 monthlyCV_daily';
13 monthlyCV_monthly';
14 d10std';
15 monthlystd_dailydata';
16 monthlystd_monthlydata';

GCM list

1 ACCESS1
2 bcc_csm1
3 BNU-ESM
4 CanESM2
5 CMCC-CESM
6 CSIRO-mk3-6
7 FGOALS-G2
8 GFDL-CM3
9 GFDL-ESM2G
10 GFDL-ESM2M
11 HadGEM2-CC
12 INM-CM4
13IPSL-CM5A-LR
14 MIROC-ESM
15MPI-ESM-LR
16MRI-CGCM3
17 NorESM1-M

Reliable Future information?

How are the results
for other variables?
using other observation data as reference?
at other spatial resolution?



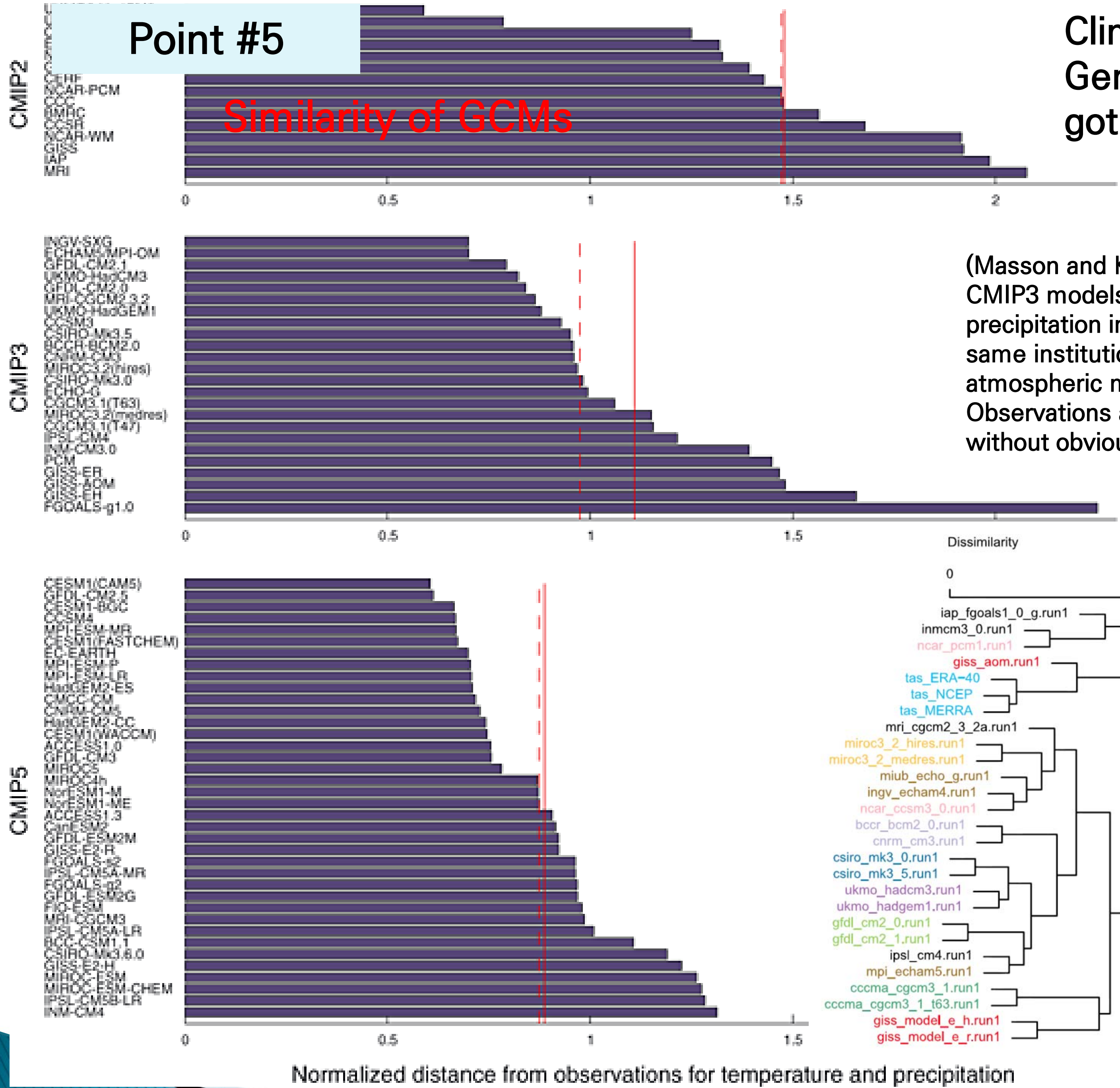
What if we have different inferences for future change?

UNCERTAINTY

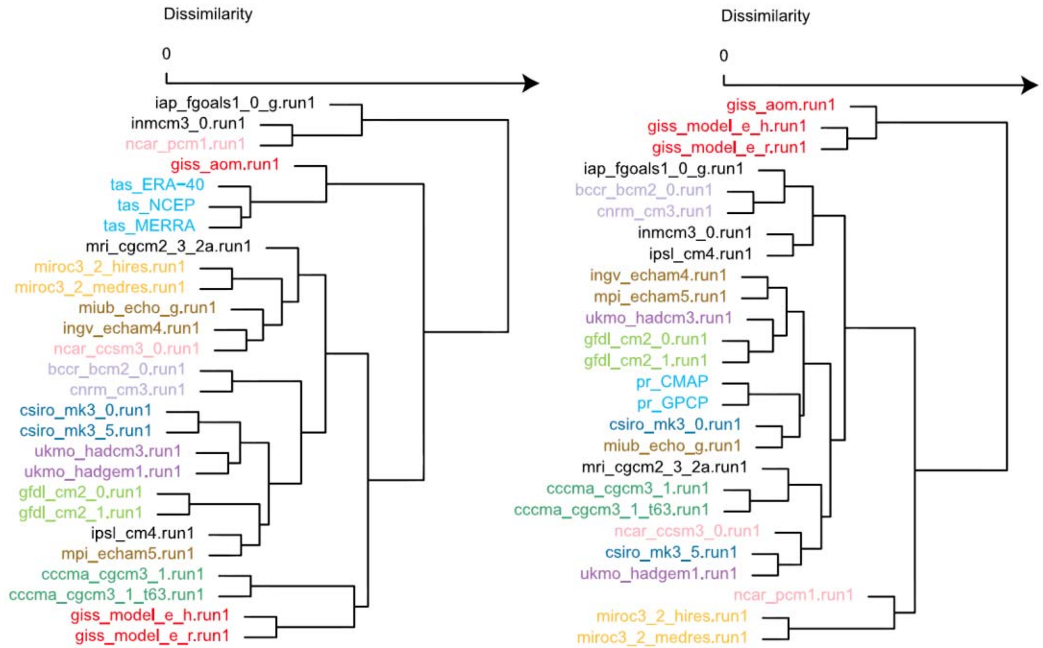
Point #5

Similarity of GCMs

Climate model genealogy: Generation CMIP5 and how we got there



(Masson and Knutti, 2011) Hierarchical clustering of the CMIP3 models for (left) surface temperature and (right) precipitation in the model control state. Models from the same institution and models sharing versions of the same atmospheric model are shown in the same color. Observations also are marked by the same color. Models without obvious relationships are shown in black.



Knutti, R., D. Masson, and A. Gettelman, 2013
Geophysical Research Lett.

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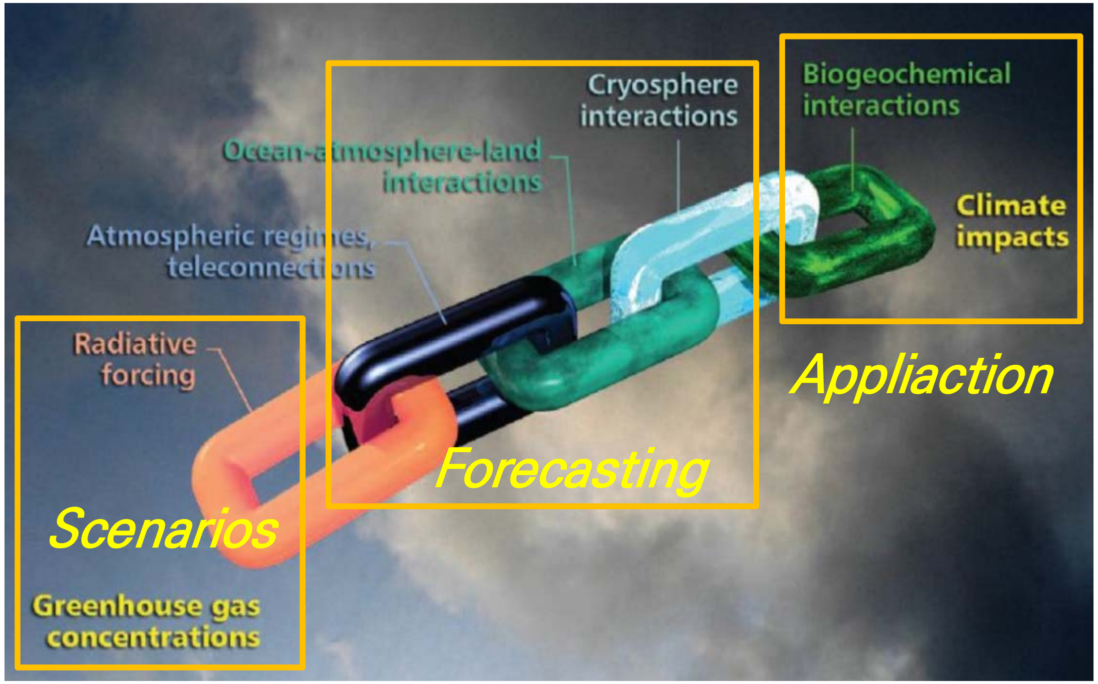
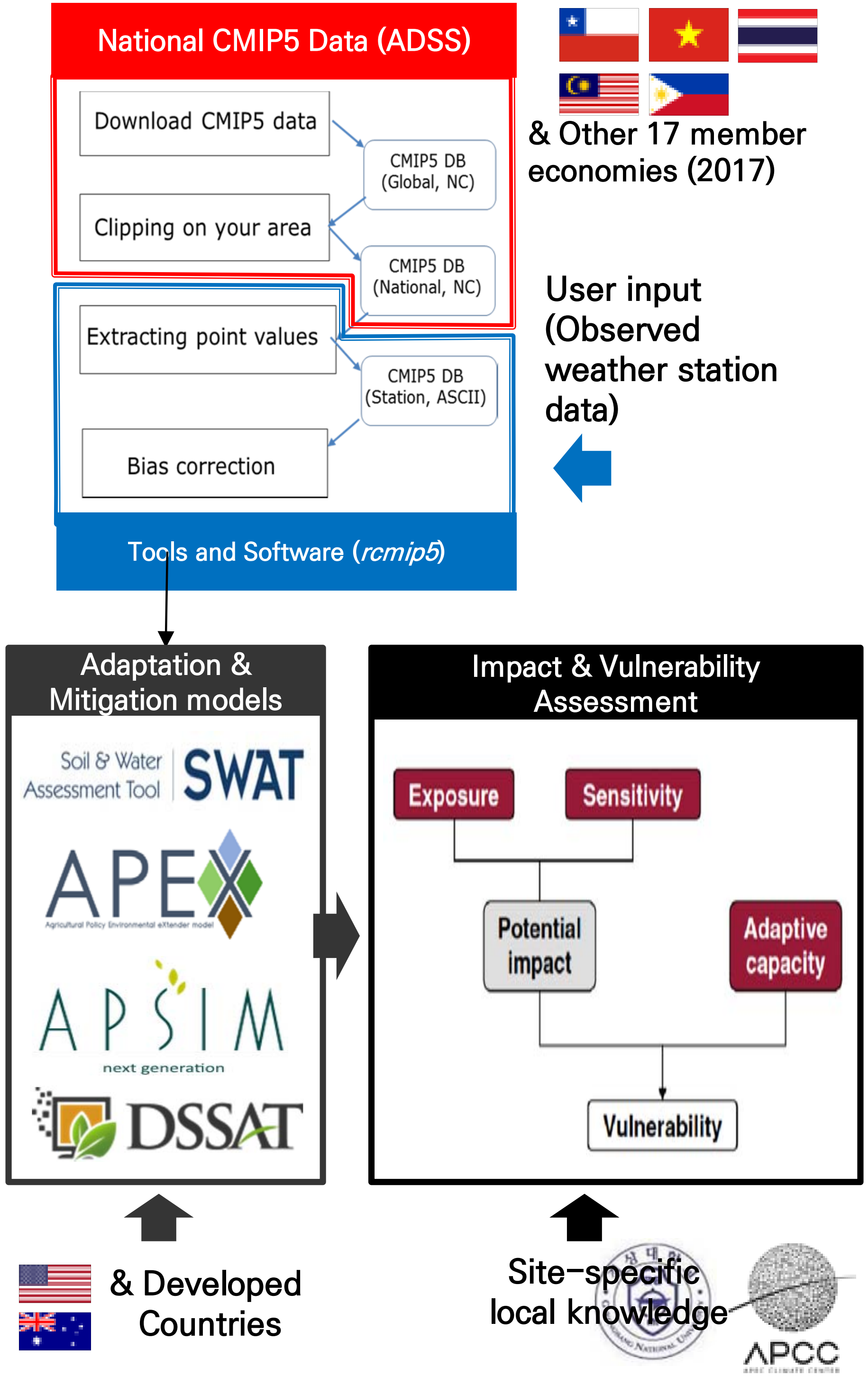
Point #6

Constraints of separation of the flow



Seamless prediction (Palmer, 2008)



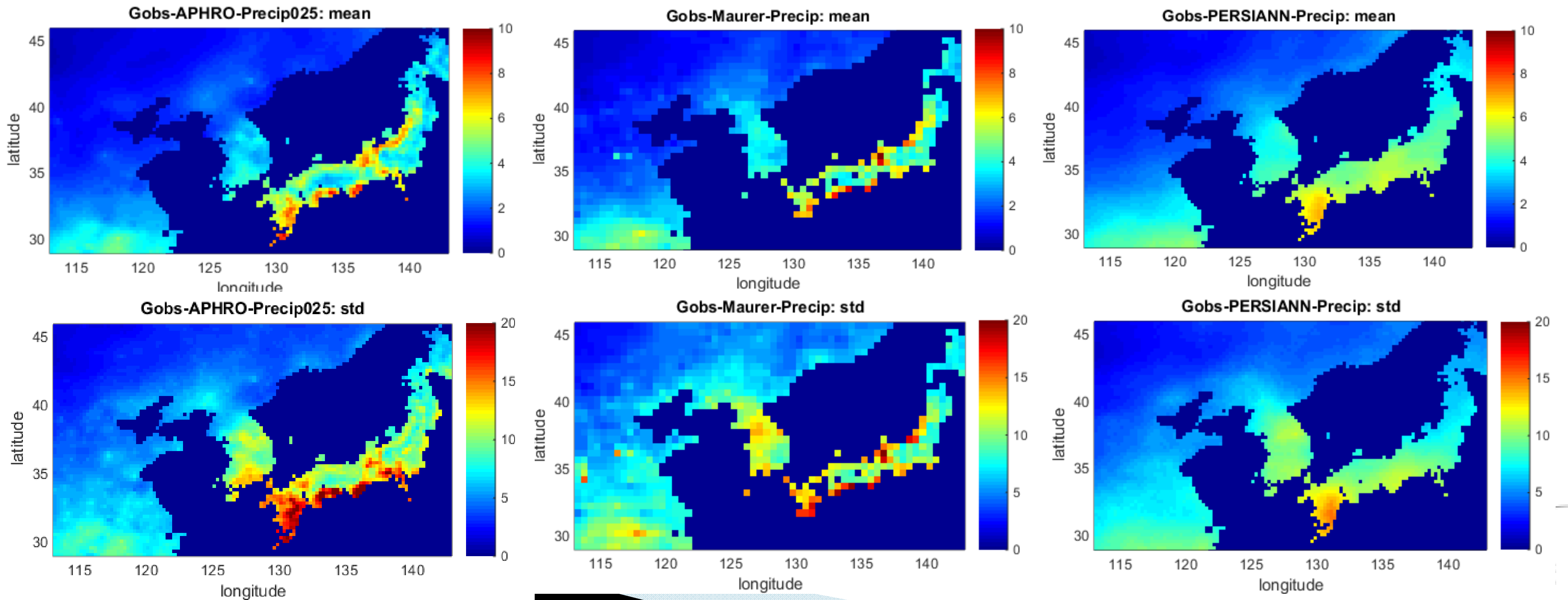
Point #7

Constraints of limited data that we have been observed/generated

Gridded observation data

	period	variable	res.	coverage	reference
Maurer’s data	1950-1999	precipitation, tmax, tmin, surfwind	$0.50^\circ \times 0.50^\circ$	global	Maurer et al., 2002
APHRODITE	1950-2007	precipitation	$0.25^\circ \times 0.25^\circ$	Asia	Yatagai et al., 2012
PERCIANN-CDR	1983-2015	precipitation	$0.25^\circ \times 0.25^\circ$	global	Ashouri et al., 2015

Spatial distributions of mean and standard deviation of daily observation data for precipitation



What is Downscaling?

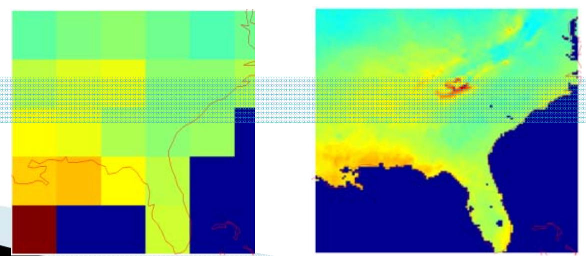
Objective of Downscaling

Downscaling: obtaining subgrid-scale information from coarser resolution fields

Climate model downscaling "Bridges mismatch" of spatial scale between the scale of global climate models and the resolution needed for impacts assessments

Climate model downscaling "bridges the gap" between what is provided by global climate modelers and what is needed by decision-makers and impact assessors

What high res. is useful for coupling climate models to other models that require high resolution!
In certain specific contexts, provides insights on realistic climate response to high resolution forcing (e.g. mountains)



The ‘Mismatch’ of Scale Issue

- “Most GCMs neither incorporate nor provide information on scales smaller than a few hundred kilometers. The effective size or scale of the ecosystem on which climatic impacts actually occur is usually much smaller than this. We are therefore faced with the problem of estimating climate changes on a local scale from the essentially large-scale results of a GCM.” Gates (1985)

- “One major problem faced in applying GCM projections to regional impact assessments is the coarse spatial scale of the estimates.” Carter et al. (1994)

- “downscaling techniques are commonly used to address the scale mismatch between coarse resolution GCMs … and the local catchment scales required for … hydrologic modeling” Fowler and Wilby (2007)

- “Motivation: Most of the population lives in areas having sharp climatic gradients: along coastlines, lakes, mountains,…

  These features are not resolved by global climate models,

  for which grid cells are 100-200 km” John Walsh (2011)

Downscaling?

Weather Forecast

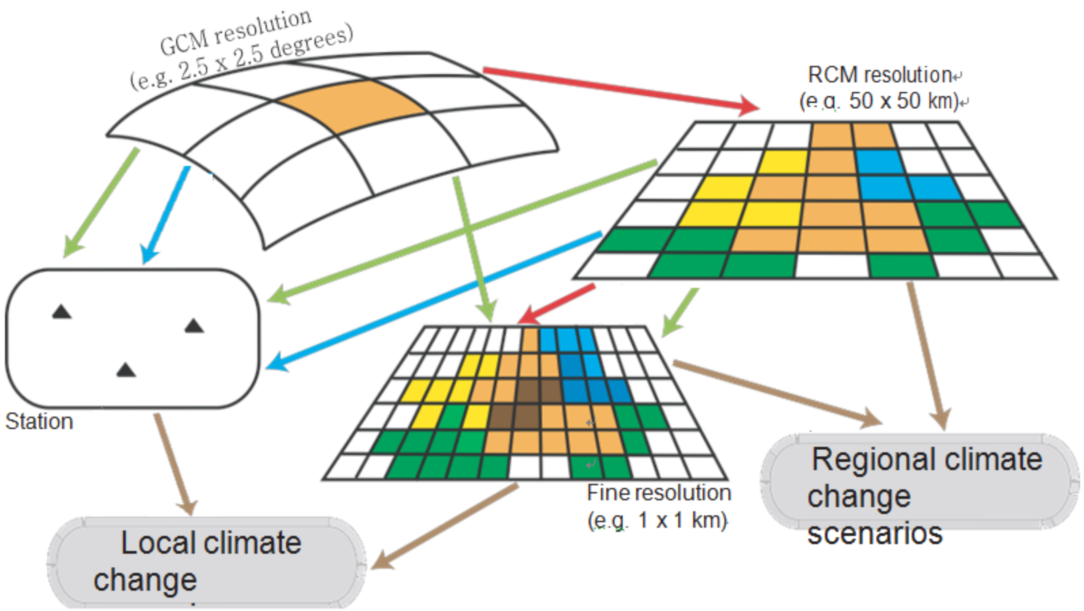
Climate Forecast

Perfect-prog
- direct use of climate model output
- regression

Dynamical downscaling

MOS (the model output statistics)

statistical downscaling



Winkler et al., 2011

does not need to simulate the chaotic component of weather forecasting

attempts to reproduce only the long-term statistics of local conditions

It does require a robust record of historical observation to permit calibration at the local scale

Comparative summary of the relative merits of statistical and dynamical downscaling techniques

- adapted from Wilby and Wigley, 1997

	Statistical downscaling	Dynamical downscaling
Advantages	• Comparatively cheap and computationally efficient • Can provide point-scale climatic variables from GCM-scale output • Can be used to derive variables not available from RCMs • Easily transferable to other regions • Based on standard and accepted statistical procedures • Able to directly incorporate observations into method	• Produces responses based on physically consistent processes • Produces finer resolution information from GCM-scale output that can resolve atmospheric processes on a smaller scale
Disadvantages	• Require long and reliable observed historical data series for calibration • Dependent upon choice of predictors • Non-stationarity in the predictor-predictand relationship • Climate system feedbacks not included • Dependent on GCM boundary forcing; affected by biases in underlying GCM • Domain size, climatic region and season affects downscaling skill	• Computationally intensive • Limited number of scenario ensembles available • Strongly dependent on GCM boundary forcing

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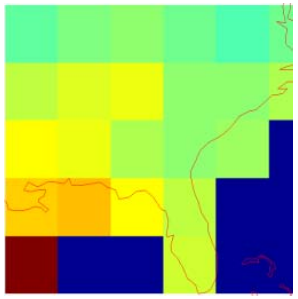
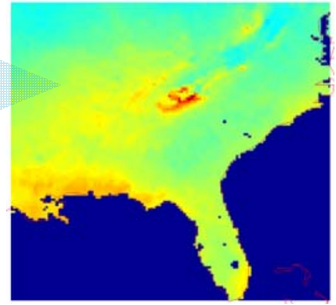


Statistical downscaling

- Coarse resolution
- GCM outputs
- GCM+RCM outputs

SQM, QM, DQM, QDM
weather generator
Regression
Weather typing



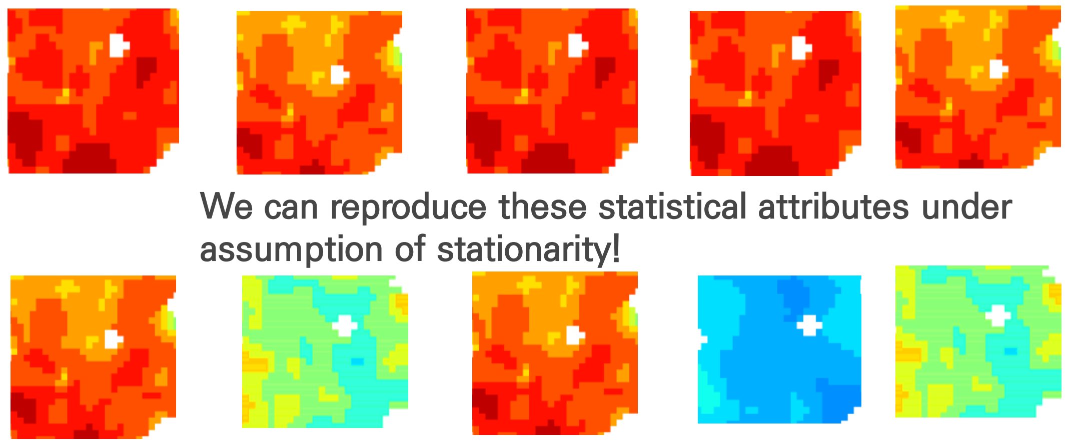
- Fine resolution
- Station based info.

Ultimate goal of downscaling: Statistically reproduce attributes of a climate variable

GCM future information

Temporal Statistics
(Mean, Std., distribution, Auto-correl., etc.)

Downscaled distribution (future)



We can reproduce these statistical attributes under assumption of stationarity!

None!

spatial Statistics
(spatial correlation, covariance, etc.)

None!

spatial Pattern
(Local characteristics)

?

But cannot determine the spatial pattern of precipitation events on daily basis.

Generate plausible patterns and use those as scenarios!

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Statistical downscaling

Review of methods

- Wilby and Wigley (1997) Downscaling general circulation model output: A review of methods and limitations
- Fowler et al., (2007) Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling
- Wilby et al., (2004) Guidelines for use of climate scenarios developed from statistical downscaling methods
- Wood et al., (2004) Hydrologic implications of dynamical and statistical approaches to downscaling climate model outputs
- Schmidli et al., (2007) Statistical and dynamical downscaling of precipitation: An evaluation and comparison of scenarios for the European Alps

- Dynamical modeling
- Statistical method

- Statistical Downscaling
- Dynamical Downscaling

The changes of Classification

- Delta method
- More sophisticated Statistical Downscaling
- Dynamical downscaling

- Simple downscaling
  - Delta
  - More sophisticated method
- Statistical Downscaling
- Dynamical downscaling

Statistical Approaches

- **Simple techniques**
  - Adding coarse scale climate changes to higher resolution observations (the delta approach)
  - More sophisticated –interpolation of coarser resolution results (Maurer et al. 2002, 2007)
    - Bias-correction method!
    - Bias-correction + Spatial disaggregation (Wood et al., 2002: interpolation)
    - Spatial disaggregation + Bias-correction
    - Bias-correction + Constructed analogue (Hidalgo et al., 2008)
      - (weather type analogue + regression)
    - Bias-correction + Stochastic Analogue (Hwang and Graham, 2013)
      - (weather generator concept) => generated library + bias-corrected daily GCM
      - Weather typing concept+ stochastic weather generator (Corte-Real et al. (1999), Hwang and Graham, 2014)

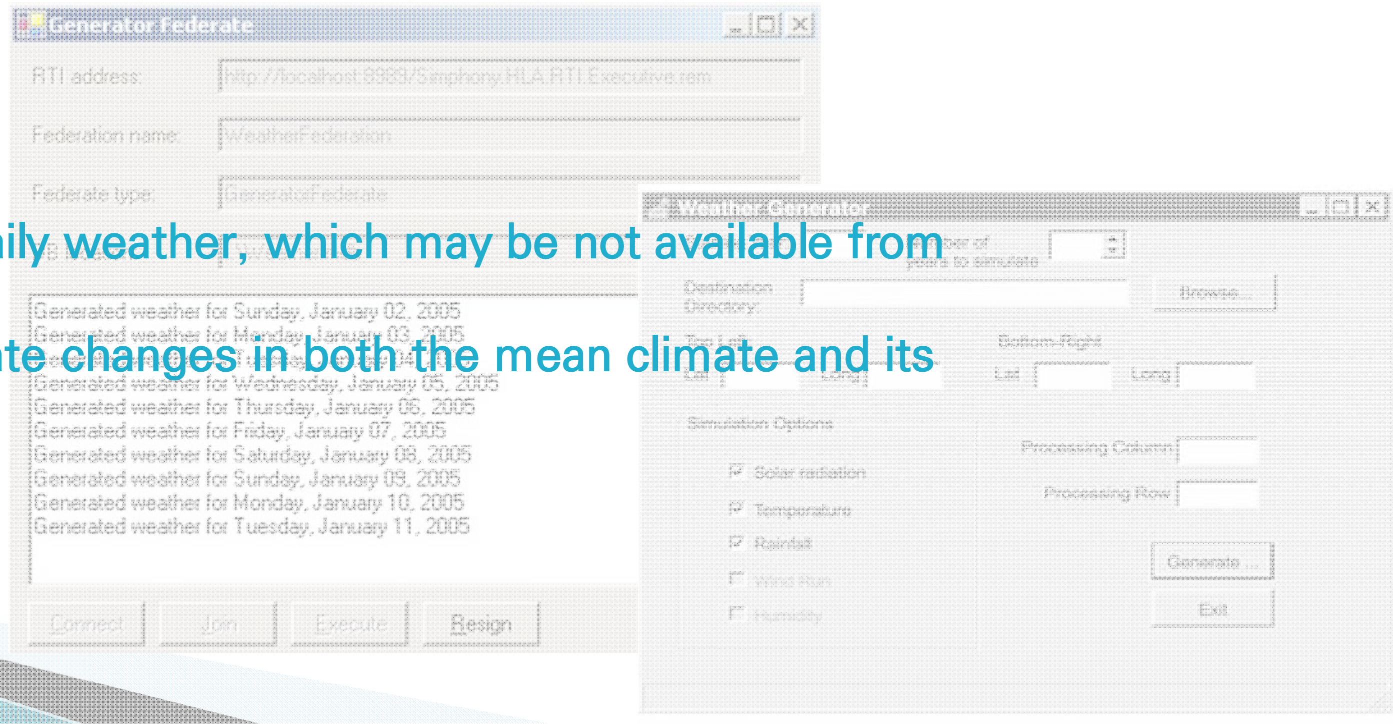
- **Statistical:** Statistically relating large scale climate features (predictors) to local climate (predictands)
  - Weather Classification
  - Regression Methods
  - Weather generator

1. Weather Generators

- Statistically reproduce attributes of a climate variable, e.g, mean and variance, and usually used to produce time series (e.g., daily) of a climate variable or sets of climate variables (precipitation, temperature, solar radiation)
- Parameters of weather generator are then conditioned on large scale predictors, such as the NAO or ENSO.

requirements:

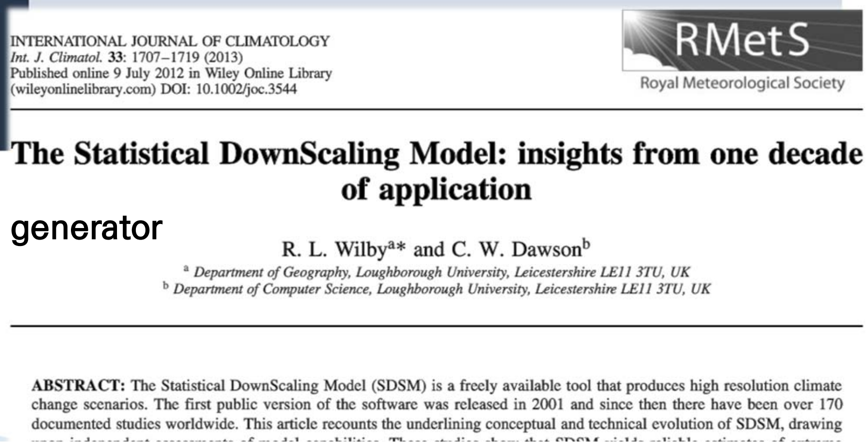
- Long time series of daily weather, which may be not available from observational records
- The ability to investigate changes in both the mean climate and its inter-daily variability



2. Regression Methods

- Earliest efforts related a variable at coarse scale to same variable at local scale (e.g., regional temperature used to estimate local temperature, Wigley et al. 1990)
- More typical, multiple regression relating pressure, humidity fields to local precipitation
- Common problem of underestimating variance of predictand

statistical relationships, based on multiple linear regression, are developed between large-scale predictors and local predictands


INTERNATIONAL JOURNAL OF CLIMATOLOGY
Int. J. Climatol. **33**: 1707–1719 (2013)
Published online 9 July 2012 in Wiley Online Library
(wileyonlinelibrary.com) DOI: 10.1002/joc.3544

RMetS
Royal Meteorological Society

The Statistical DownScaling Model: insights from one decade of application

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ABSTRACT: The Statistical DownScaling Model (SDSM) is a freely available tool that produces high resolution climate change scenarios. The first public version of the software was released in 2001 and since then there have been over 170 documented studies worldwide. This article recounts the underlining conceptual and technical evolution of SDSM, drawing

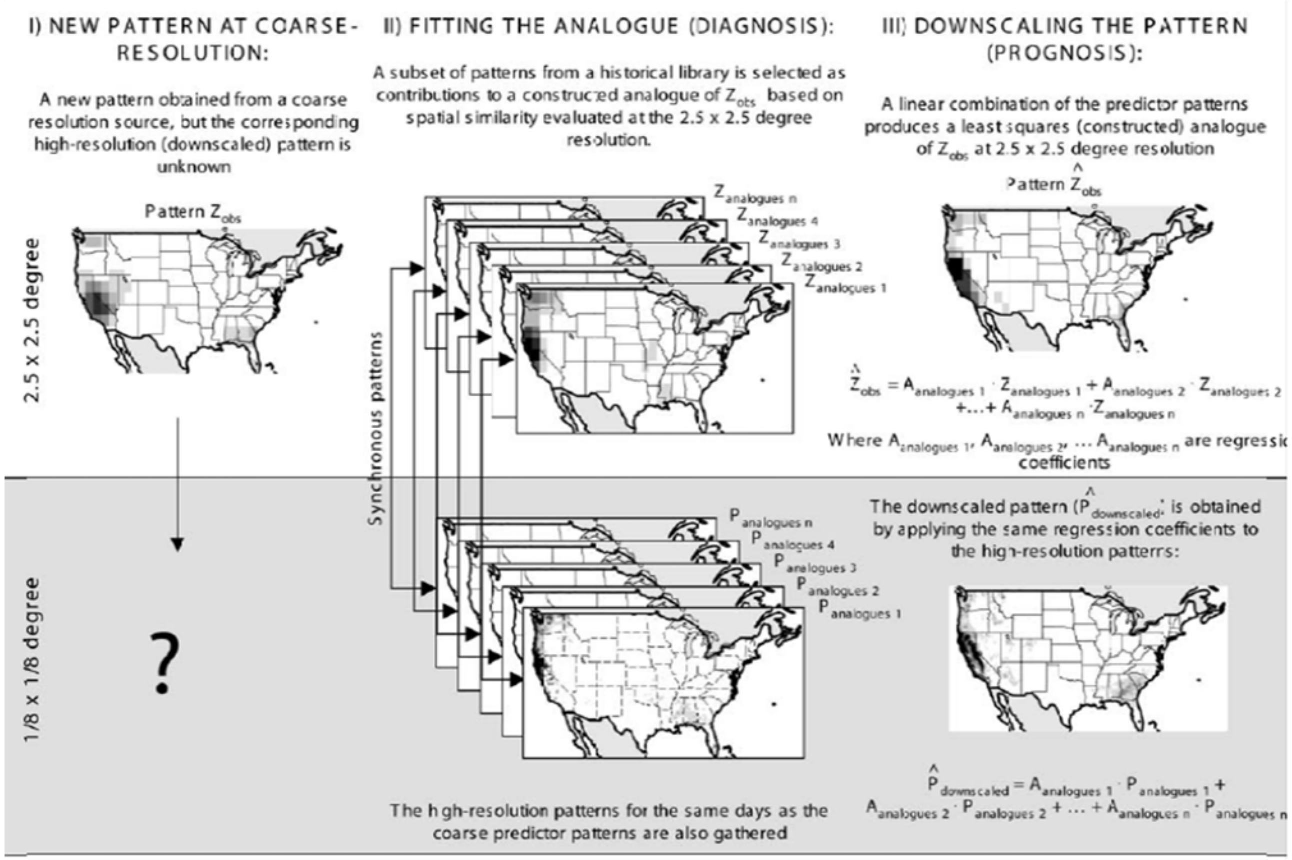
Multiple linear regression & stochastic weather generator

3. Weather Classification

- Relate weather classes or categorizations to local climate variable
  - Discrete weather types are grouped according to cluster techniques

- Typical example is relating different pressure patterns to surface temperature

- Assumes same weather pattern in the future will be associated with the same local responses in the future
  - Changes in frequency of types



Schematic of the method of constructed analogues for downscaling reanlysis fields from 2.5° x 2.5° grids to 1/8° x 1/8°

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A summary of the strength and weaknesses of the main SD methods

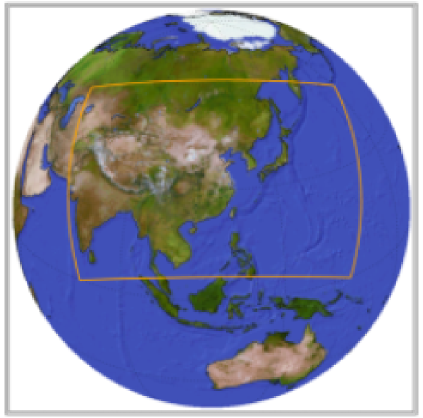
Method	Strengths	Weaknesses
Weather typing (e.g. analogue method, hybrid approaches, fuzzy classification, self organizing maps, Monte Carlo methods).	• Yields physically interpretable linkages to surface climate • Versatile (e.g., can be applied to surface climate, air quality, flooding, erosion, etc.) • Compositing for analysis of extreme events	• Requires additional task of weather classification • Circulation-based schemes can be insensitive to future climate forcing • May not capture intra-type variations in surface climate
Weather generators (e.g. Markov chains, stochastic models, spell length methods, storm arrival times, mixture modelling).	• Production of large ensembles for uncertainty analysis or long simulations for extremes • Spatial interpolation of model parameters using landscape • Can generate sub-daily information	• Arbitrary adjustment of parameters for future climate • Unanticipated effects to secondary variables of changing precipitation parameters
Regression methods (e.g. linear regression, neural networks, canonical correlation analysis, kriging).	• Relatively straightforward to apply • Employs full range of available predictor variables • 'Off-the-shelf' solutions and software available	• Poor representation of observed variance • May assume linearity and/or normality of data • Poor representation of extreme events

Dynamical downscaling

The CORDEX vision is to advance and coordinate the science and application of regional climate downscaling through global partnerships.

http://www.cordex.org/

COordinated
Regional Climate
Downscaling
Experiment



Ref: Description of the CORDEX domains
(23/06/2015 version)

RCMs (in rotated coordinates):
RotPole (296.3; 61.0)
TLC (316.77; 32.90)
Nx=396
Ny=251

B) For non-rotated polar RCMs (in actual coordinates):
TLC (51.59; 50.50)
CNB (116.70; 61.90)
TRC (181.50; 50.31)
CWB (67.11; 25.72)
CPD (116.57; 34.40)
CEB (165.94; 25.56)
BLC (76.91; -0.10)
CSB (116.51; 6.90)
BRC (156.08; -0.24)

Website:
EAST ASIA CORDEX

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hsasaki (at) mri-jma.go.jp
- Hyun-Suk Kang (SAT member) - Climate Research Laboratory, Korea
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Statistical downscaling contact:
- Koji Dairaku, - National Research Institute for Earth Science and Disaster Resilience, Japan
dairaku (at) bosai.go.jp

https://cordex-ea.climate.go.kr/main/aboutCordexPage.do

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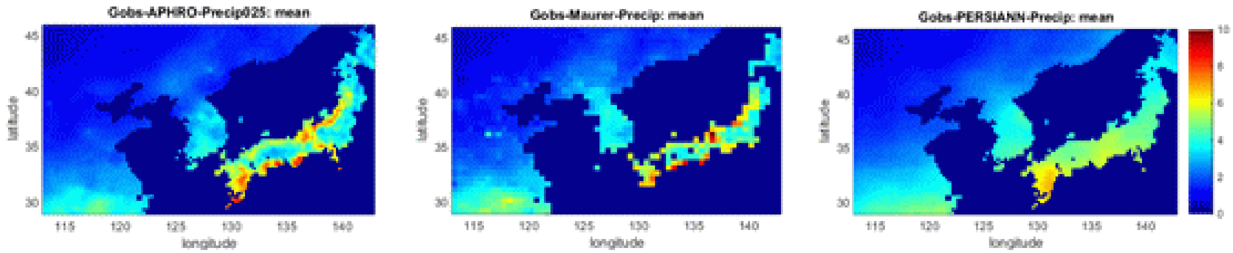
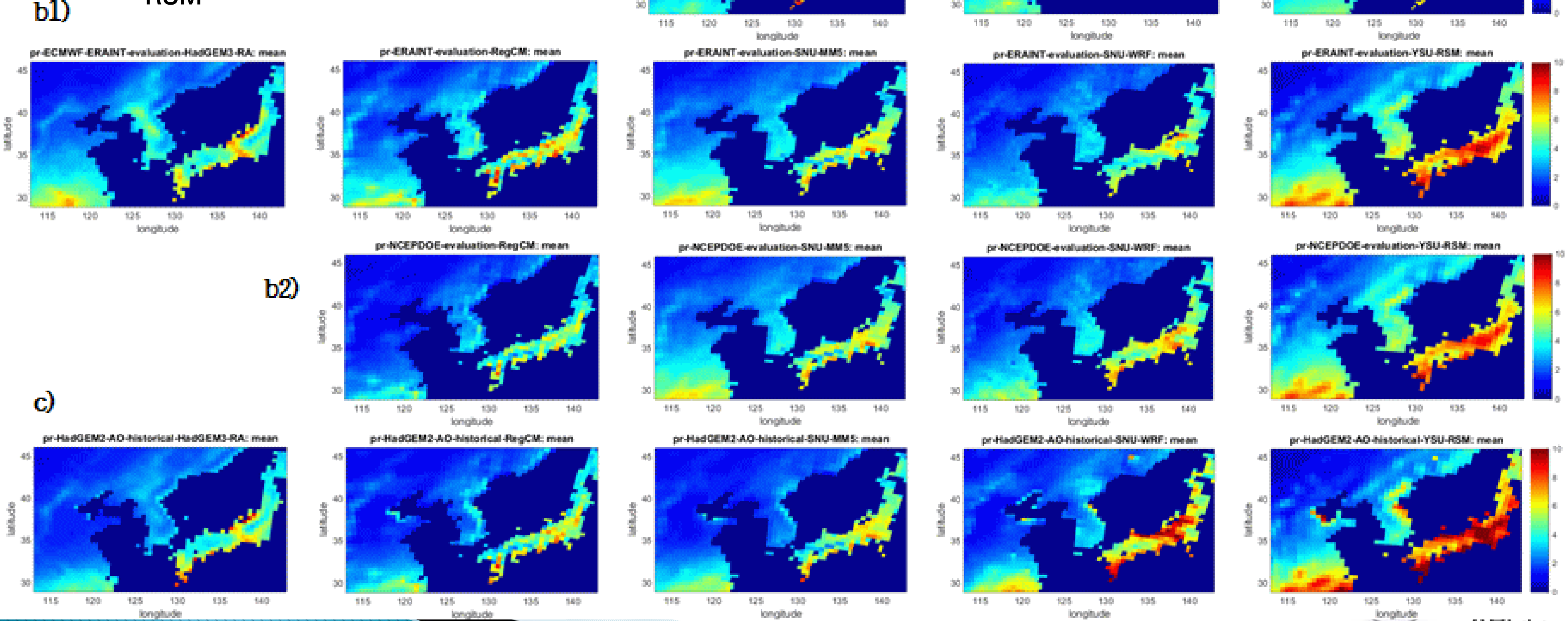
CORDEX

Basic stats – historical simulation & hindcast

- Spatial distribution of mean precipitation (1979~2005)
  - a) Gridded observation (APHRODITE, MAURER's, and PERSIANN)
  - b1) Historical simulation (ECMWF reanalysis data))
  - B2) Historical simulation (NCEPDOE)
  - c) Hindcast (HadCEM2-AO+RCMs)

    RCMs: HadGEM3-RA, RegCM, SNU-MM5, SNU-WRF, YSU-RSM



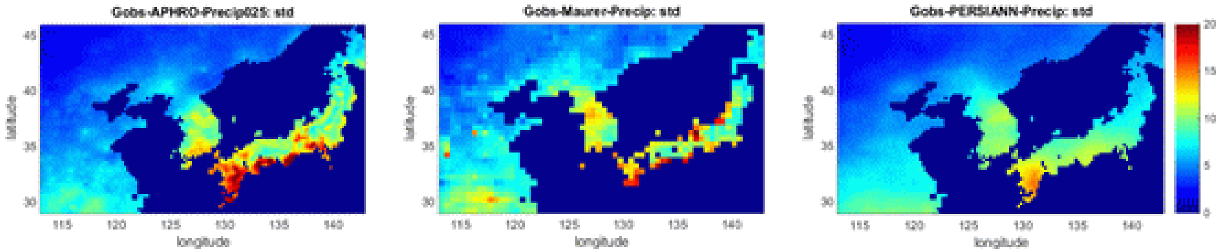


CORDEX

- Spatial distribution of standard deviation of daily precipitation (1979~2005)
  - a) Gridded observation (APHRODITE, MAURER's, and PERSIANN)
  - b1) Historical simulation (ECMWF reanalysis data))
  - B2) Historical simulation (NCEPDOE)
  - c) Hindcast (HadCEM2–AO+RCMs)

    RCMs: HadGEM3–RA, RegCM, SNU–MM5, SNU–WRF, YSU–RSM

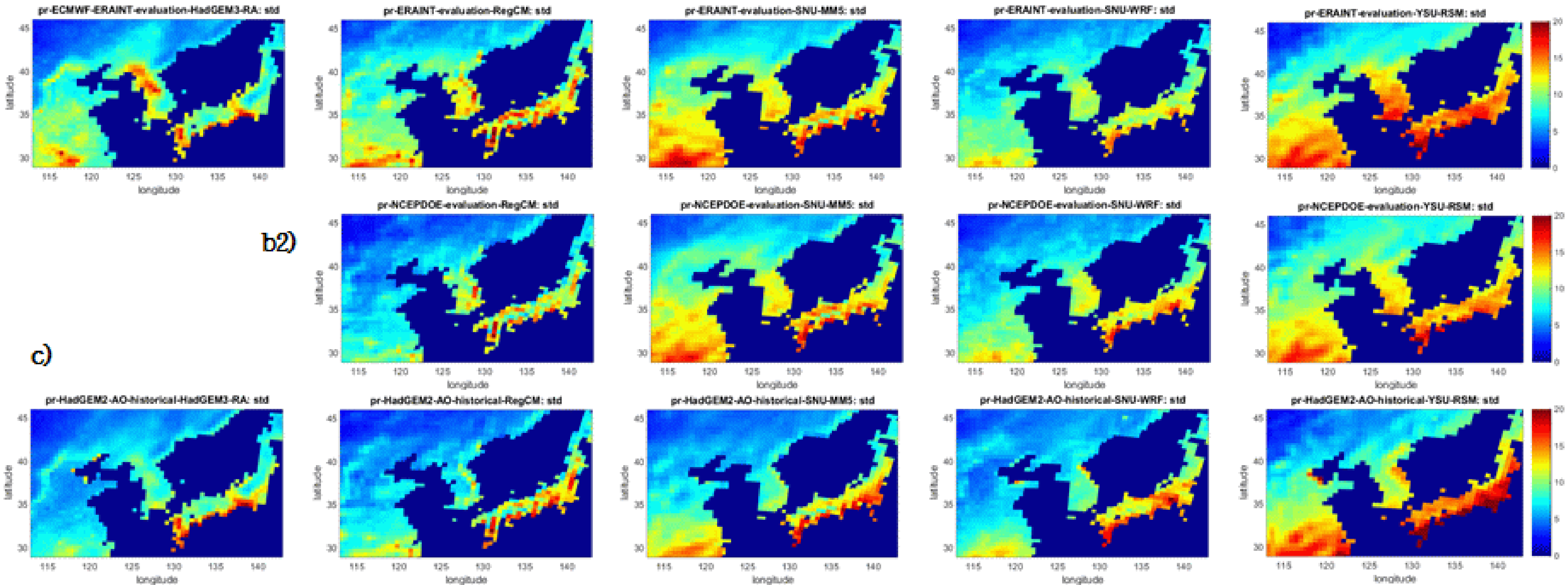
a)



b1)

b2)

c)



CORDEX

Extreme index

- Spatial distribution of 90^{th} percentile of daily precipitation (1979~2005)

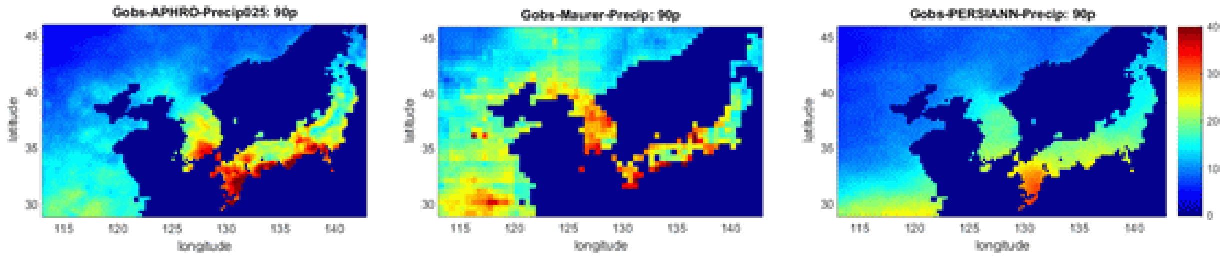
  a) Gridded observation (APHRODITE, MAURER's, and PERSIANN)

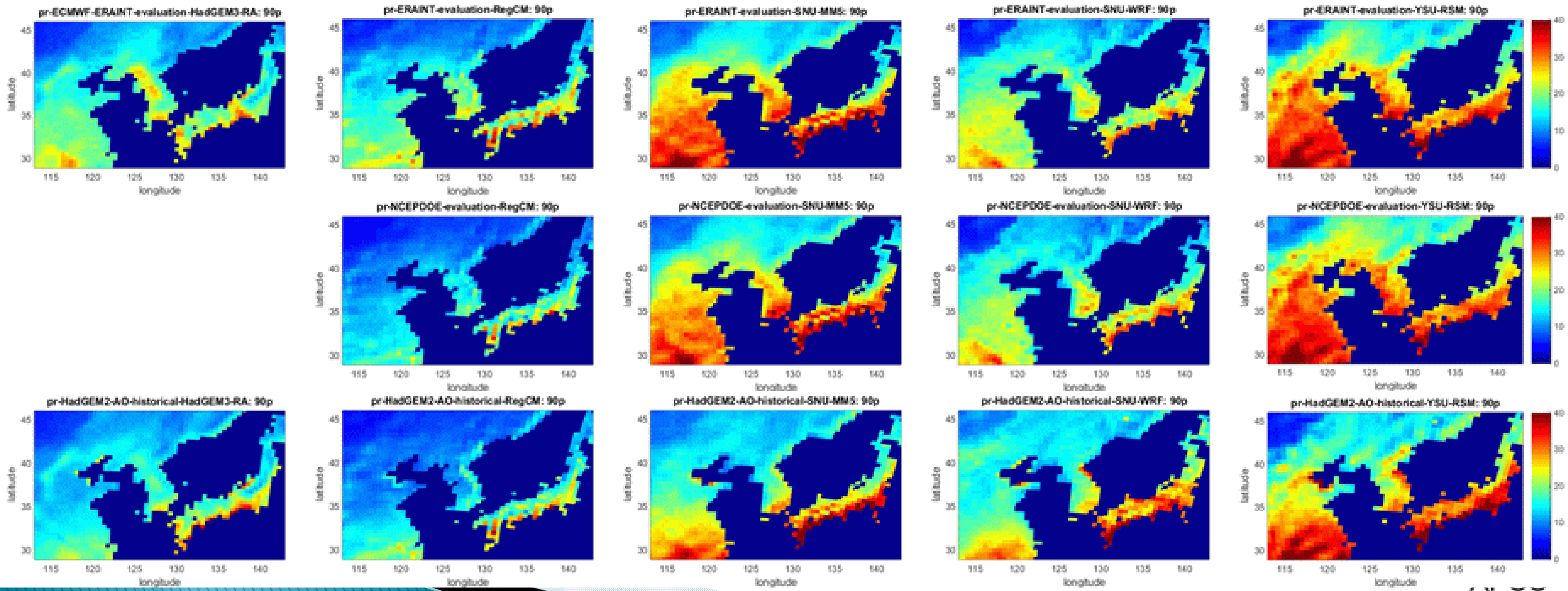
  b1) Historical simulation (ECMWF reanalysis data))

  B2) Historical simulation (NCEPDOE)

  c) Hindcast (HadCEM2-AO+RCMs)

  RCMs: HadGEM3-RA, RegCM, SNU-MM5, SNU-WRF, YSU-RSM





CORDEX

Extreme index

- Spatial distribution of max5d(greatest 5-day total precipitation)

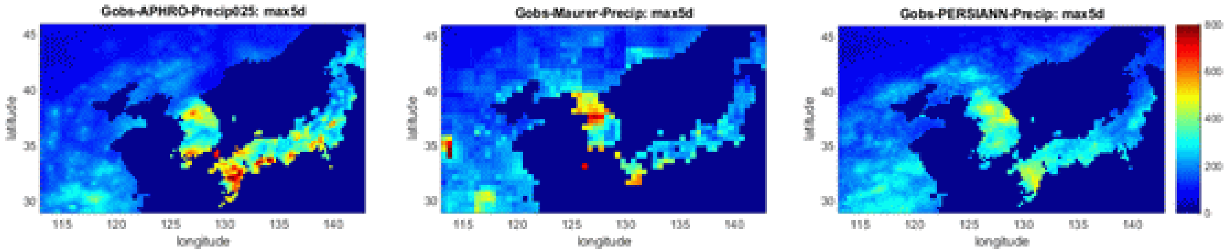
  a) Gridded observation (APHRODITE, MAURER's, and PERSIANN)

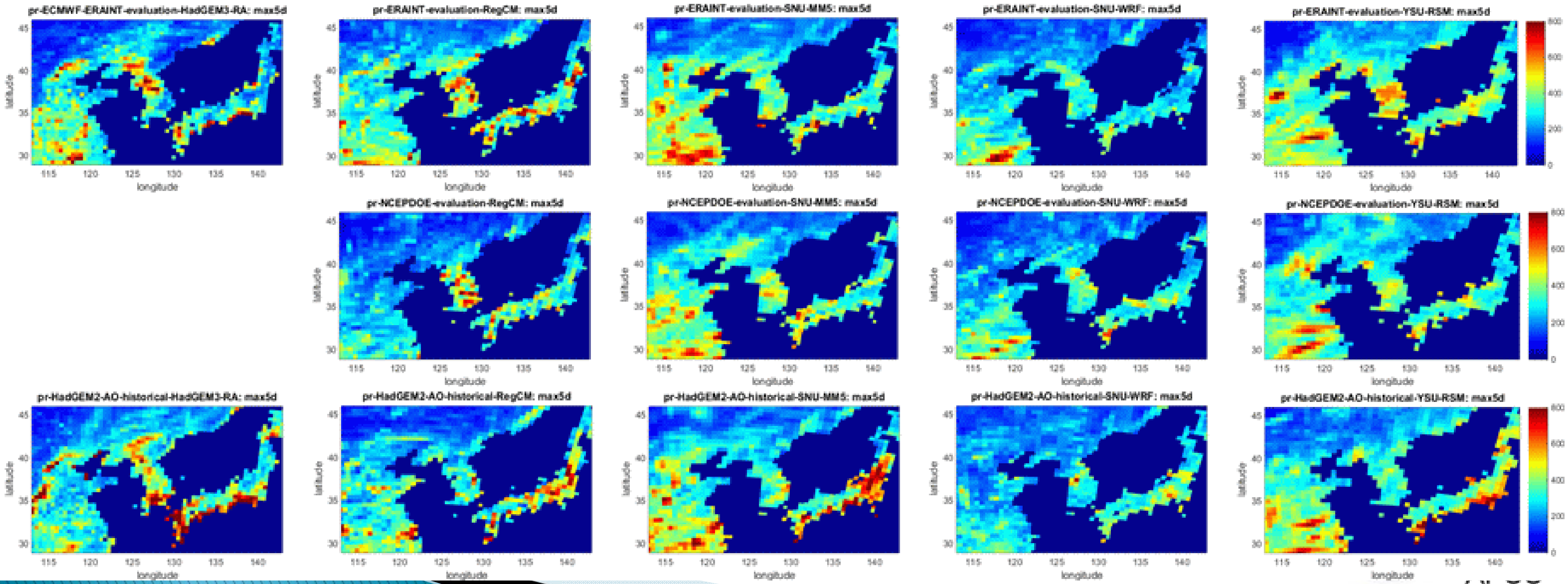
  b1) Historical simulation (ECMWF reanalysis data))

  B2) Historical simulation (NCEPDOE)

  c) Hindcast (HadCEM2-AO+RCMs)

  RCMs: HadGEM3-RA, RegCM, SNU-MM5, SNU-WRF, YSU-RSM





CORDEX

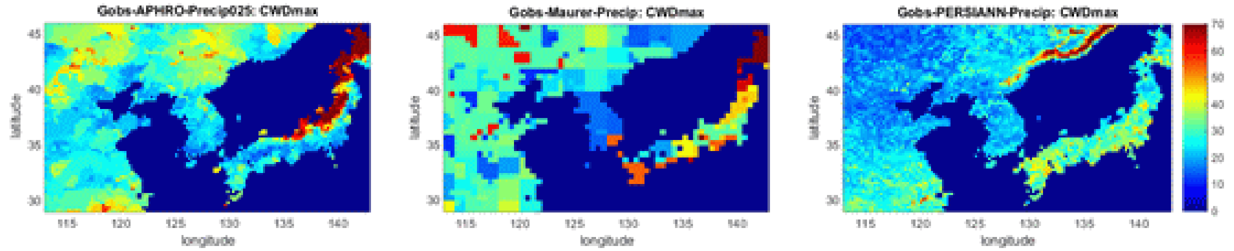
Precipitation pattern

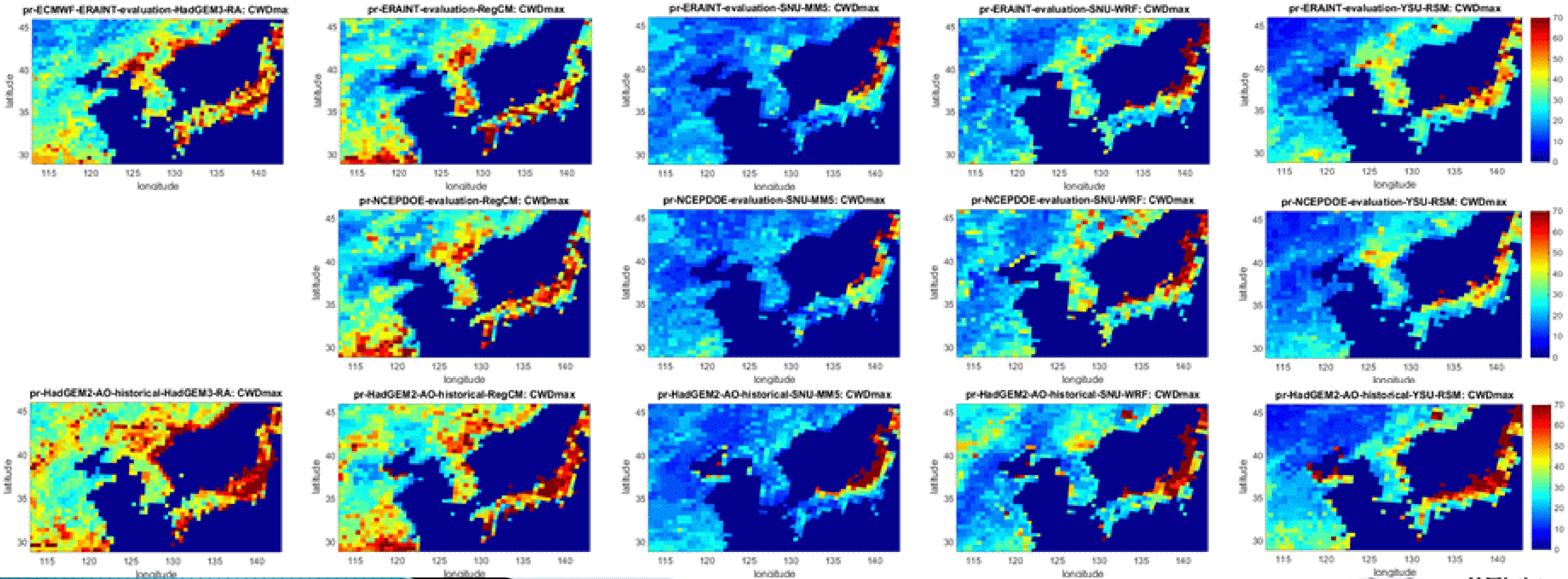
- Spatial distribution of CWDmax(maximum number of consecutive wet days (>0.1mm/day))
- a) Gridded observation (APHRODITE, MAURER's, and PERSIANN)

  b1) Historical simulation (ECMWF reanalysis data))

  B2) Historical simulation (NCEPDOE)

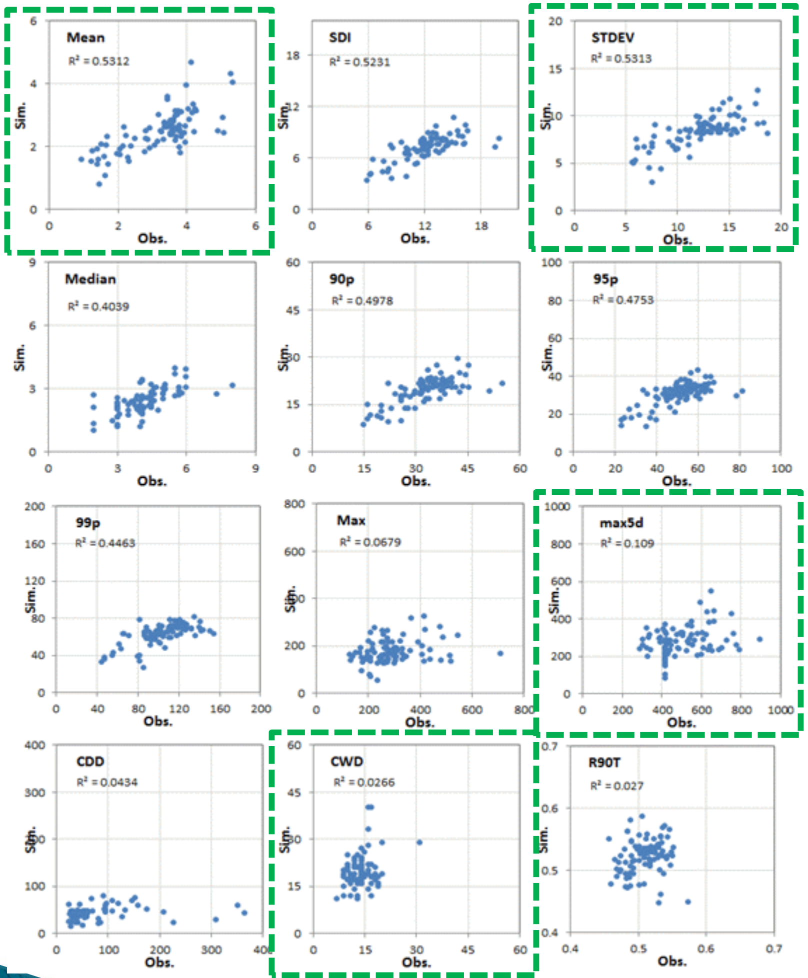
  c) Hindcast (HadCEM2-AO+RCMs)

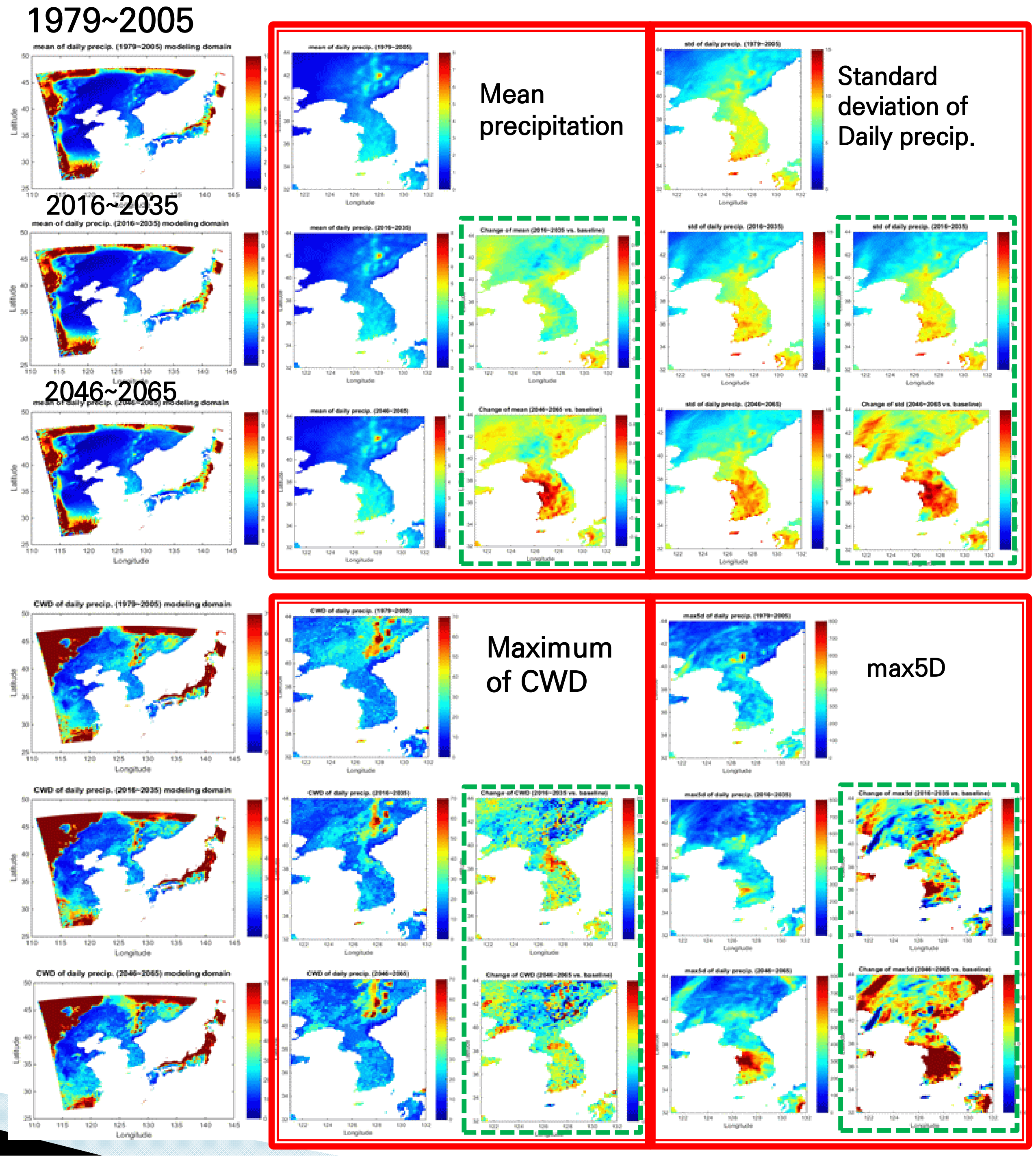




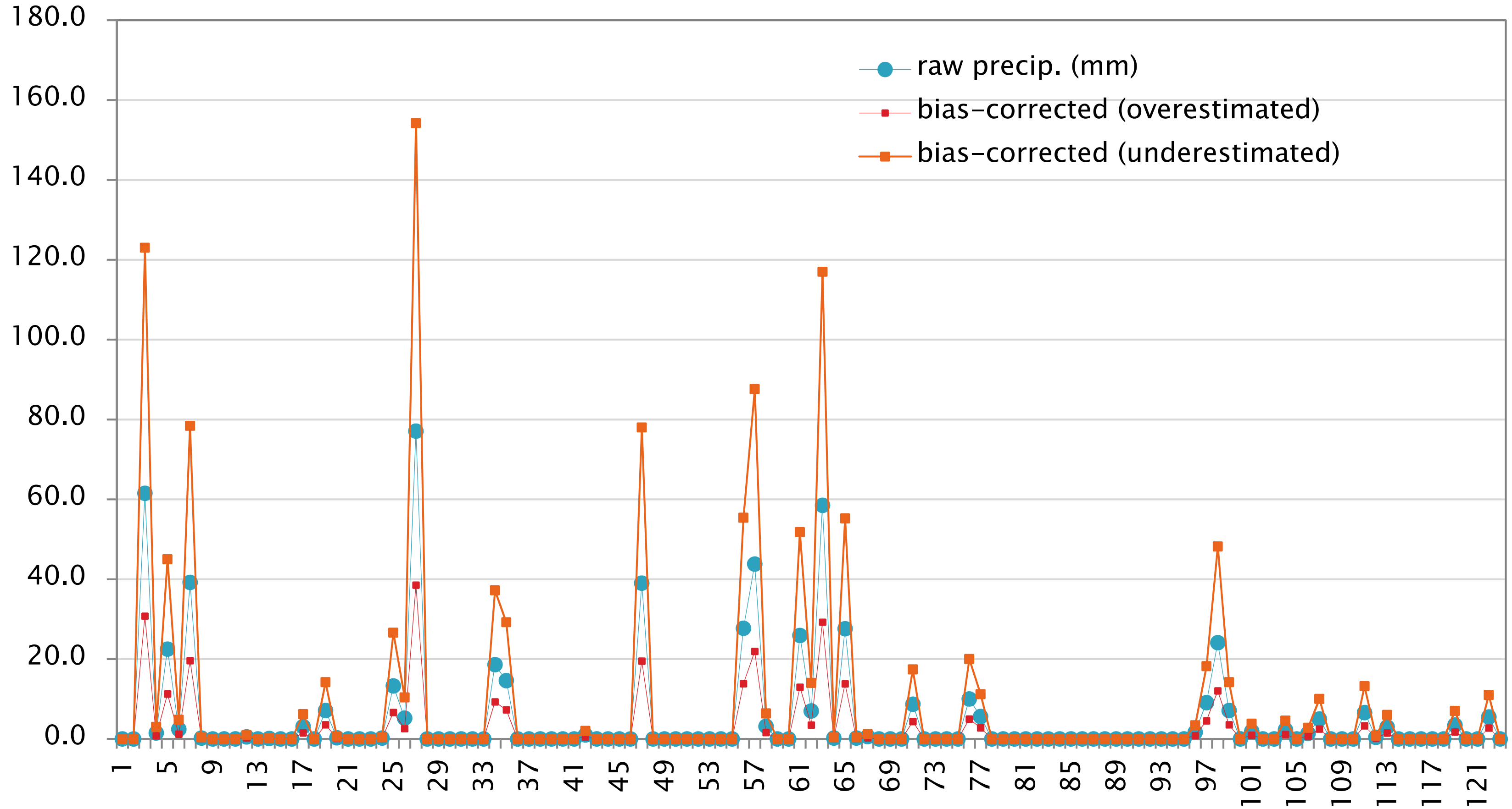
Internal effort for Regional climate modeling (South Kor.)

Performance of SNU_WRF.
(vs. Station-based observation data)

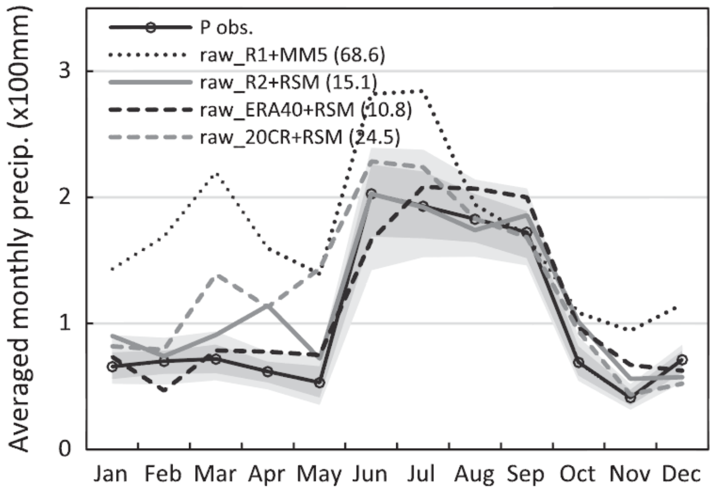




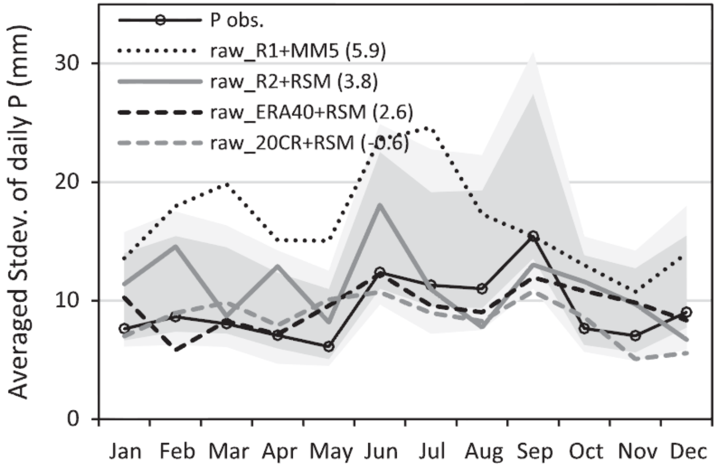
Bias-correction
Necessity!

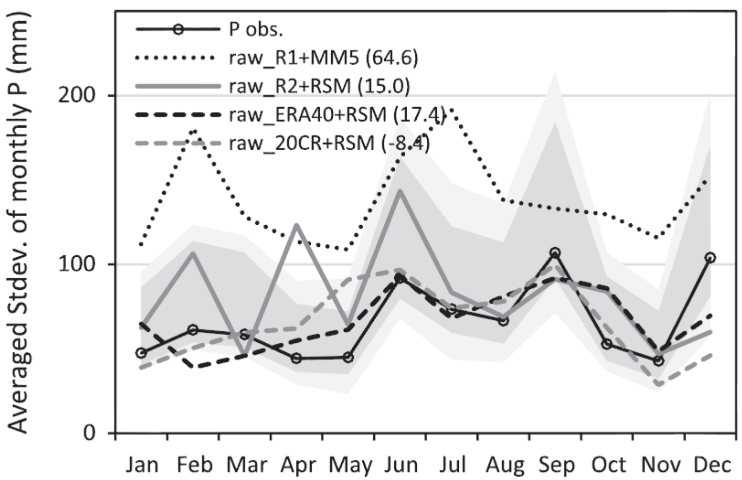


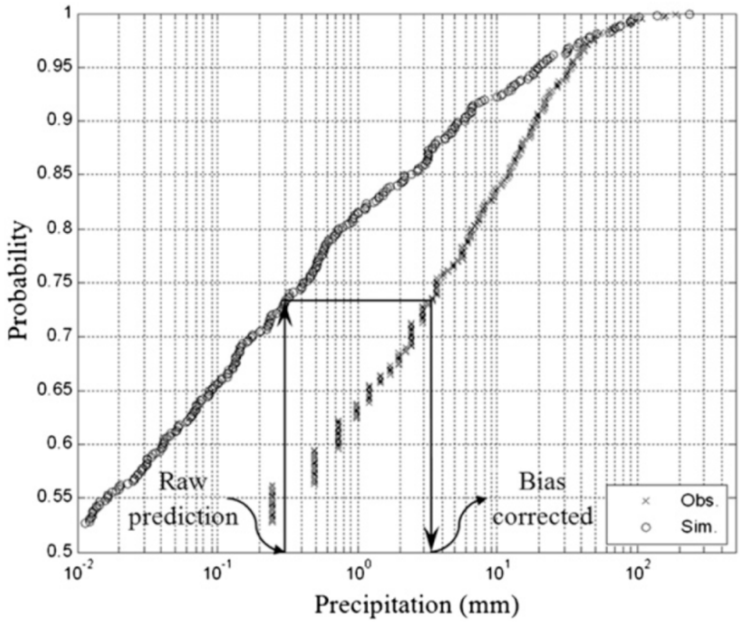
Look at the Raw climate model outputs!



Comparison of the mean monthly precipitation over the study period for raw regional reanalysis data to basin based observations

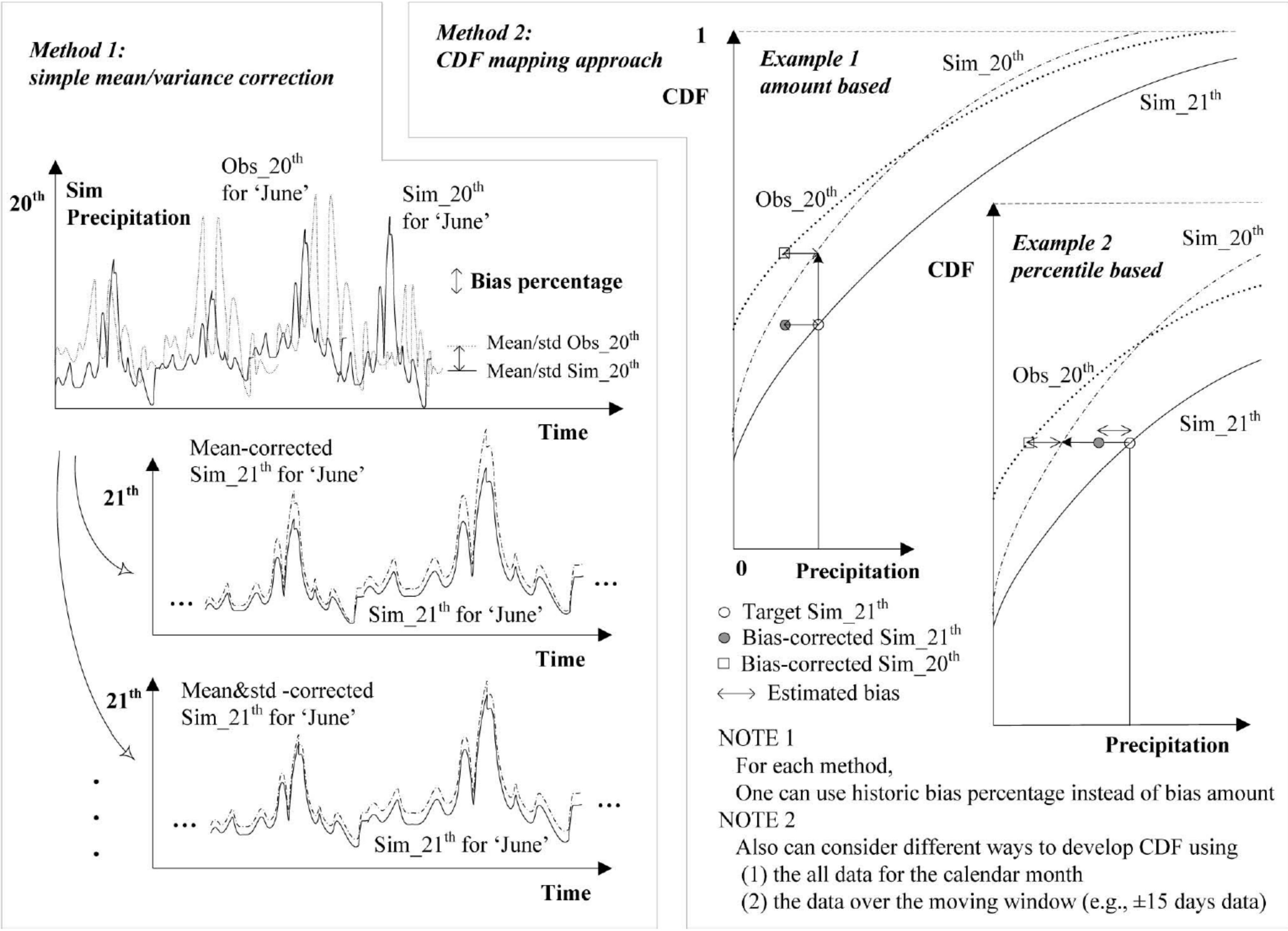






Example of CDF for simulated results (September) and observations at a station and CDF mapping methodology for bias-correction

Methods: Schematic representation of bias-correction procedures



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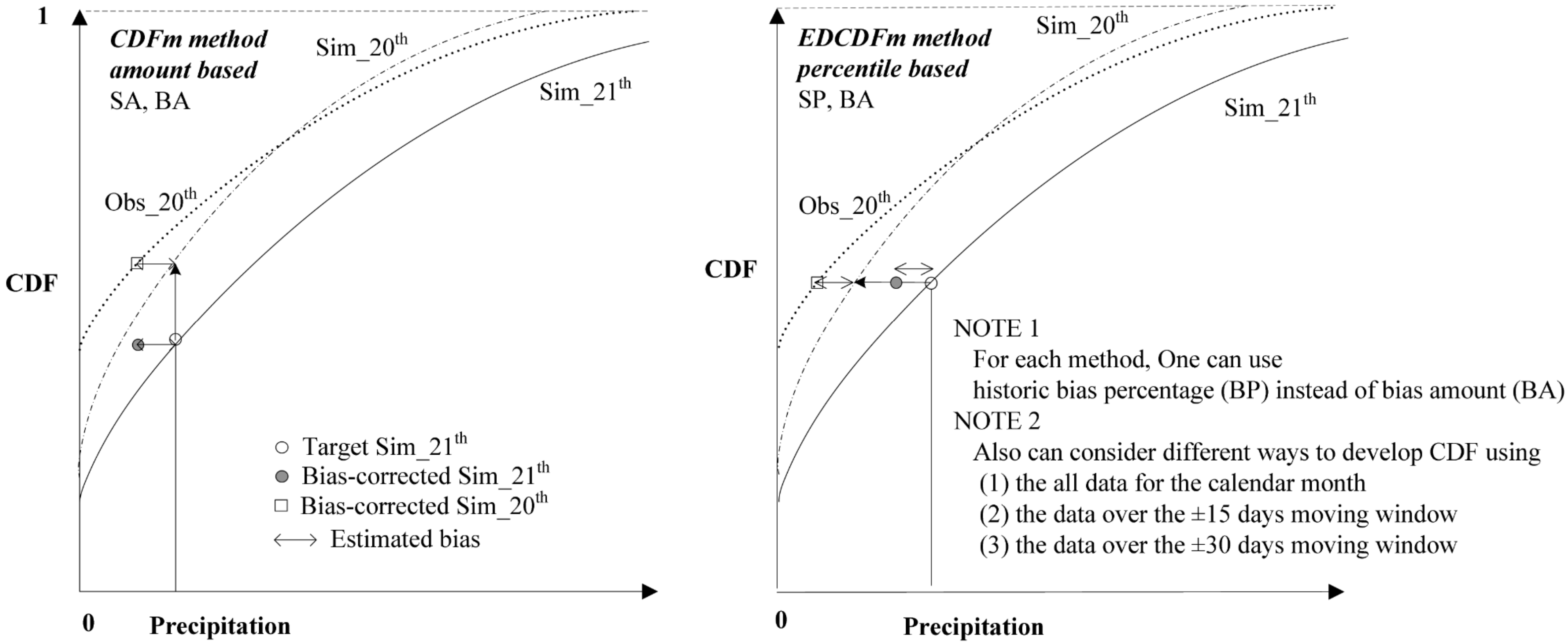
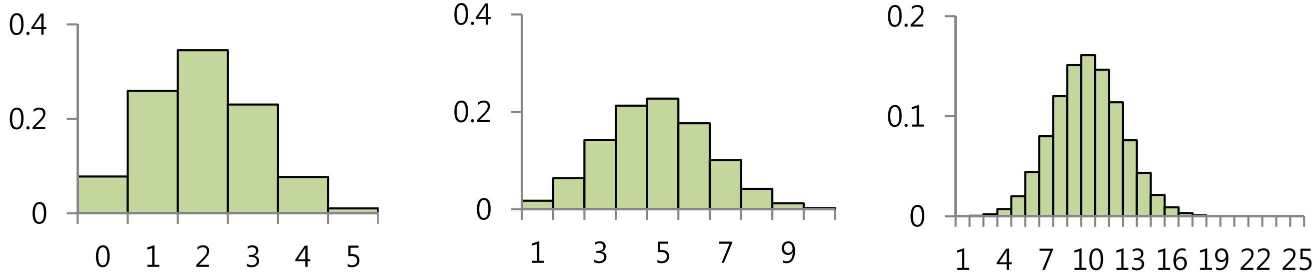
Methods: CDF mapping



Basic theory

Probability concepts
PDF
CDF
CDF mapping

Histogram



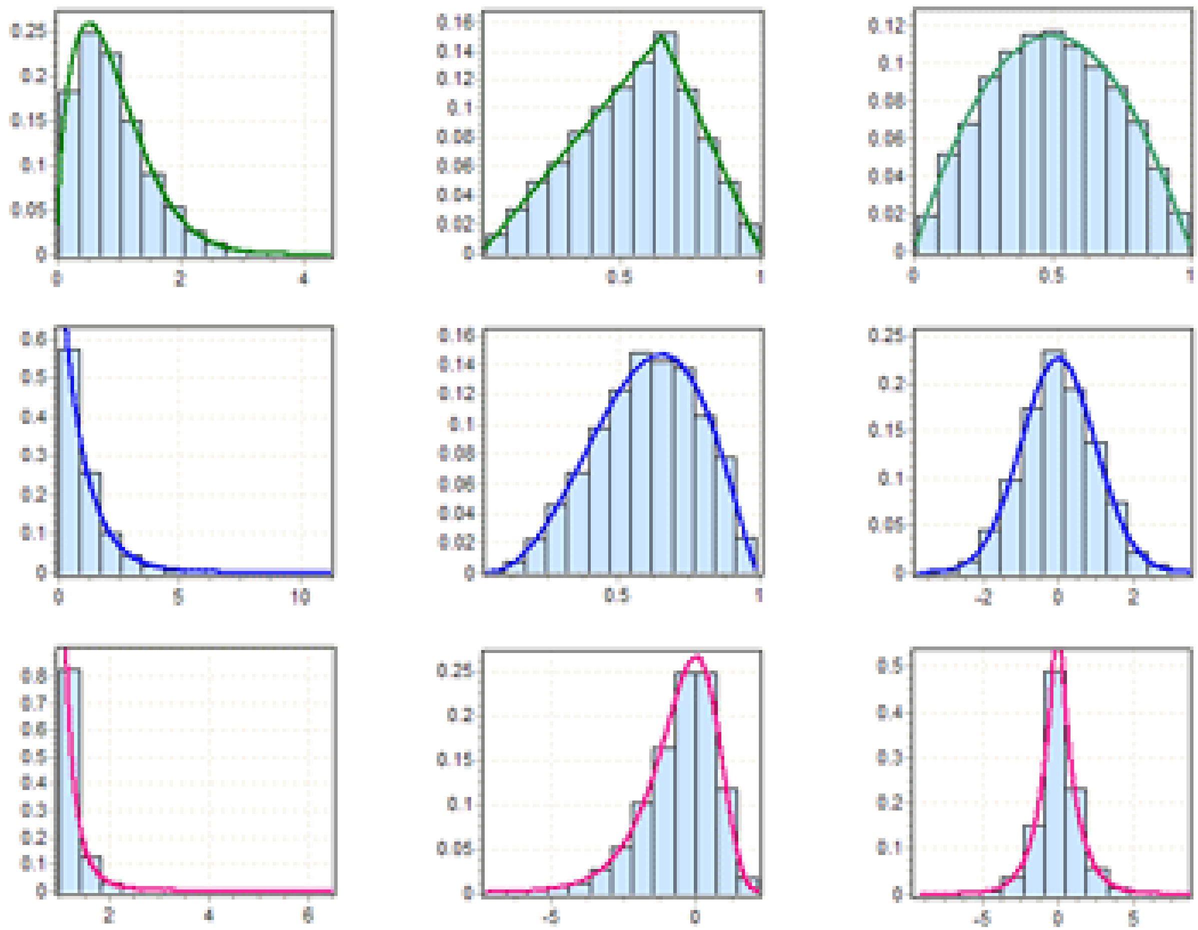
- A histogram is a graph that consists of a number of “bins", or vertical bars, into which the sample values are sorted.
- The height of each histogram bar indicates how many of your data points fall into that bins, relative to the total number of data values, so this kind of chart is also called the relative frequency histogram.
- Number of bins and width
  - There is no "best" number of bins, and different bins sizes can reveal different features of the data.
  - The number of bins k can be assigned directly or can be calculated from a suggested bins width h as:

$$k = \left\lceil \frac{x_{max} - x_{min}}{h} \right\rceil$$

*k: bins (=width)
x_{max}: The maximum value
x_{min}: The minimum value
h: Number of Interval

Histogram

- The histogram graphically shows various properties of your data, including the location, scale, and shape, helping you visually identify an underlying probability distribution:



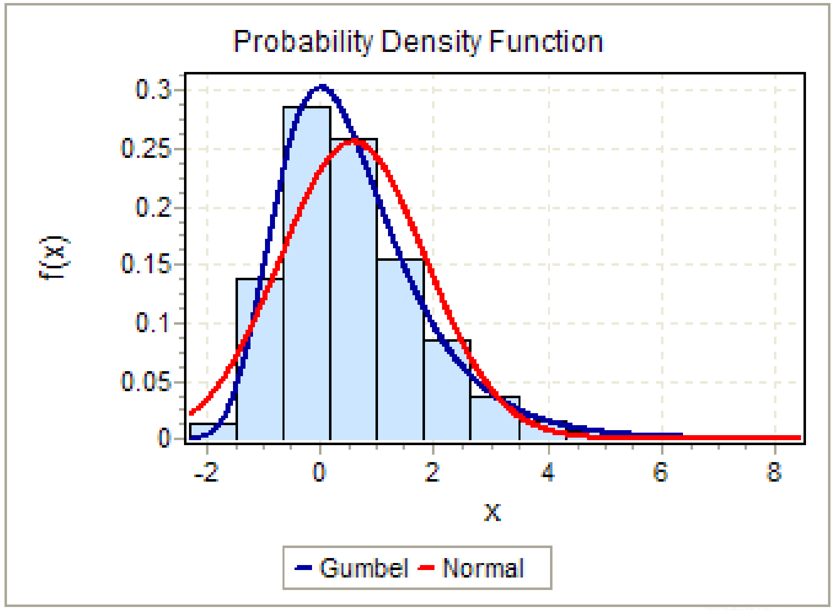
*Ref: mathwave (www.mathwave.com)

PDF (Probability Density Function)

- For a continuous function, the probability density function (PDF) is the probability that the variate has the value x.
- Since for continuous distributions the probability at a single point is zero, this is often expressed in terms of an integral between two points.

$$\int_a^b f(x)dx = P\{a \le x \le b\}$$

- The Probability Density Function graph displays the theoretical PDF of the fitted distribution (or several distributions) and the histogram of your sample data:



*Ref: mathwave (www.mathwave.com)

CDF (Cumulative Distribution Function)

- The cumulative distribution function (CDF) is the probability that the variate takes on a value less than or equal to x:

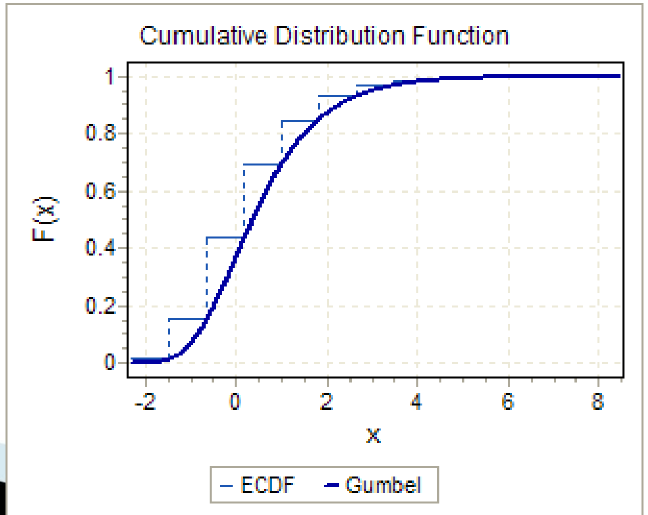
$$F(x) = P\{X \leq x\}$$

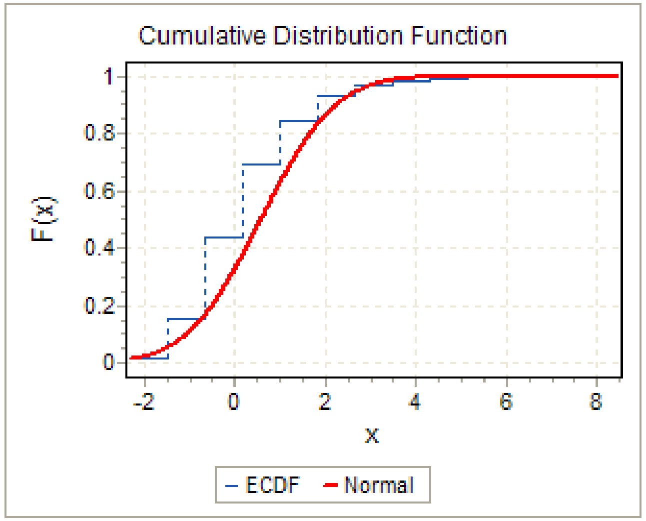
- This can be expressed as:

$$F(x) = \begin{cases} \sum_{t=-\infty}^{x} f(t) & \text{if } X : DRV \\ \int_{-\infty}^{x} f(t)dt & \text{if } X : CRV \end{cases}$$

*DRV: discrete random variable
CRV: continuous random variable

- The Cumulative Distribution Function graph displays the theoretical CDF of the fitted distributions and the empirical CDF based on your sample data.
- While the PDF graph mainly shows the shape of your data, the CDF graph is useful to actually determine how well the distributions fit to data:
- The empirical CDF graph also depends on the number of bins chosen. As you increase this number, the ECDF curve gets smoother:

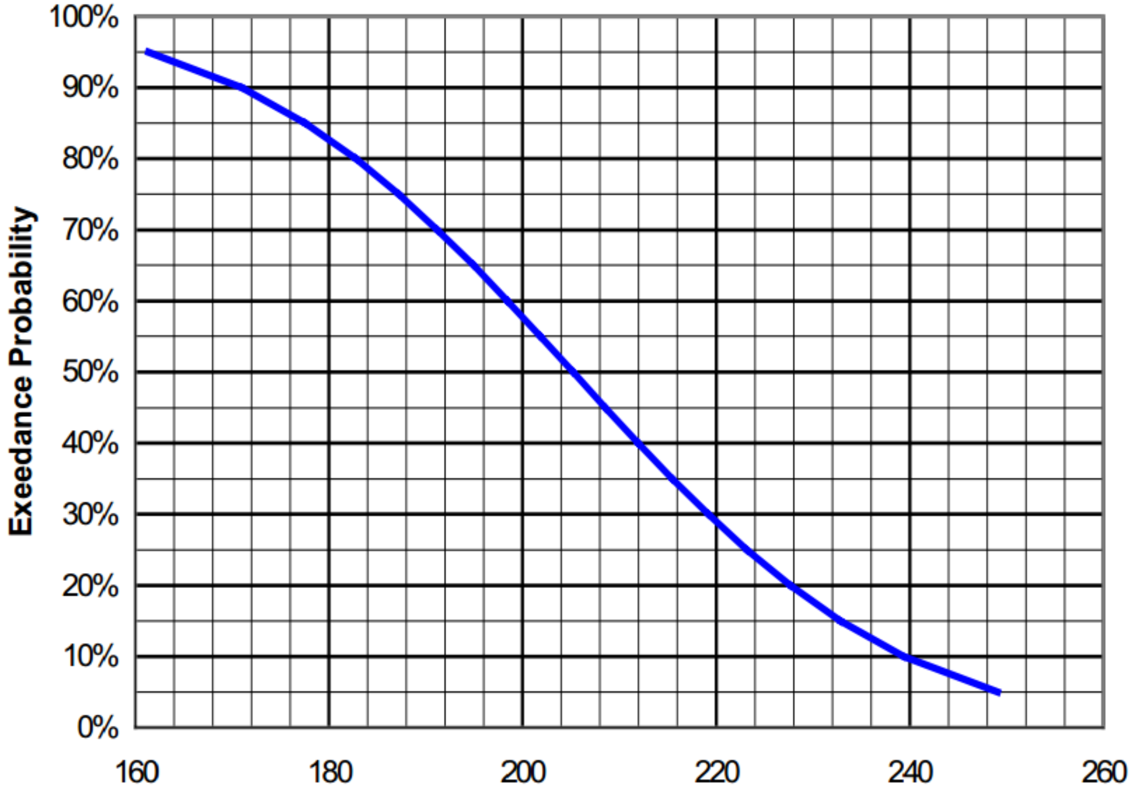




Exceedance probability

The probability that a given data (e.g., rainfall total) accumulated over a given duration will be exceeded in any data period

- Example

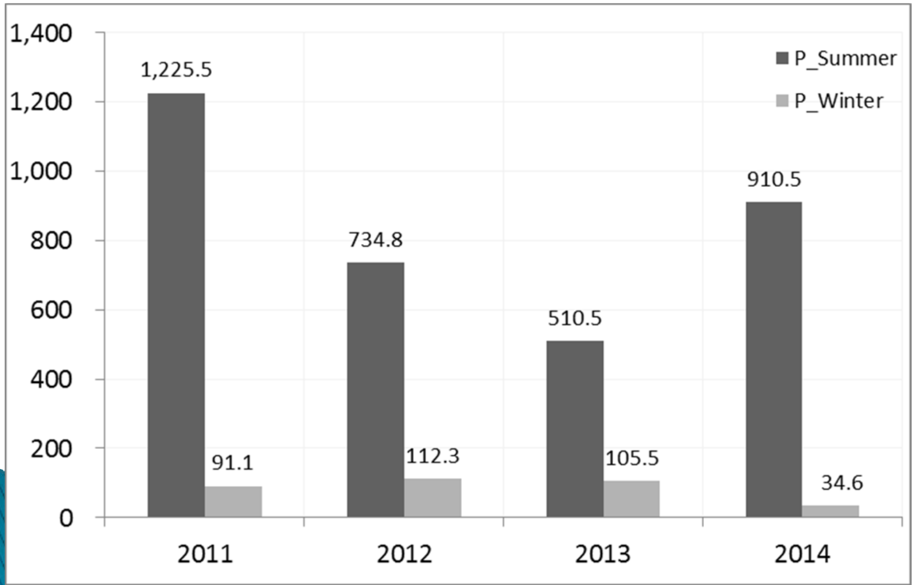


	Exceedance Probability P
249.1	5%
239.4	10%
232.9	15%
227.7	20%
223.2	25%
219.2	30%
215.5	35%
212.0	40%
208.6	45%
205.2	**50%**
201.9	55%
198.4	60%
194.9	65%
191.2	70%
187.2	75%
182.8	80%
177.6	85%
171.0	90%
161.3	95%

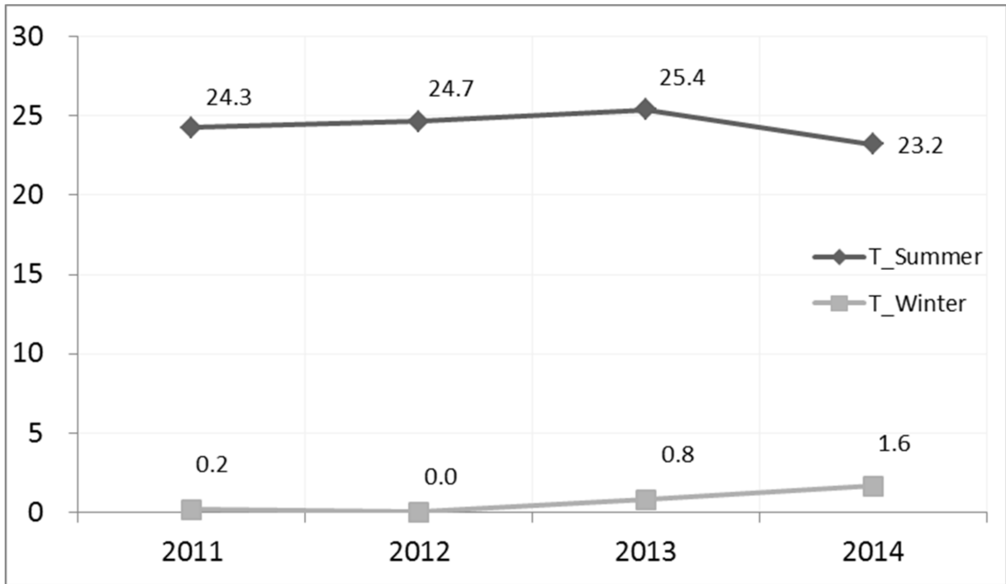
Practice using sample data

- Climate data at Jinju station, Gyeongsangnam-do, South Korea
  - Daily precipitation, daily mean temperrature
    - Summer (6, 7, 8월), Winter (12, 1, 2월)

Year	Precipitation (mm)		Temperature (℃)	
	Summer	Winter	Summer	Winter
2011	1,225.5	91.1	24.3	0.2
2012	734.8	112.3	24.7	0.0
2013	510.5	105.5	25.4	0.8
2014	910.5	34.6	23.2	1.6



Precipitation



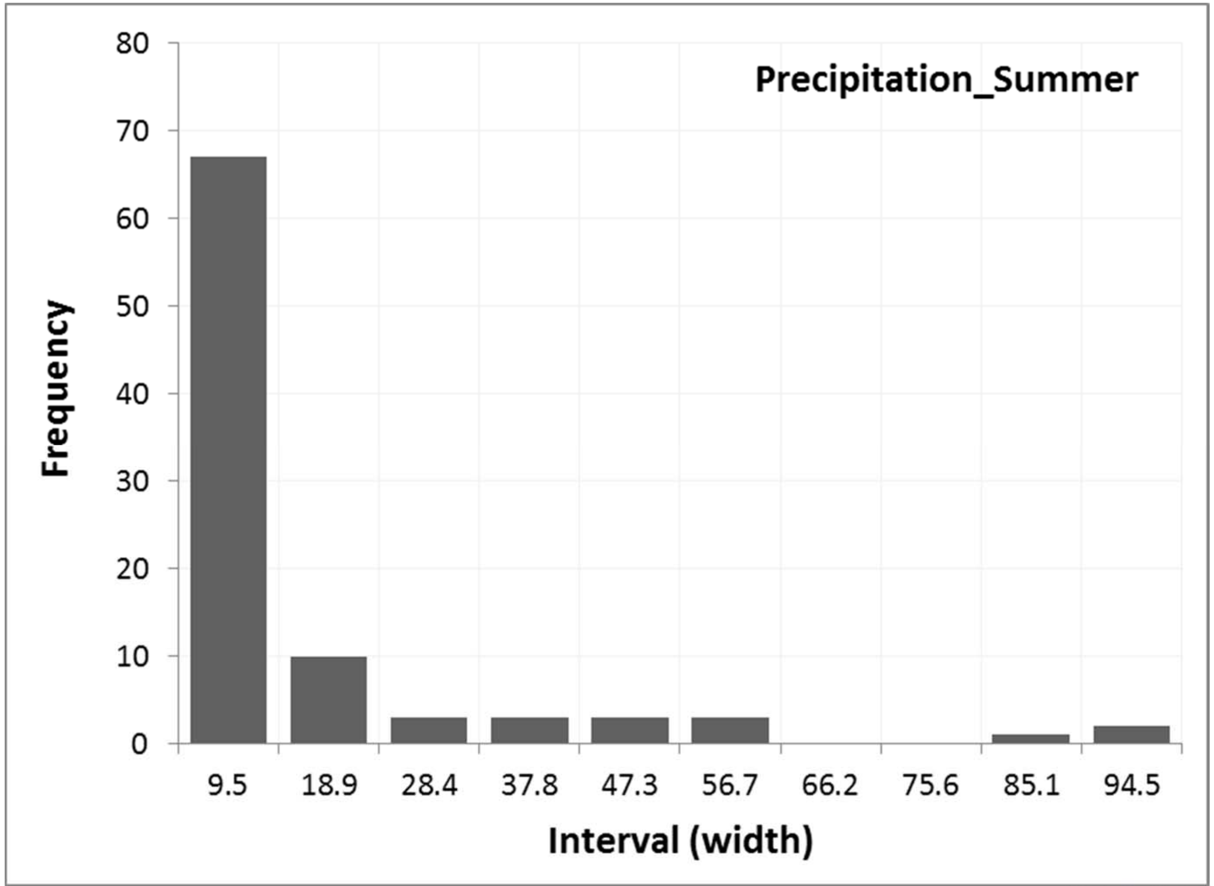
Temperature

Histogram

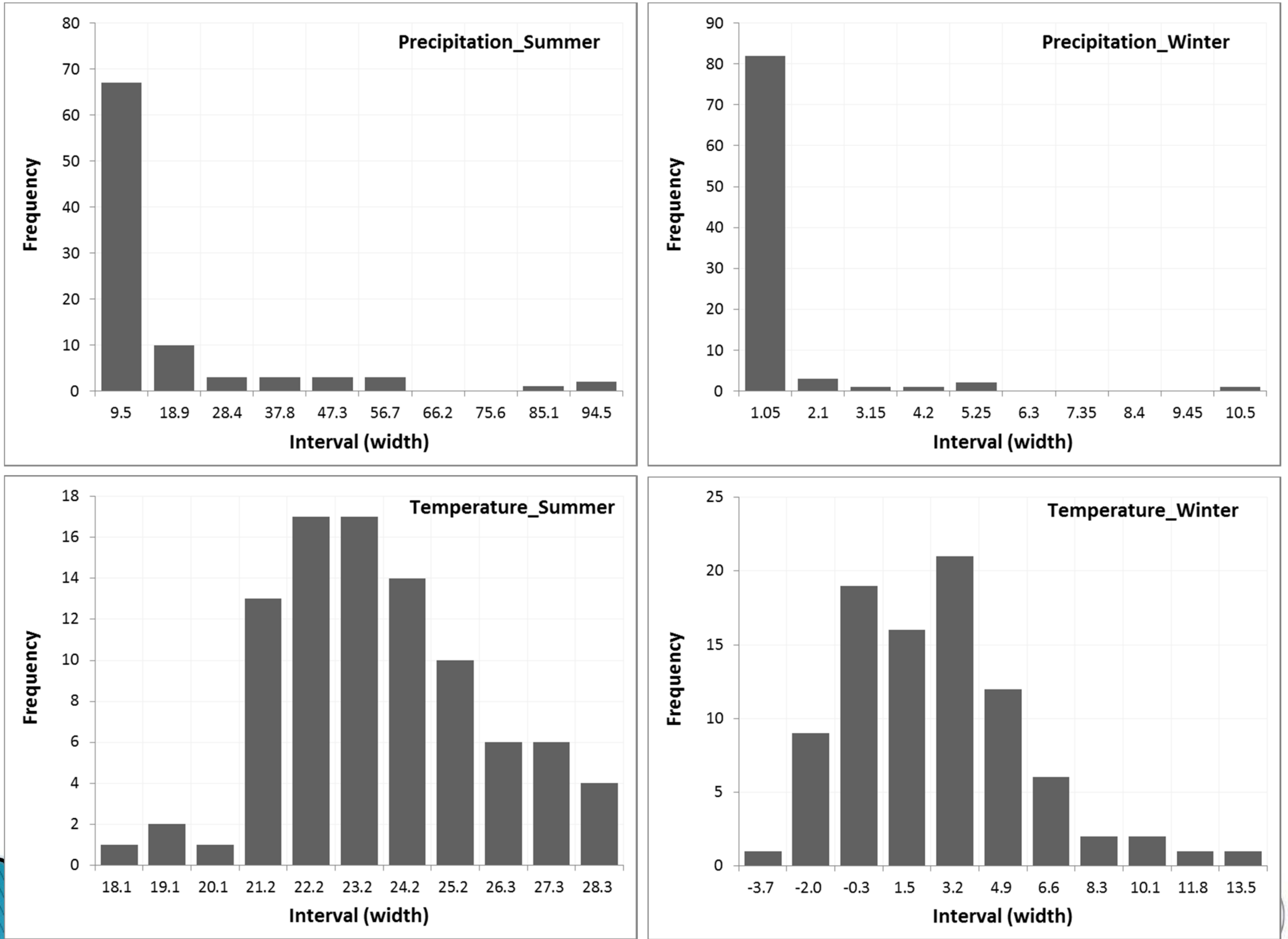
- ex) maximum Precipitation: 94.5mm/day, minimum: 0.0
- bin:

$$k = \left[\frac{94.5 - 0.0}{10} \right] = 9.45$$

Interval	Frequency
9.5	67
18.9	10
28.4	3
37.8	3
47.3	3
56.7	3
66.2	0
75.6	0
85.1	1
94.5	2



Histogram

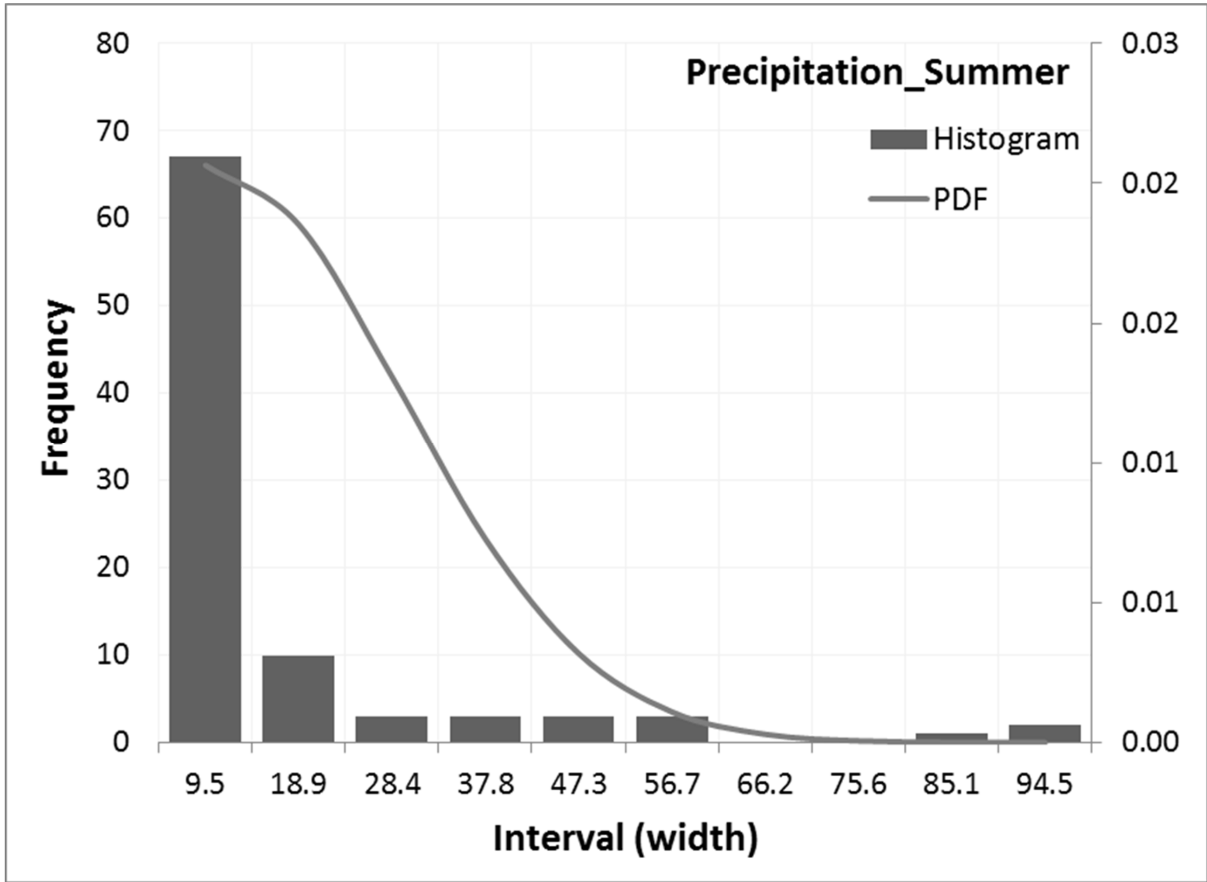


*Sample data in Jinju station from 2014

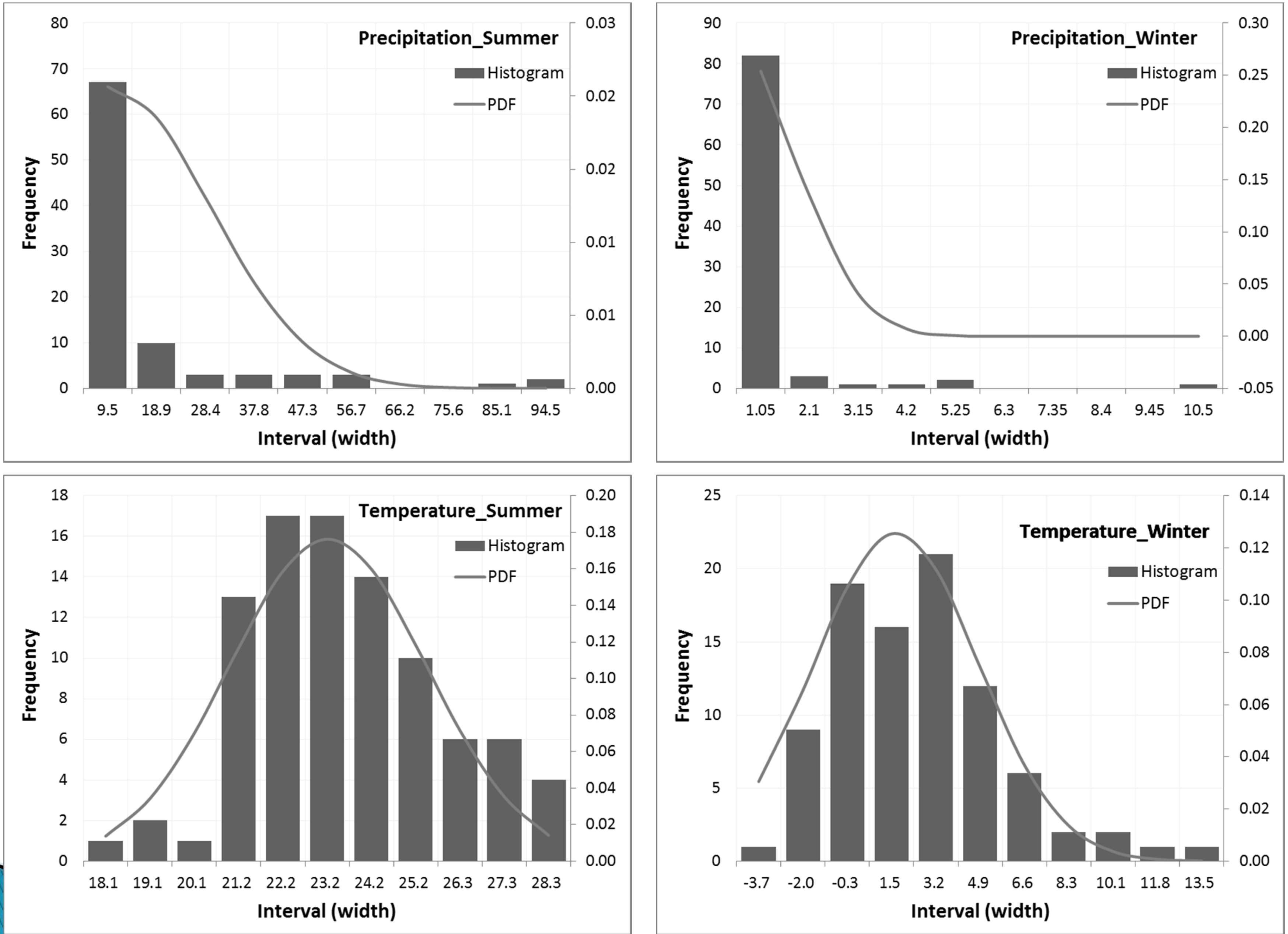
PDF (Probability Density Function)

- function excel
  - Precipitation: [LOGNorm.dist(x, mean, stdev, 0 or false)]
  - Temperature: [Norm.dist(x, mean, stdev, 0 or false)]

Mean	9.90
Stdev	19.32
Interval	PDF
9.5	0.02064
18.9	0.01852
28.4	0.01309
37.8	0.00728
47.3	0.00319
56.7	0.00110
66.2	0.00030
75.6	0.00006
85.1	0.00001
94.5	0.00000



PDF (Probability Density Function)

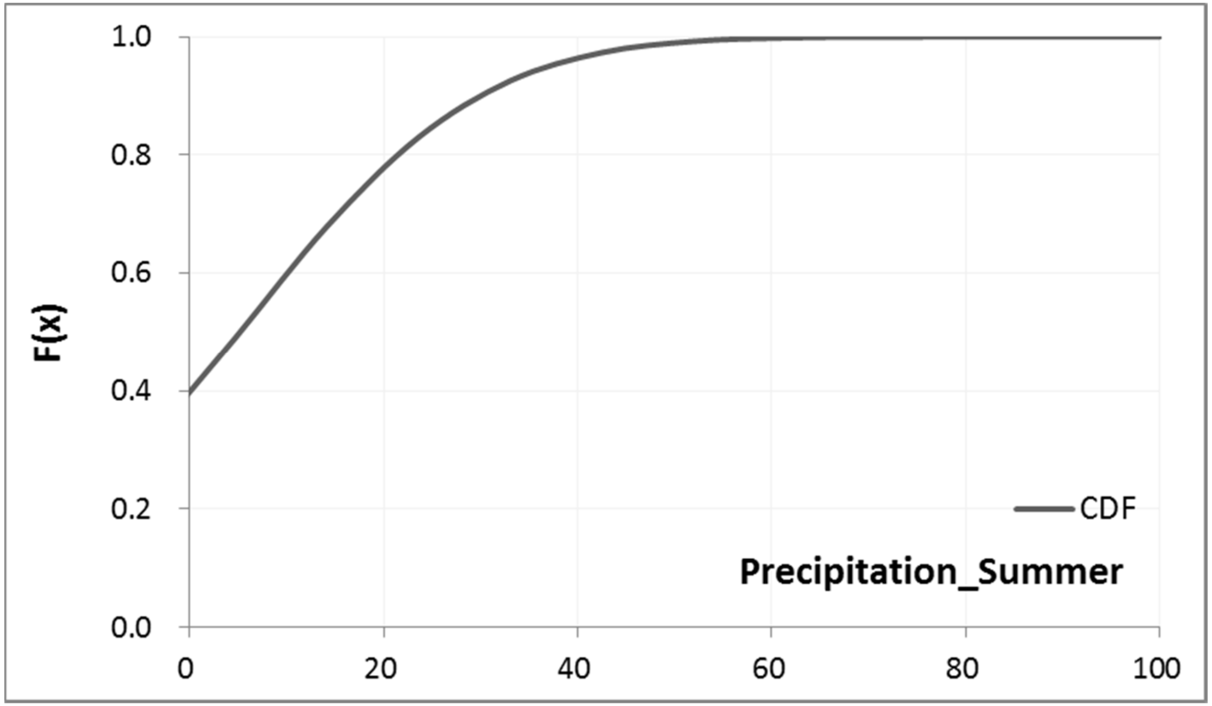


*Sample data in Jinju station from 2014

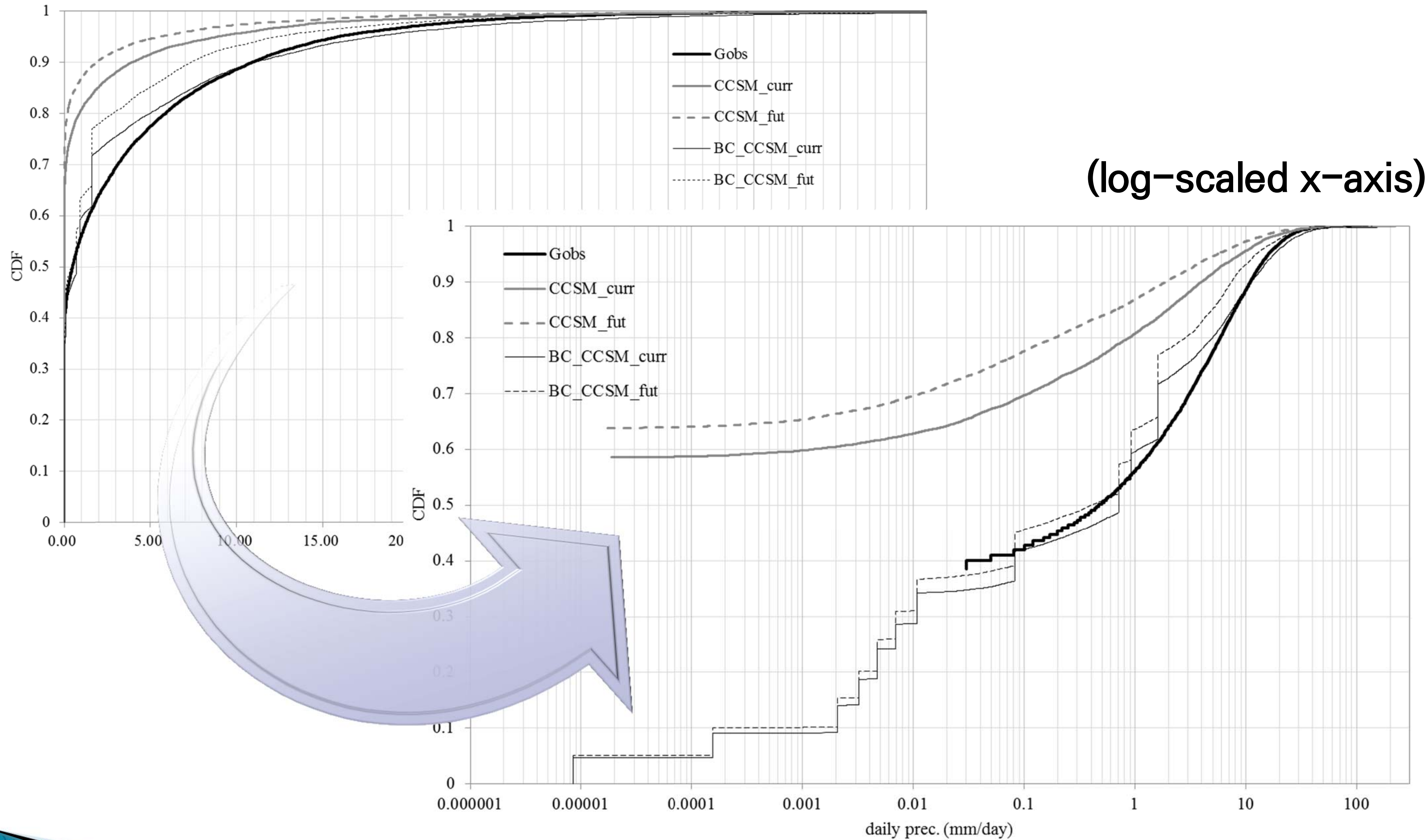
CDF (Cumulative Distribution Function)

- function excel
  - Precipitation: [LOGNorm.dist(x, mean, stdev, 1 or true)]
  - Temperature: [Norm.dist(x, mean, stdev, 1 or true)]

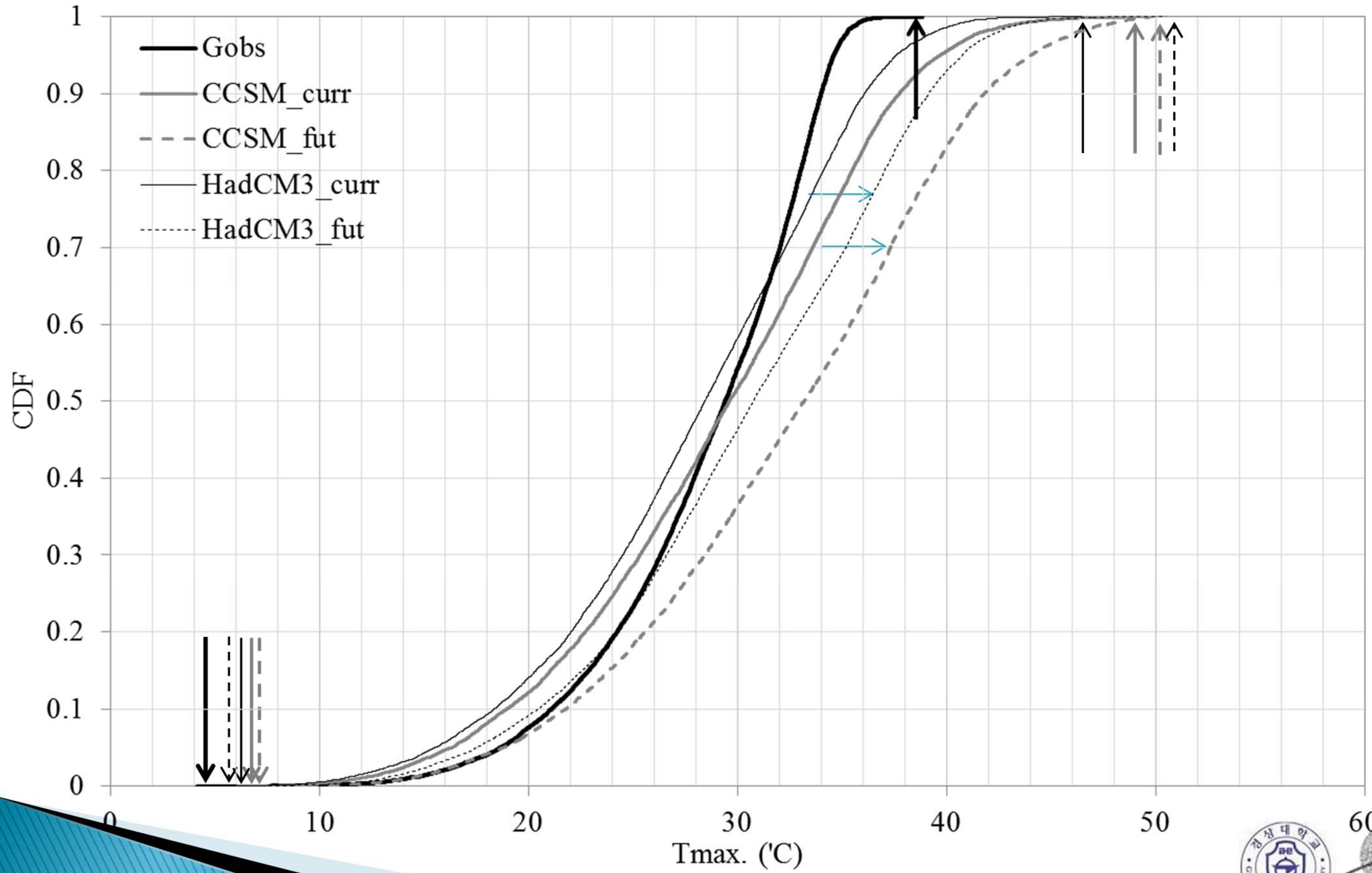
Mean	9.90
Stdev	19.32
Interval	CDF
9.5	0.4908
18.9	0.6794
28.4	0.8302
37.8	0.9257
47.3	0.9734
56.7	0.9923
66.2	0.9982
75.6	0.9997
85.1	0.9999
94.5	1.0000



Example of CDFs of observed precipitation and Raw and bias-corrected model outputs



Example of CDFs of observed temperature and Raw model outputs



CDF mapping for Bias-correction

- To remove biases in
  - Mean and STDEV of daily Tmax and Tmin at each spatio-temporal scale
- Reproduce
  - Distribution of daily Tmax and Tmin (CDF)
  - Spatial structure of mean Tmax and Tmin (map)

For current sim., Xc : $$x_c{}' = CDF_{obs}^{-1}\left(CDF_{sim\_c}(x_c)\right)$$

For future sim., Xs : $$x_s{}' = \left\{x_{c\_min} < x_s < x_{c\_max} \mid CDF_{obs}^{-1}\left(CDF_{sim_c}(x_s)\right)\right\}$$

$$x_s{}' = \left\{x_{c\_max} < x_s \mid x_s + \left(CDF_{obs}^{-1}\left(CDF_{sim_c}(x_{c\_max})\right) - x_{c\_max}\right)\right\}$$

$$x_s{}' = \left\{x_s < x_{c\_min} \mid x_s + \left(CDF_{obs}^{-1}\left(CDF_{sim_c}(x_{c\_min})\right) - x_{c\_min}\right)\right\}$$

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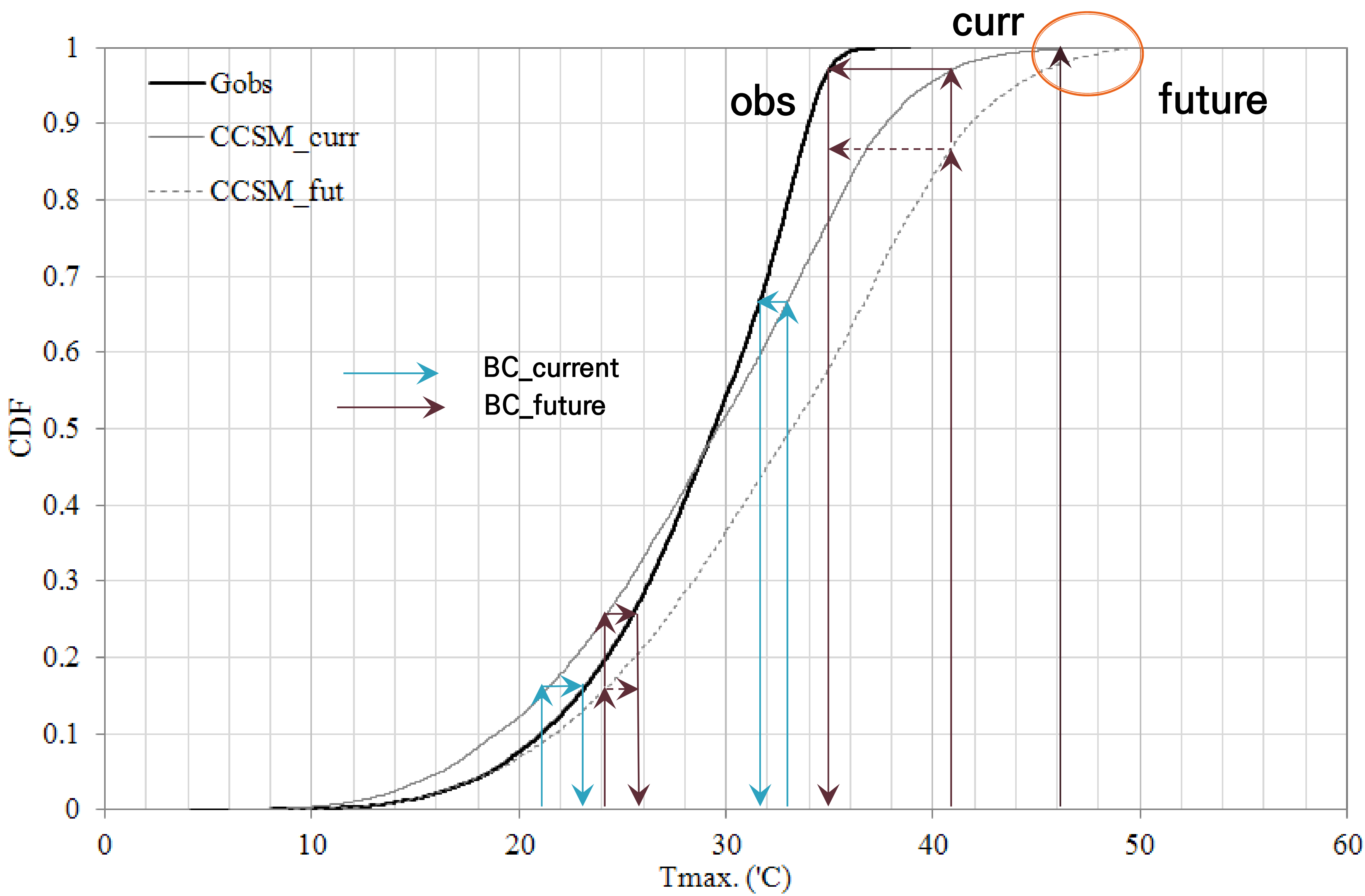
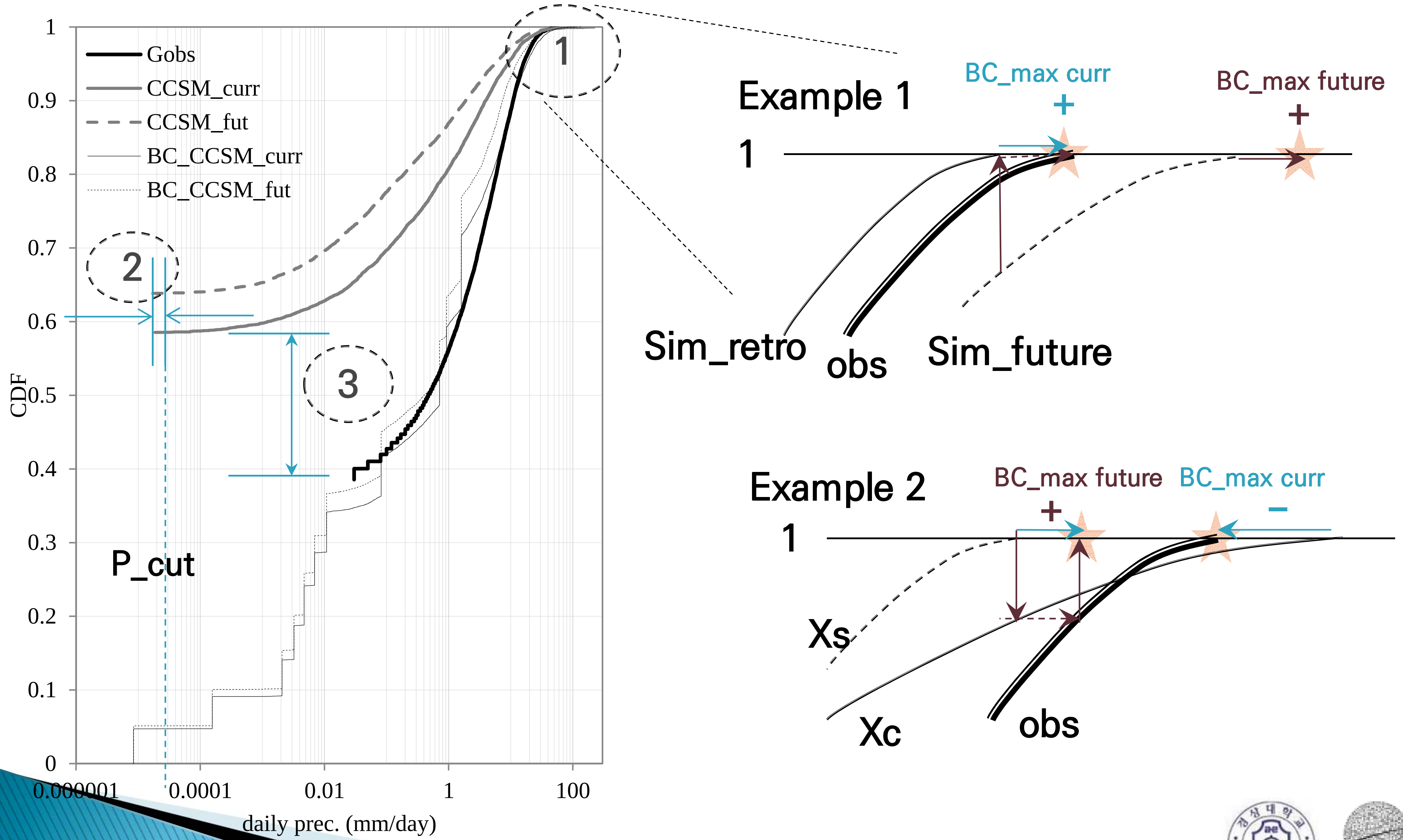
Schematic…

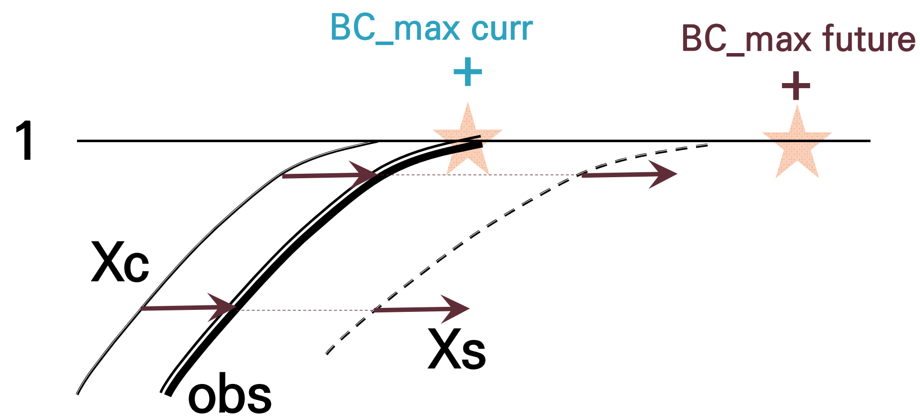


curr
obs
future
Gobs
CCSM_curr
CCSM_fut
BC_current
BC_future
CDF
Tmax. ('C)
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
10
20
30
40
50
60

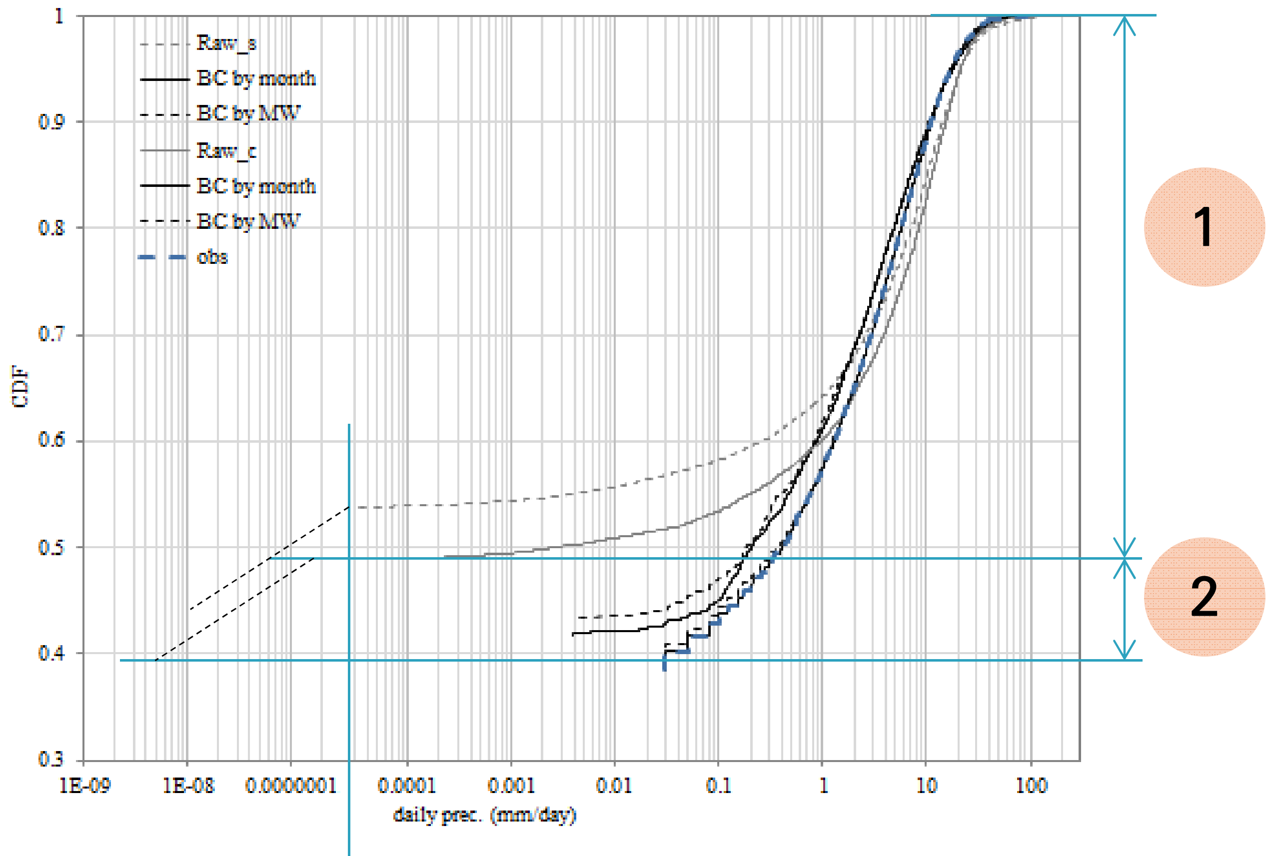
Problems in Bias-correction on monthly basis



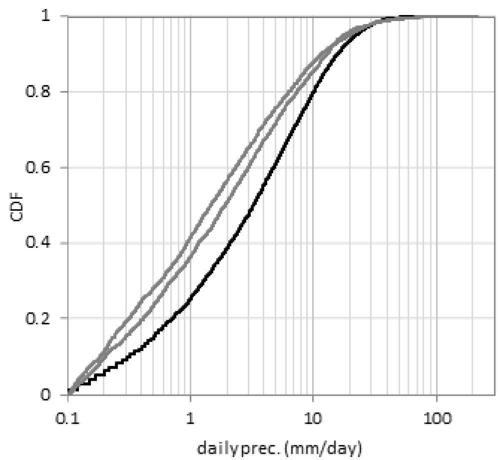
Schematic….



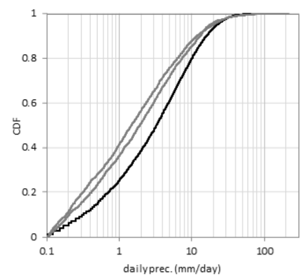
BC_max curr
BC_max future
1
Xc
Xs
obs



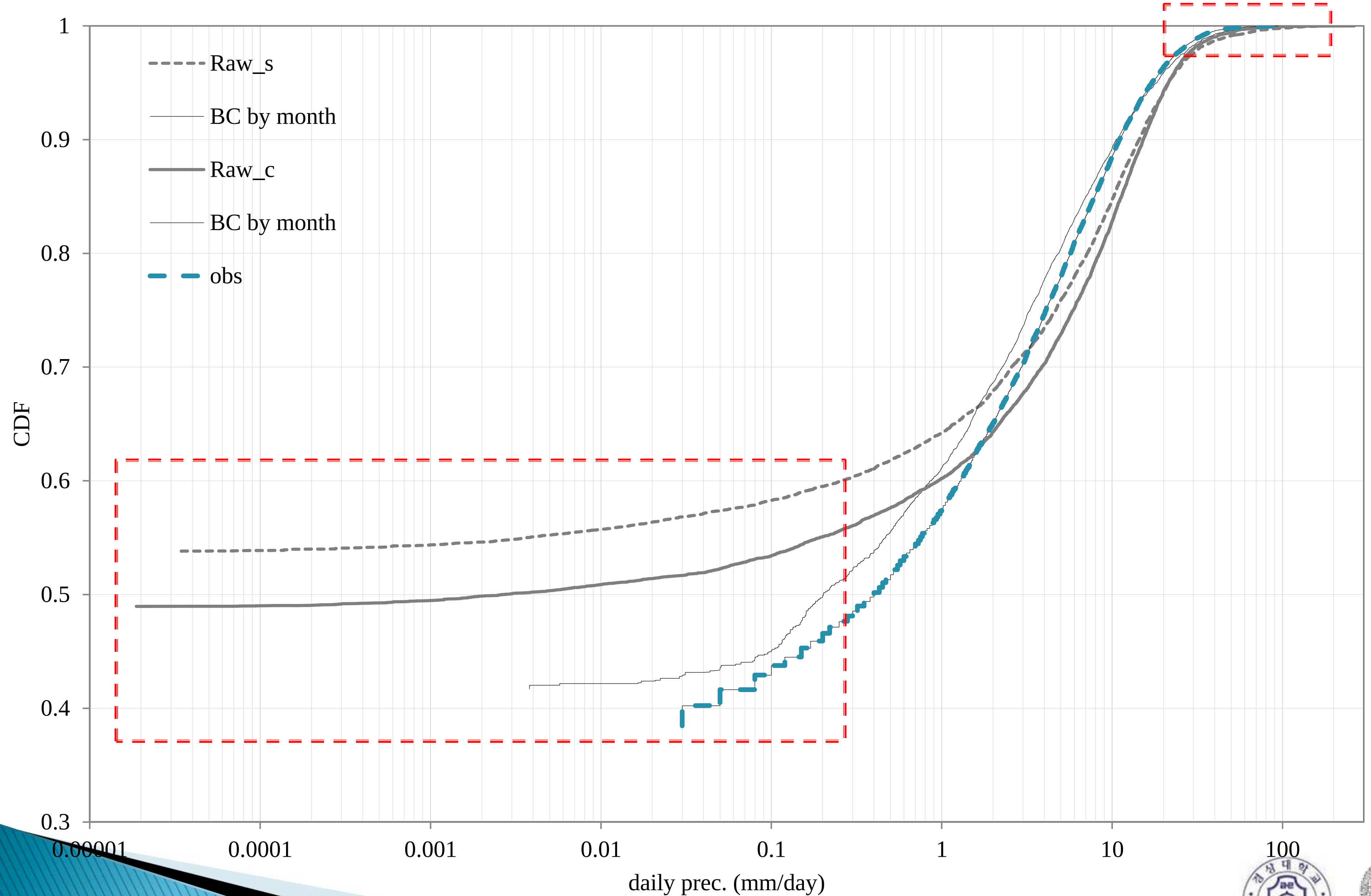
Raw_s
BC by month
BC by MW
Raw_c
BC by month
BC by MW
obs
CDF
daily prec. (mm/day)
1
2



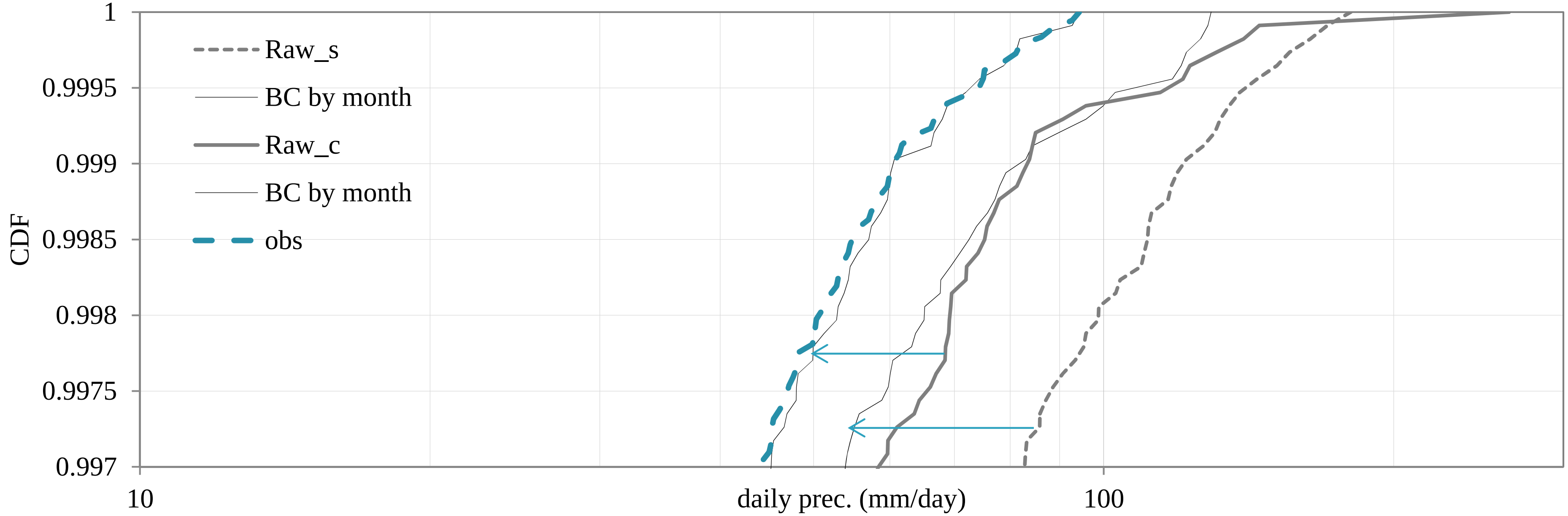
CDF
dailyprec. (mm/day)

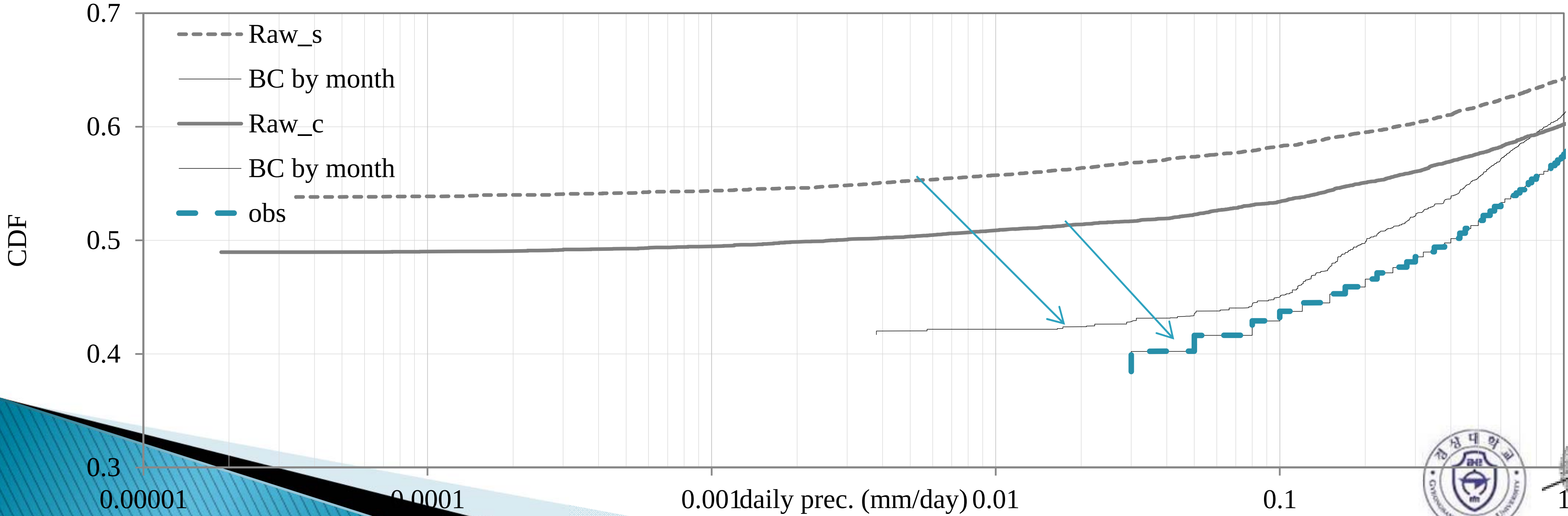


Raw and bias-corrected results for A grid



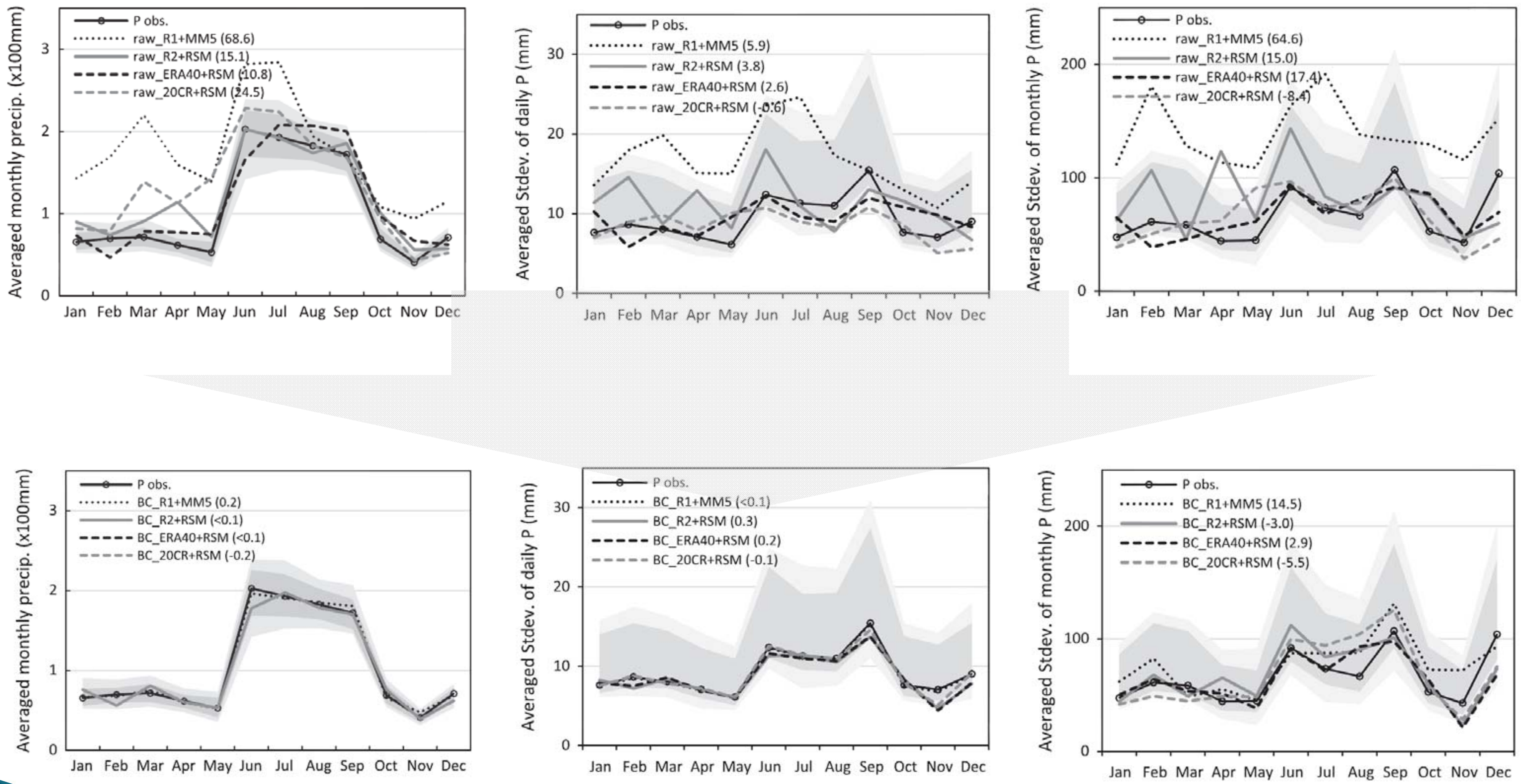
Low and high extreme





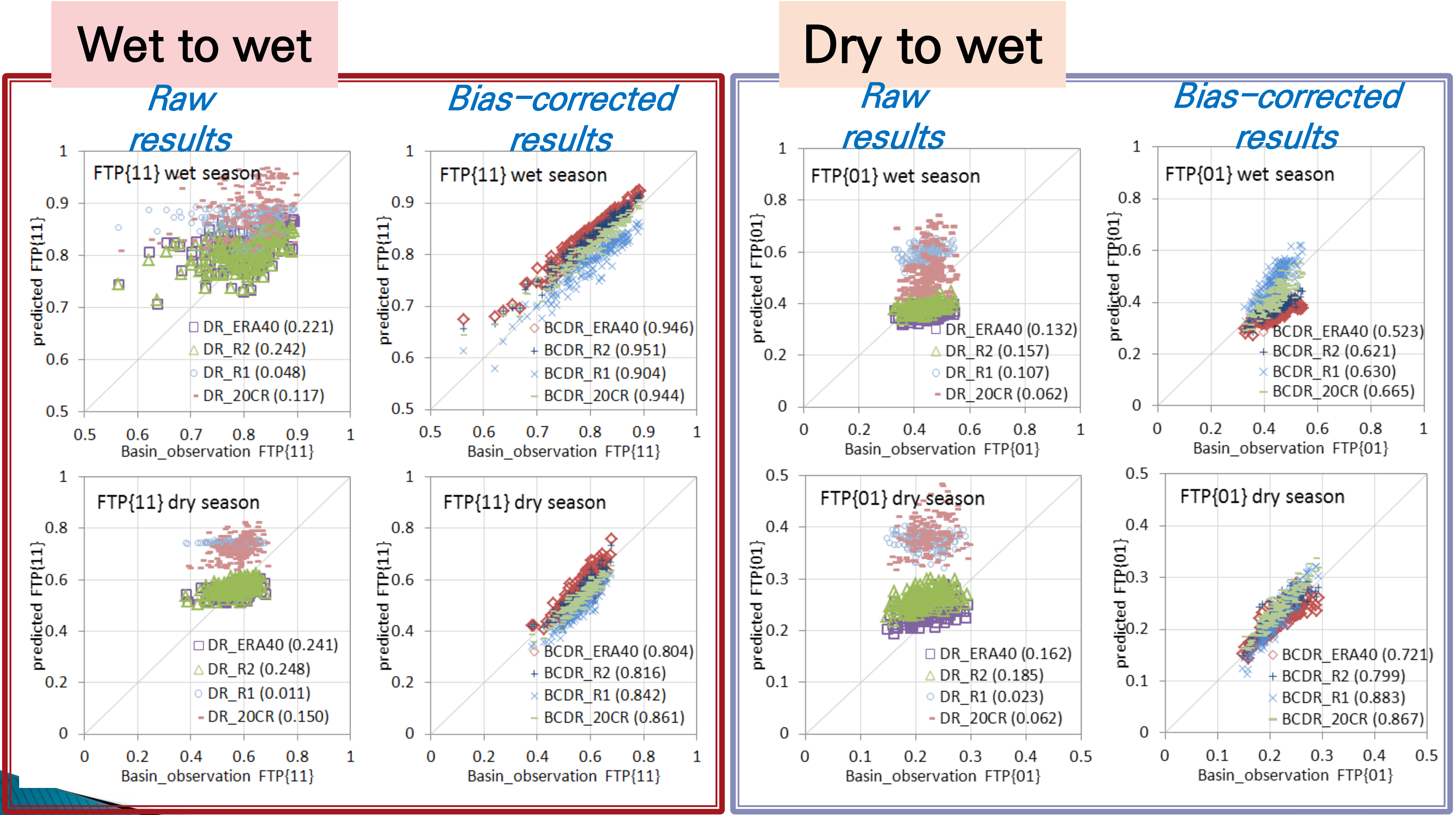
APCC

Effect of bias-correction



APCC

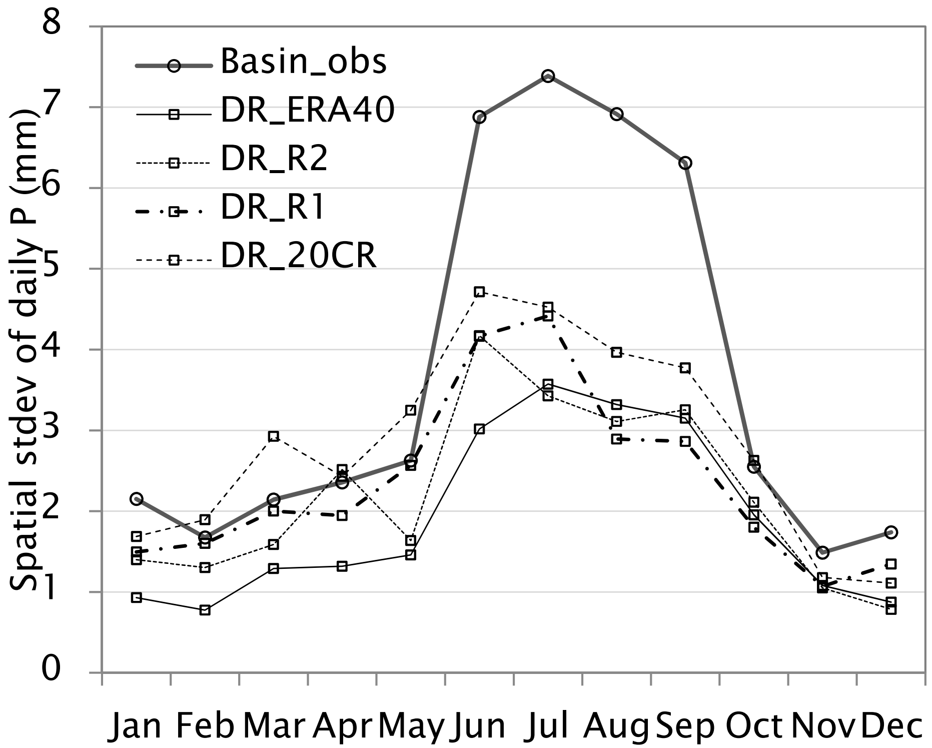
Effect of bias-correction: Transition probability



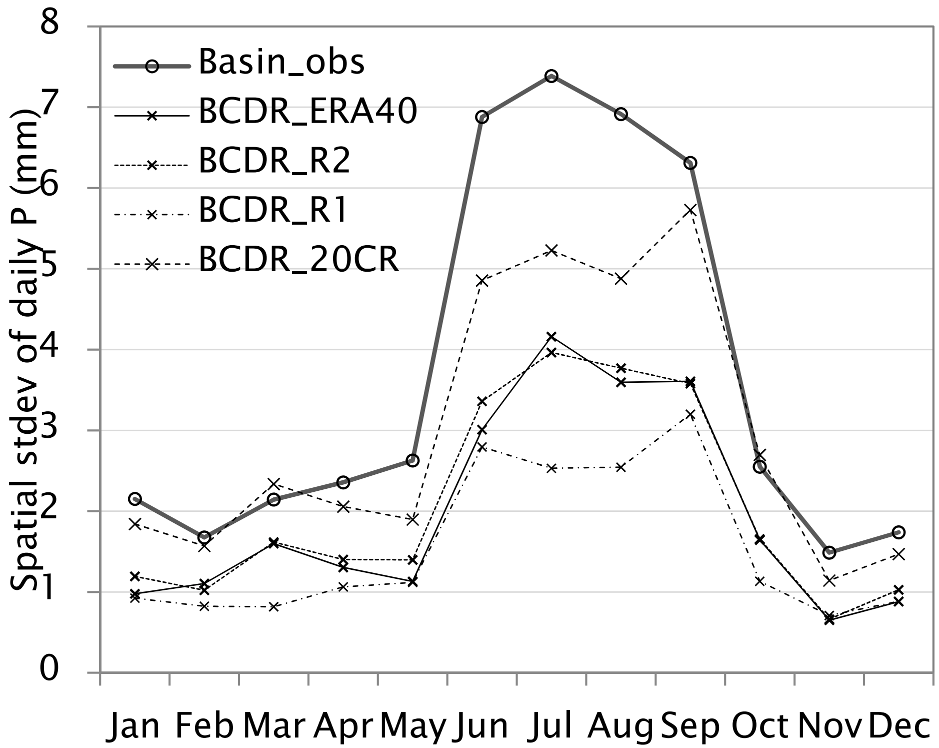
APCC

Effect of bias-correction: spatial variability

Raw results

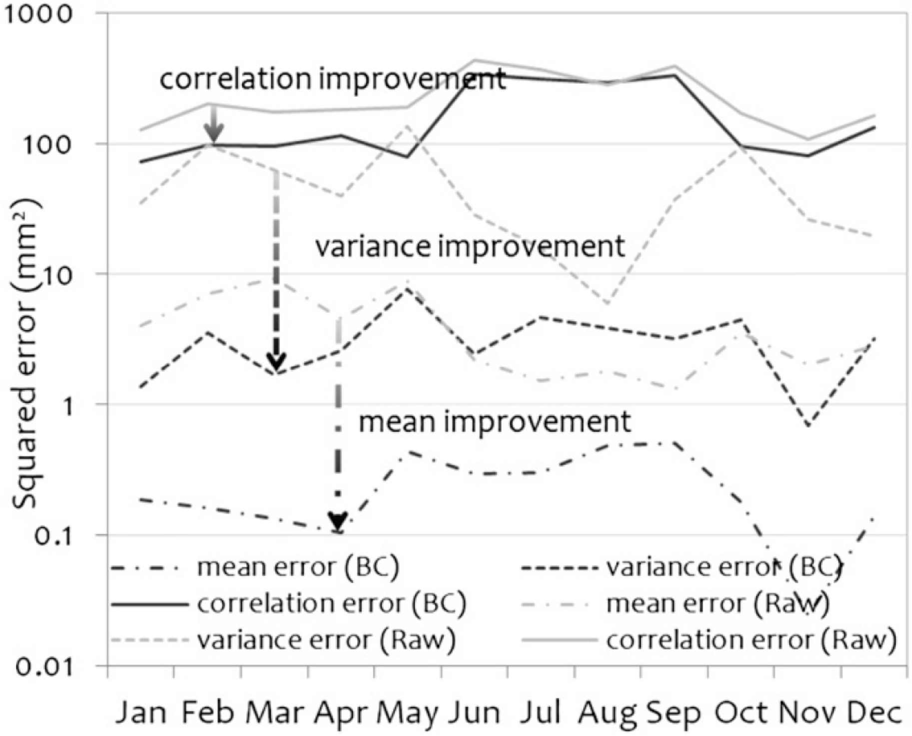


Bias-corrected results

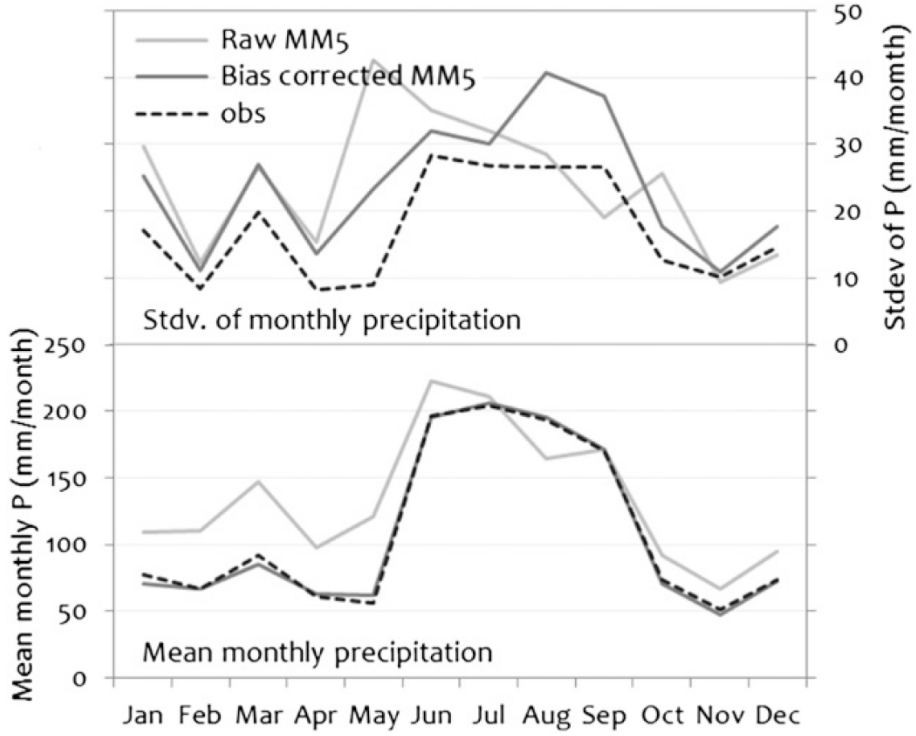


Comparison of annual cycle of spatial standard deviation of raw (left) and bias-c orrected (right) daily precipitation fields

Effect of bias-correction



Contributions of mean error (dash-dot line), variance error (dash line), and correlation error (solid line) to overall MSE for raw (darker lines) and bias-corrected (lighter lines) daily precipitation by month.



Comparison of mean monthly precipitation and standard deviation of monthly precipitation over the study period by month for raw model results, bias-corrected results, and point observations.

(Hwang and Graham, 2011)

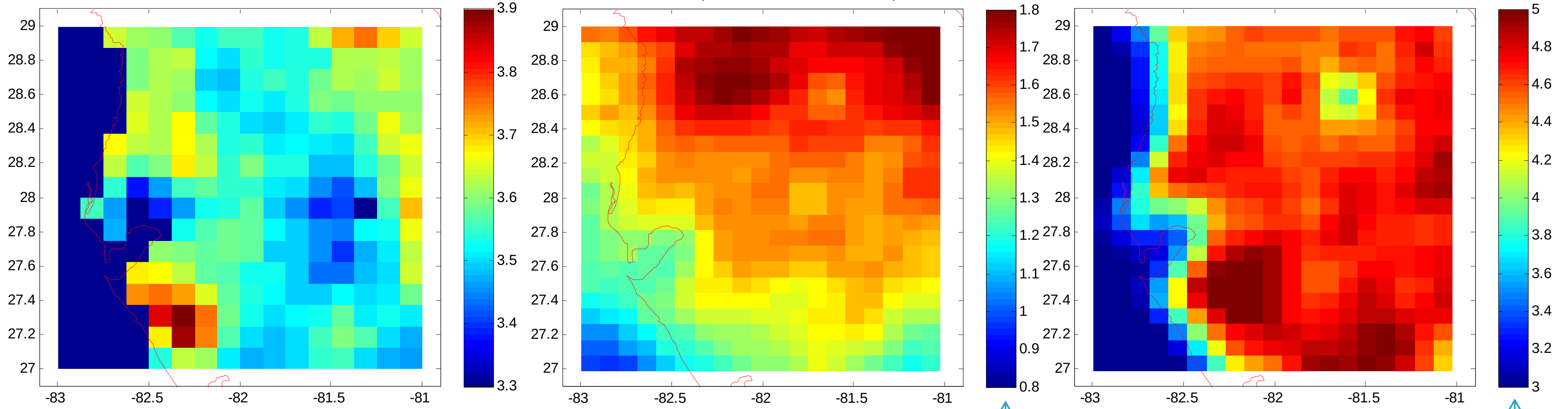
Effect of bias-correction

Raw_Precp.

Observed
MeanPrec. (Gobs: 1969-1999)

Current sim. (CCSM)
MeanPrec. (Raw-CCSM+RCM: 1969-1999)

Current sim. (HadCM3)
MeanPrec. (Raw-HadCM3+RCM: 1969-1999)

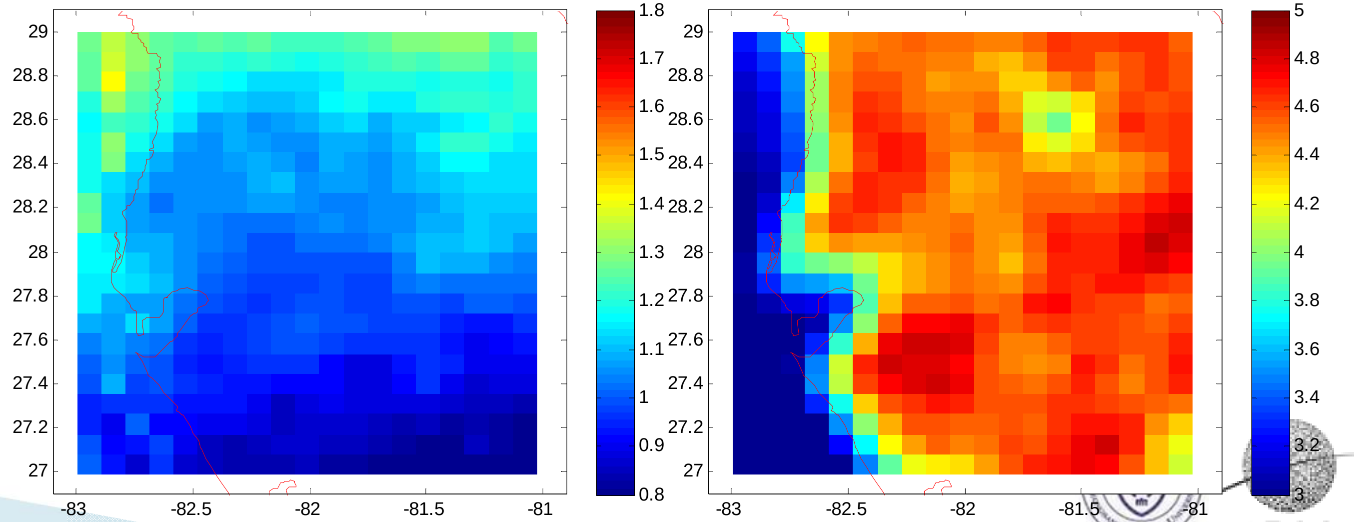


Future sim. (CCSM)
Same scale

MeanPrec. (Raw-CCSM+RCM: 2039-2069)

Future sim. (HadCM3)
Same scale

MeanPrec. (Raw-HadCM3+RCM: 2039-2069)



- Raw CCSM results significantly underestimate the mean precp. by 2.5mm over the region
- Raw HadCM3 results overestimate by 2mm
- Based on the future scenario, precipitation decreased (not significant)

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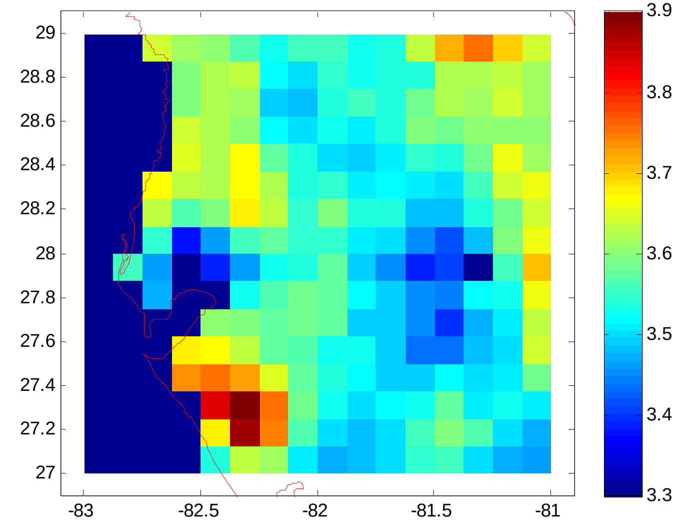
Effect of bias-correction

BC_Precp.

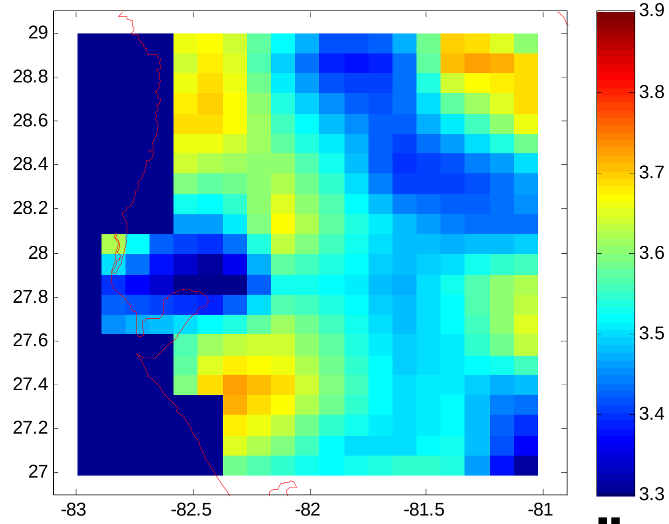
Observed

MeanPrec. (Gobs: 1969-1999)



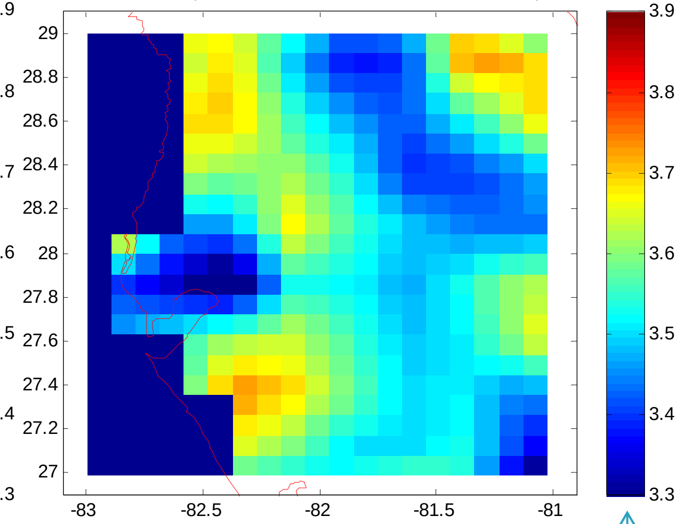
Current sim. (BC_CCSM)

MeanPrec. (BiasCorrected-CCSM+RCM: 1969-1999)



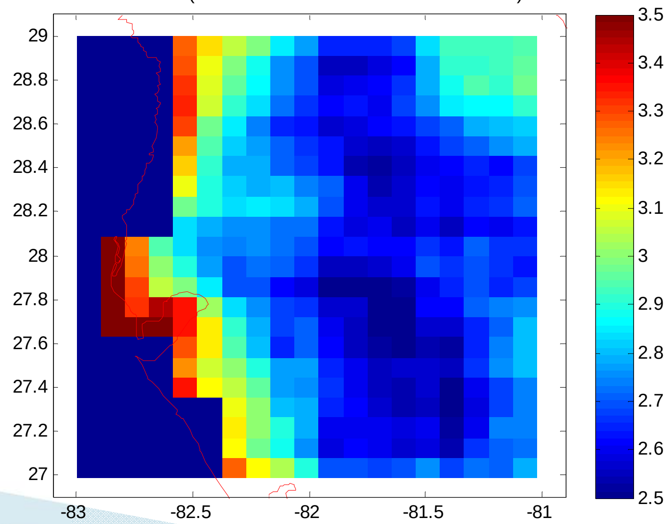
Current sim. (BC_HadCM3)

MeanPrec. (BiasCorrected-HadCM3+RCM: 1969-1999)



Future sim. (BC_CCSM)

MeanPrec. (BiasCorrected-CCSM+RCM: 2039-2069)

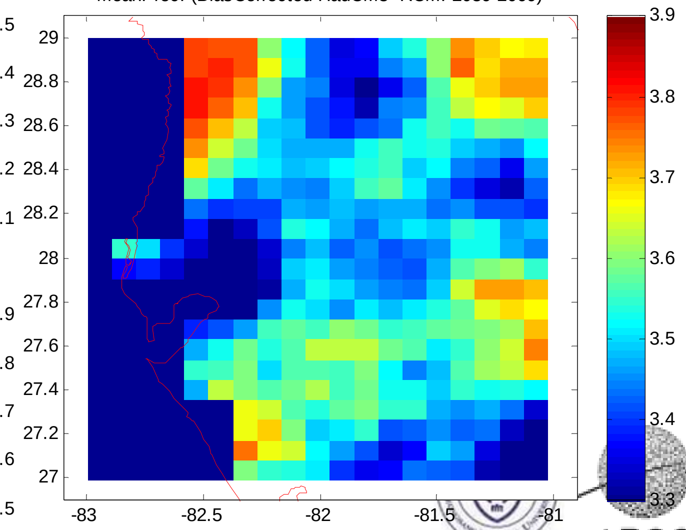


≠

Future sim. (HadCM3)

Same scale

MeanPrec. (BiasCorrected-HadCM3+RCM: 2039-2069)



- Decrease of mean precip. around by 0.5mm (CCSM) and 0.1mm (HadCM3) over the region

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Messages to take home

Statistical downscaling

Matters to be attended….

- Why downscale?… Overdoing downscaling?

- Specify the study objectives
  - For mean values, the simpler statistical downscaling methods perform comparably to the more sophisticated methods
  - For extreme values, the more sophisticated methods (e.g., quantile mapping) are needed

    → the more sophisticated the method, the *smaller* the future change projected for the warmest extreme temperatures in the U.S.

- Select technique
  - The more sophisticated, the better?

- What to evaluate
  - downscaling purpose vs. downscaled results

- How to evaluate
  - Evaluations may vary by applying different observations, resolutions, index, matrix, etc.
  - a danger of getting the right result for the wrong reason by tuning the wrong end of the model

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Messages to take home

Idea

- Future climate information
- Probablistic approach with statistically downscaled results

  =〉Stochastic concept
- Quantifying uncertainty of processes =〉credible impact assessment

Downscaling… Added value?

- Once we have more regional detail, what difference does it make in any given impacts assessment?
- What is the added value?
- Do we have more confidence in the more detailed results?

Issues

- GCM boundary conditions are a main source of uncertainty for most downscaling techniques
- Different downscaling methods can yield different scenarios even when forced with the same GCM
- Ability to downscale the current climate does not guarantee accuracy about downscaling the future

Inter-comparison of statistical downscaling techniques!

Comparison of statistical & dynamical downscaling (e.g., CORDEX)

Good luck!

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Keeping pace with a changing environment for the future!!!