Statistical/Stochastic approaches for downscaling

Simple Quantile Mapping
Spatial Disaggregation Quantile Delta Mapping
Bias-Correction & Stochastic Analog

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Outline

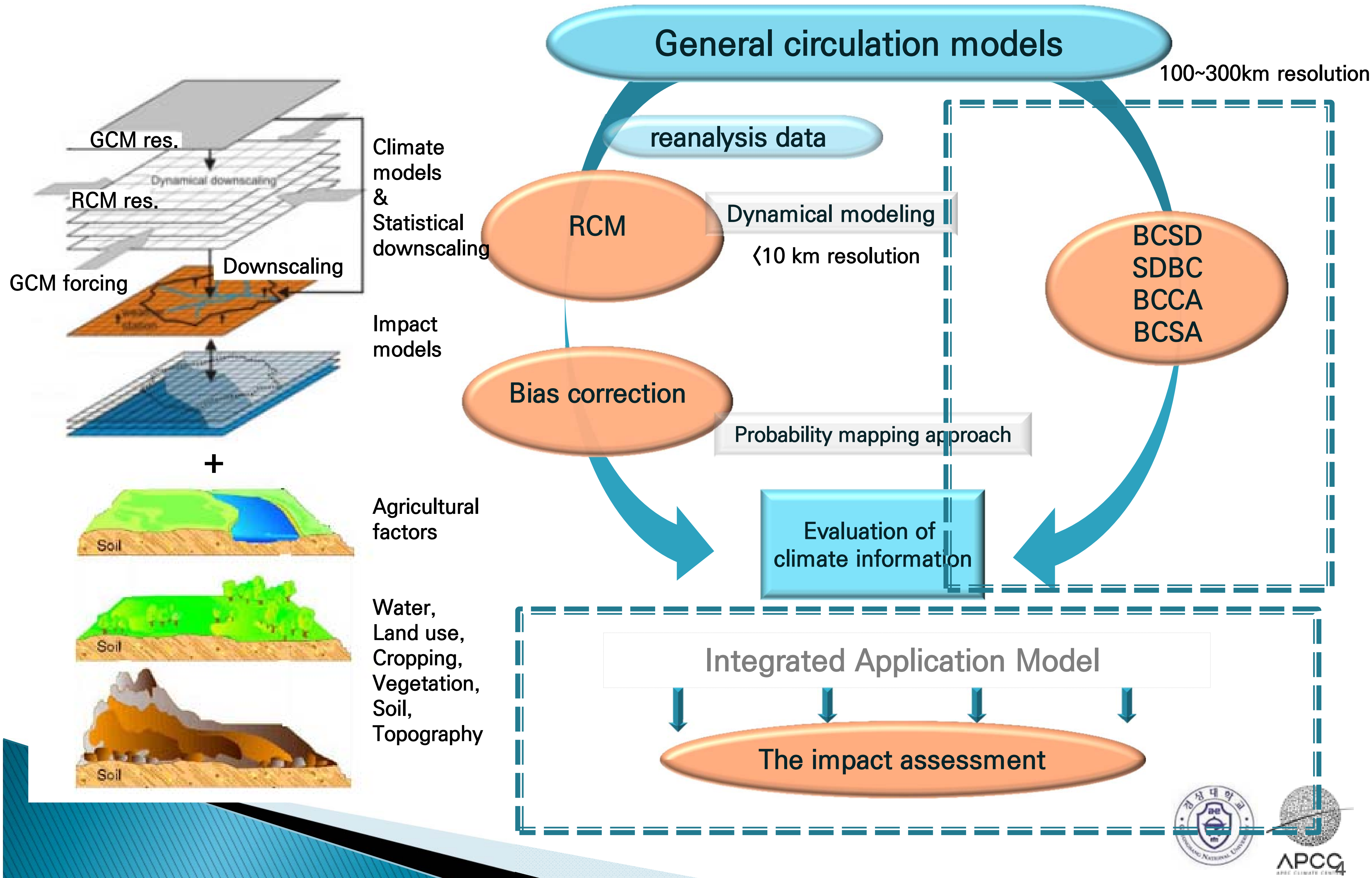
1. Stochastic downscaling
   - Methodology
   - Significance
2. Case study
   - BCSD (Bias-correction & spatial disaggregation)
   - SDBC (spatial disaggregation & Bias-correction)
   - BCCA (Bias-correction & constructed analogue)
   - BCSA (Bias-correction & stochastic analog)
3. Comparative Evaluation
4. Application
   - Hydrologic implications
5. Message to take home

Bias-Correction & Stochastic analog (BCSA)

vs. SQM, BCSD, SDBC, BCCA, SDQDM

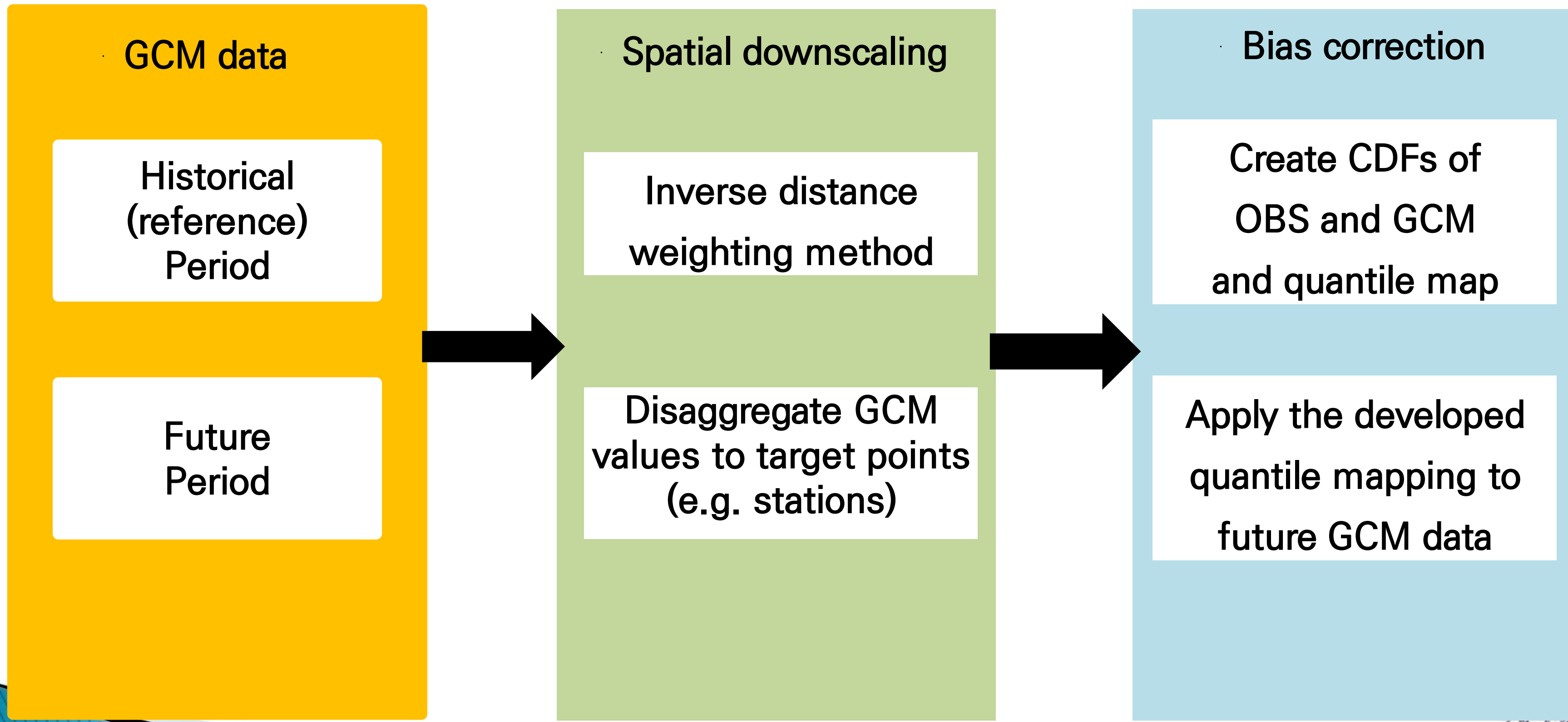
(How to evaluate the performance?)

General framework of climate change impact assessments

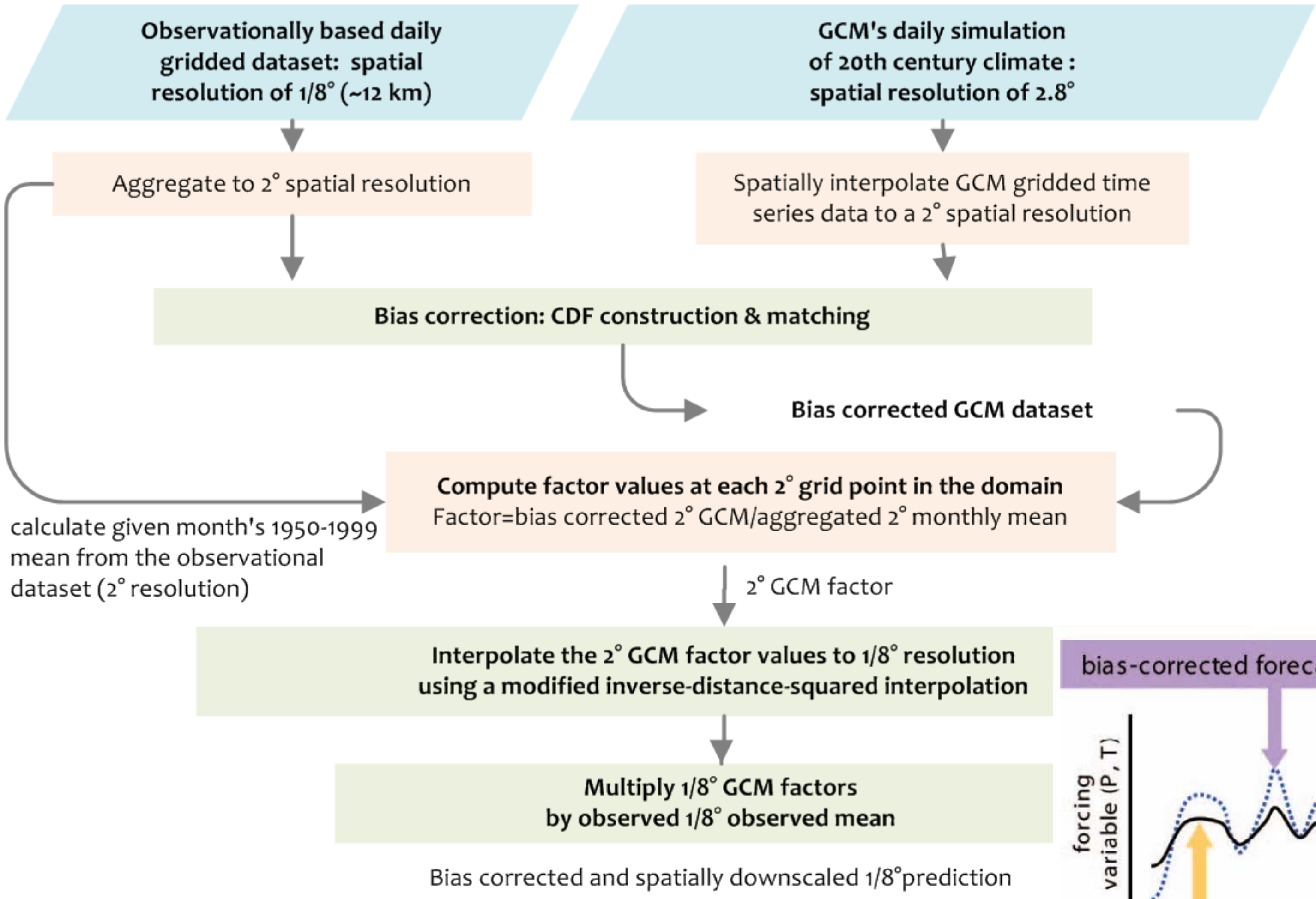


Simple Quantile Mapping (SQM)

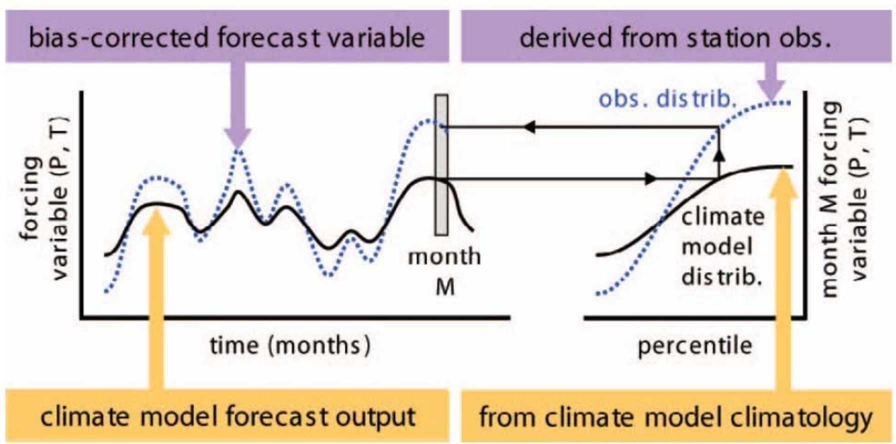
- Sampling daily data to build ECDF for a month
  - 12 ECDFs necessary



Bias Correction/Spatial Disaggregation (BCSD)

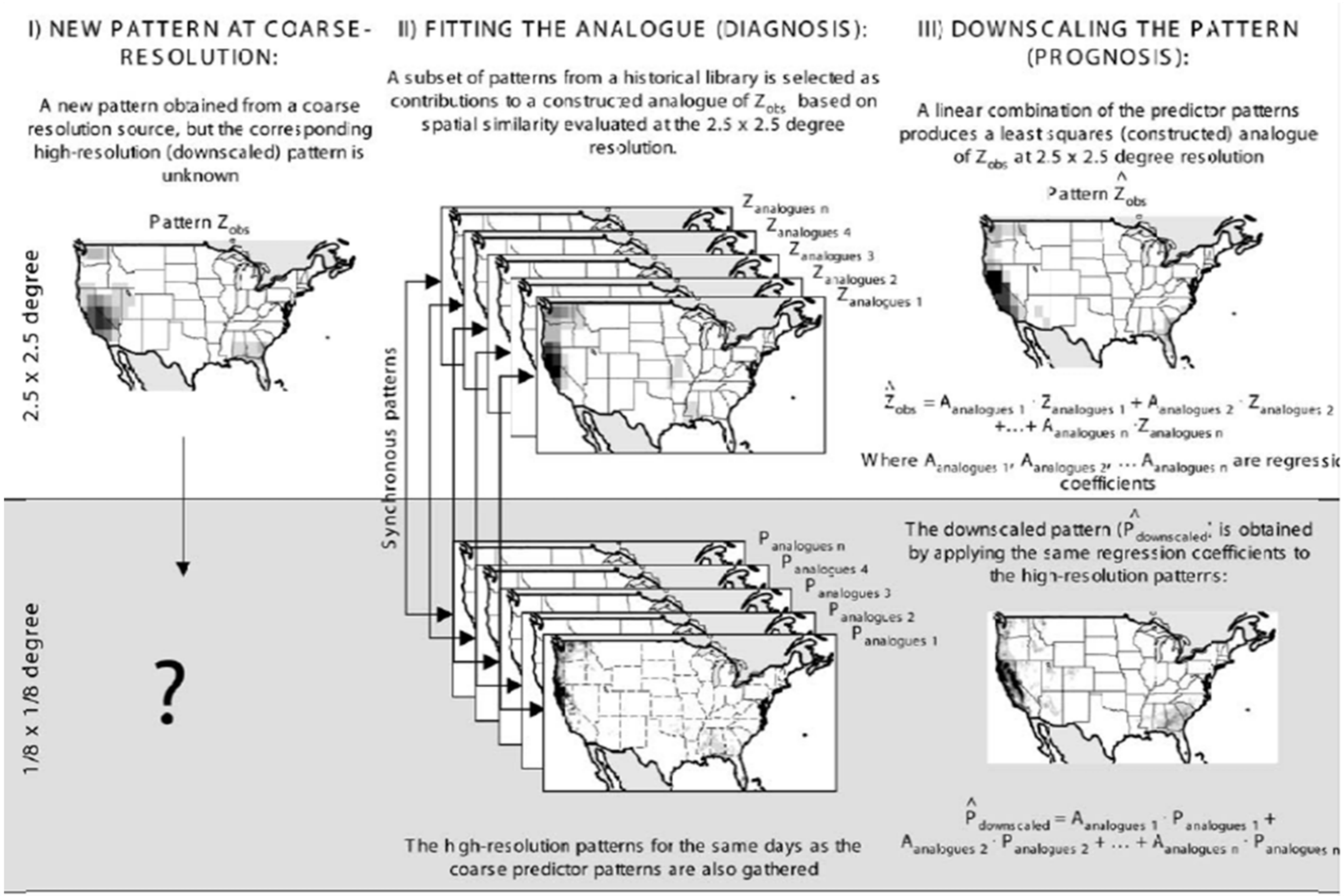


- Statistical bias correction of GCM simulations
  - Quantile mapping
- Spatial downscaling to fine scale (i.e. stations)
- Temporal disaggregation from monthly to daily



Source: Wood et al 2006, BAMS

Bias-Correction & Constructed Analogue (BCCA)



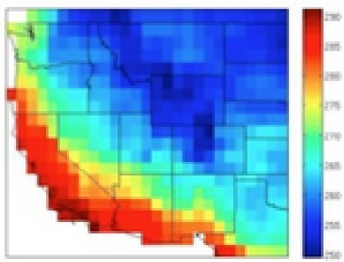
Schematic of the method of constructed analogues for downscaling reanlysis fields from 2.5° x 2.5° grids to 1/8° x 1/8°

Hidalgo et al., 2008

Need to preserve spatial distribution in the future?

- BCCA
  - Hard to find similar weather patterns from historical data
  - Not reliable climate projections

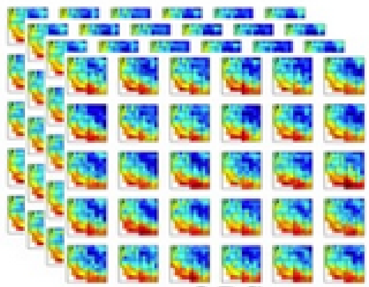
GCM target coarse pattern
(1 day, 1 year)



Z^{GCM}

- $$Z^{GCM} \approx \sum_{i=1}^{i=N} a_n Z_n^{OBS}$$

Library of OBS coarse patterns
(+/- 45 day window, all years)

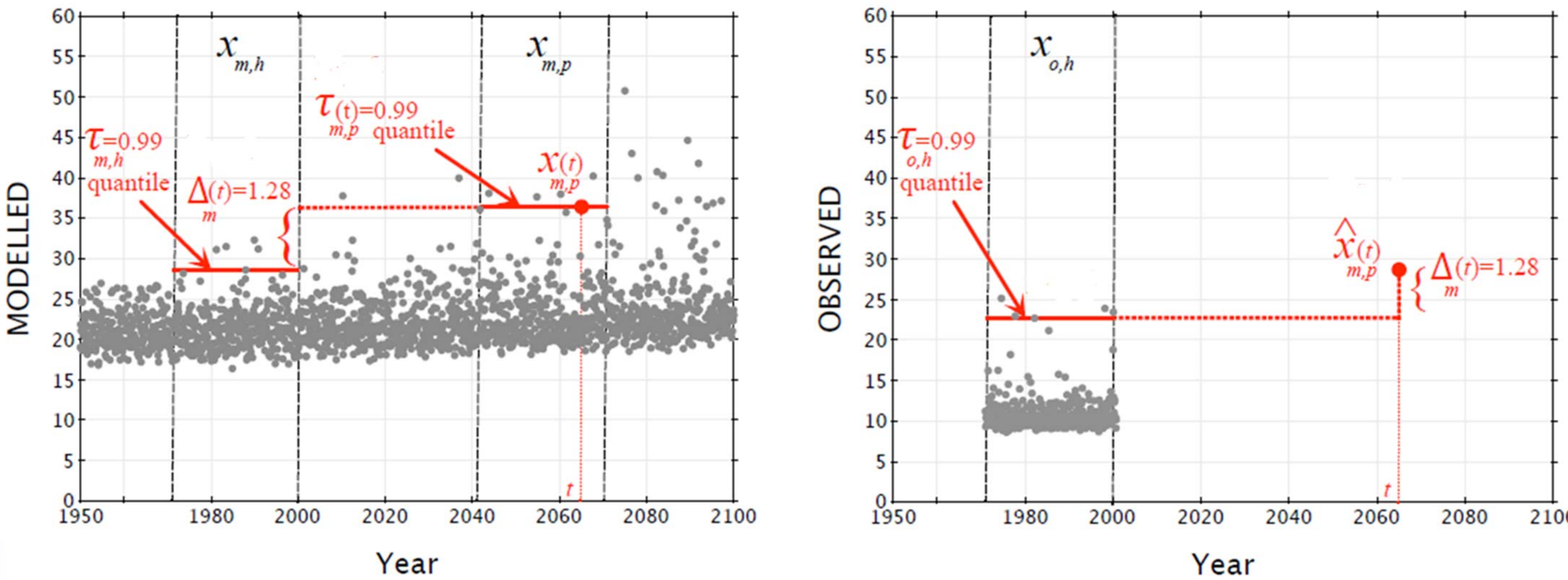


Z_n^{OBS}

Few analogs similar to future spatial structure

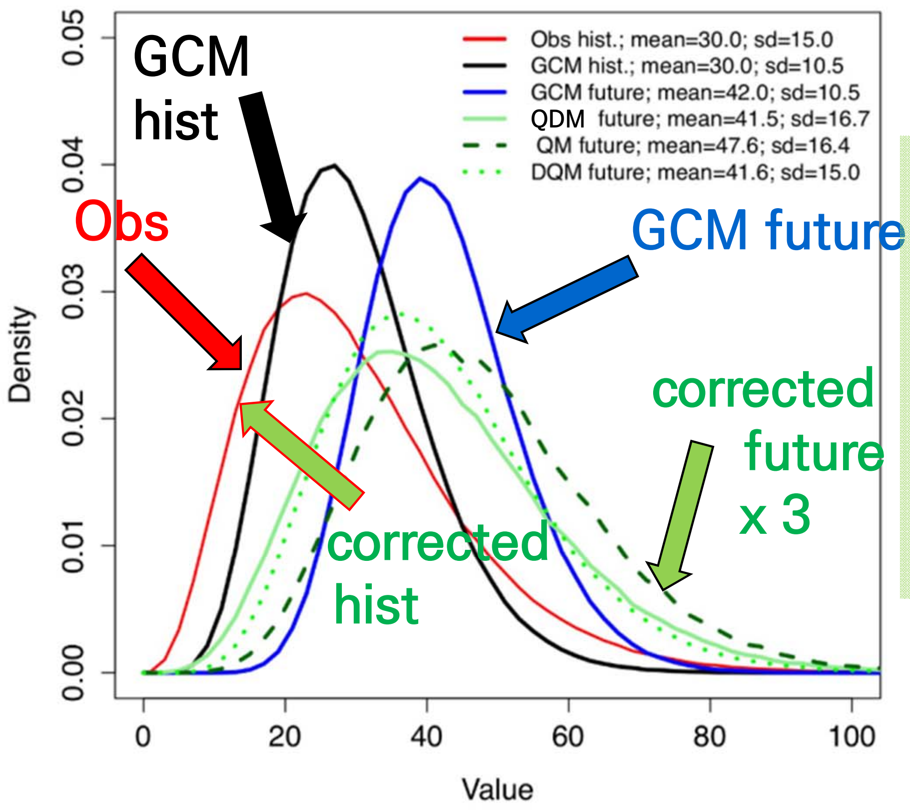
Quantile Delta Mapping (QDM)

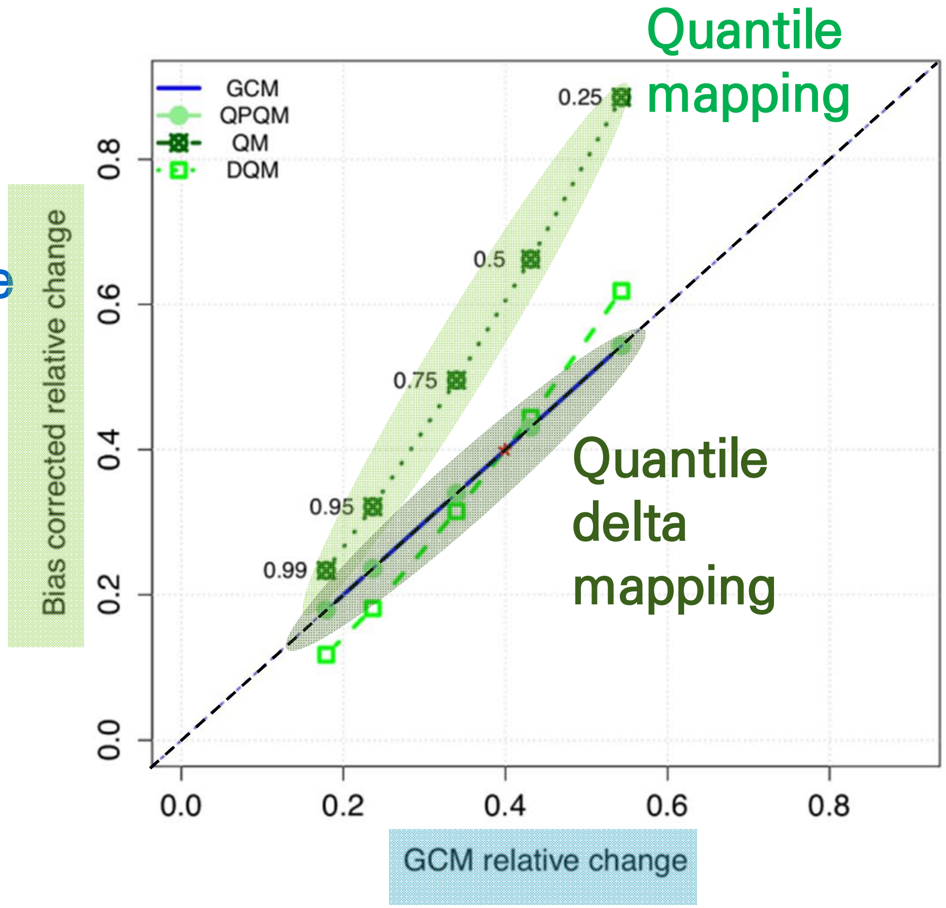
- Preserving model-projected relative changes in quantiles
- Correcting systematic biases in quantiles



Source: Cannon et al. (2015)

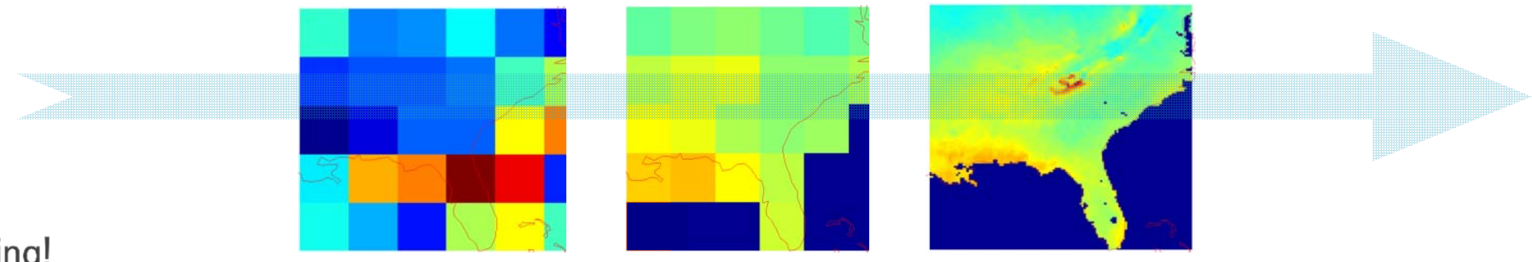
Unintended consequences…





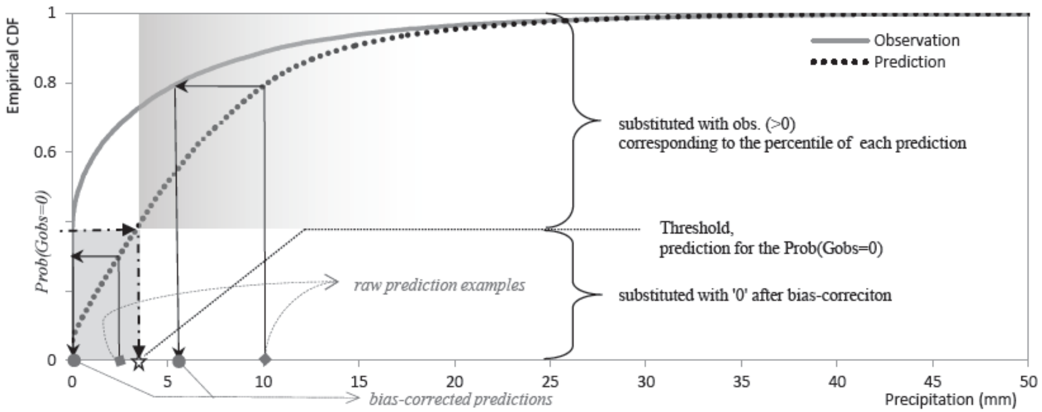
Cannon et al. (2015) J. Climate

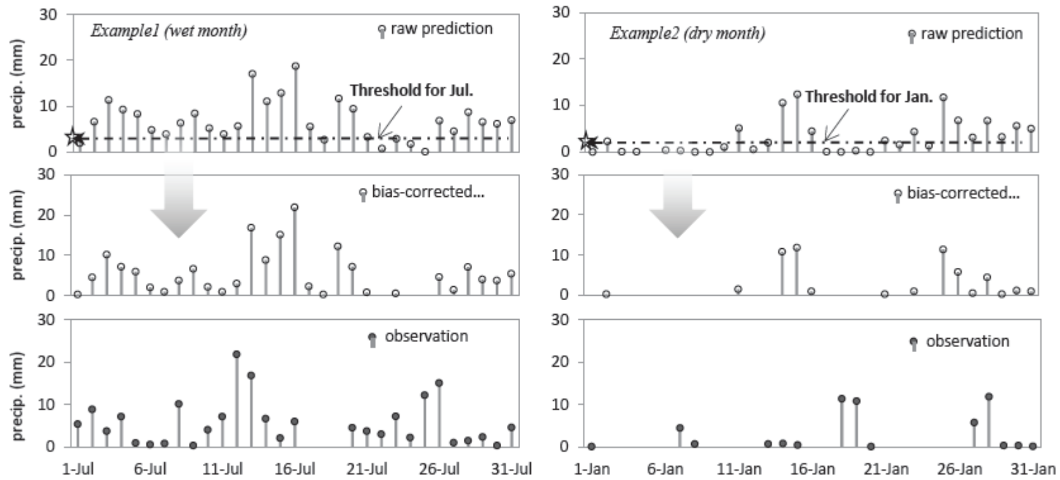
stochastic downscaling approach



Remind
CDF mapping!

Bias correction





BCSA method

Bias-Correction & Stochastic Analog

1. Take normal score transform of observed daily precipitation data at each station

$$x^*_{t,i} = G^{-1}\left(F_{obs,i}(x_{t,i})\right)$$

2. Estimate spatial correlation of normal score transformed data over all stations

$$\rho_{i,j} = \frac{1}{N}\frac{\sum_{t=1}^{N}(x^*_{t,i}-\bar{x}^*_i)(x^*_{t,j}-\bar{x}^*_j)}{\sigma^*_i\sigma^*_j} \qquad \boldsymbol{\rho} = \begin{bmatrix} \rho_{1,1} & \cdots & \rho_{1,n} \\ \vdots & \ddots & \vdots \\ \rho_{n,1} & \cdots & \rho_{n,n} \end{bmatrix}$$

3. Use the decomposition method to generate an ensemble of normal-score fields that honor observed spatial correlation structure

$$\boldsymbol{\rho} = LL^* \qquad \vec{r}_t^{*\varphi} = \vec{r}_t L^*$$

4. Back transform normal-score fields to generate an ensemble of spatially distributed precipitation fields

$$\hat{x}_{t,i} = F^{-1}_{obs,i}\left(F_{norm,i}(x^{\varphi}_{t,i})\right)$$

5. For each daily GCM prediction, randomly select realization from ensemble with spatial mean equal to bias-corrected GCM prediction but observed small-scale spatial structure

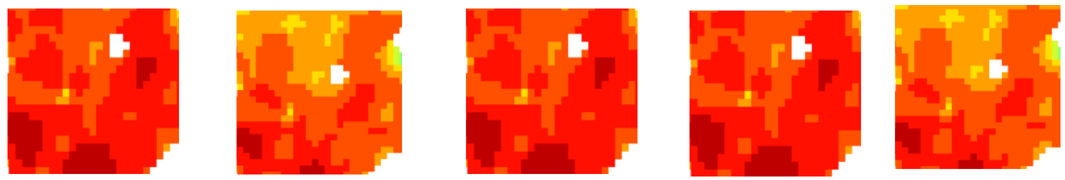
Hwang and Graham, 2013

Motive for developing BCSA

GCM future information

Downscaled distribution (future)

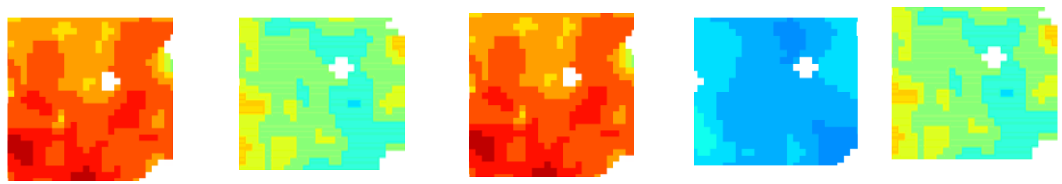
Temporal Statistics
(Mean, Std., distribution, Auto−correl., etc.)



We can reproduce these statistical attributes under assumption of stationarity!

None!

spatial Statistics
(spatial correlation, covariance, etc.)



None!

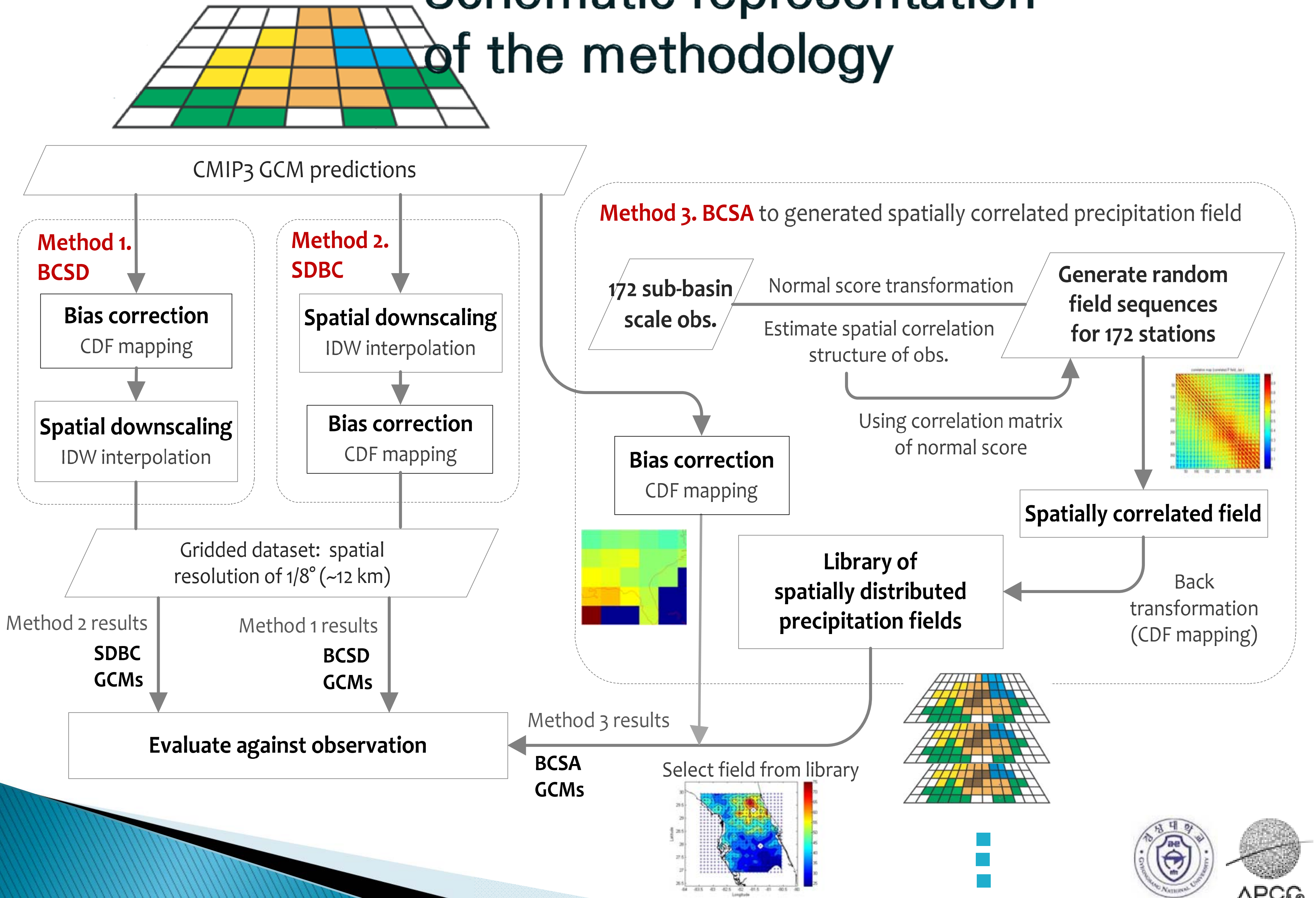
spatial Pattern
(Local characteristics)

?

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

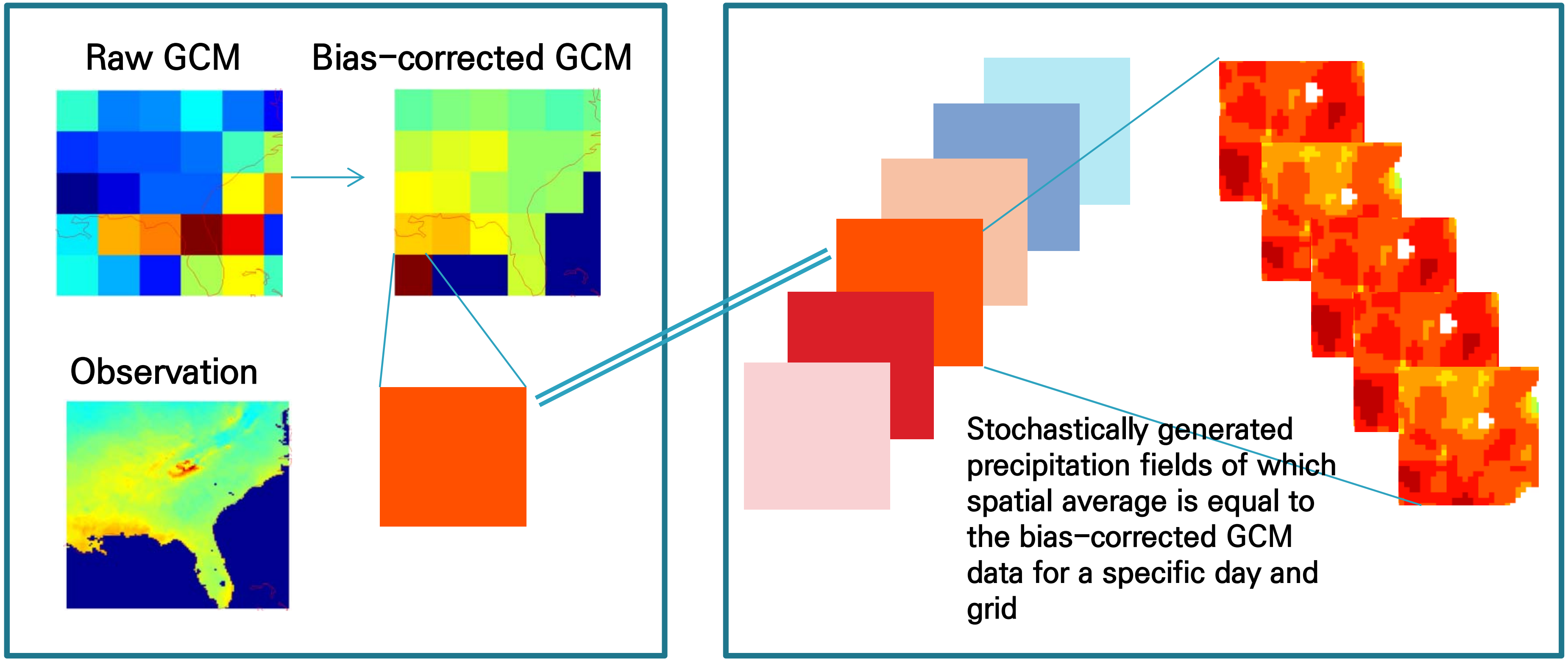
Generate plausible patterns and use those as scenarios!

Schematic representation of the methodology



Bias-Correction & Stochastic Analogue (BCSA)

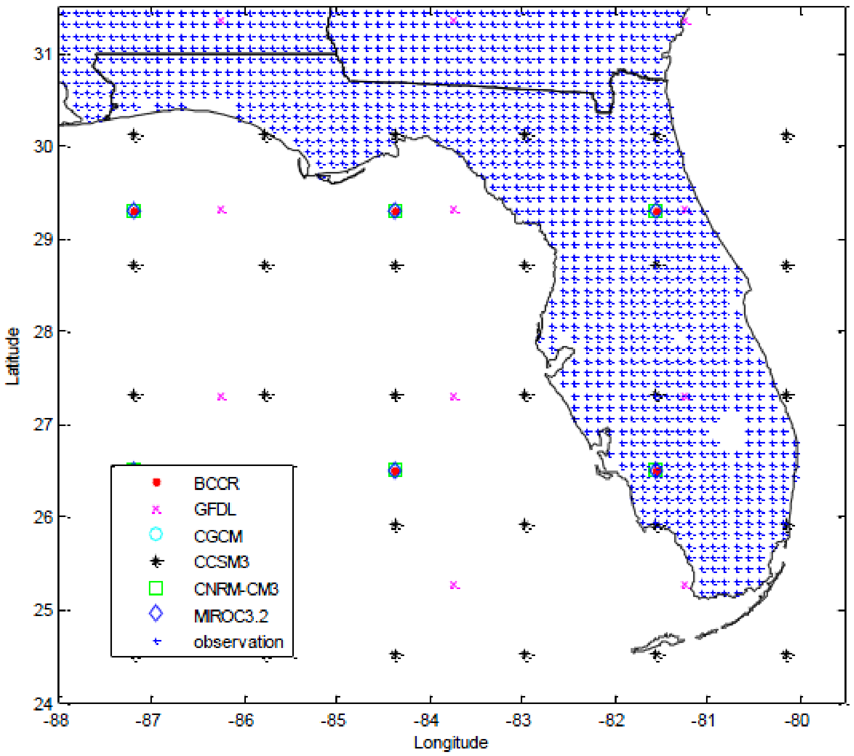
- Day 1



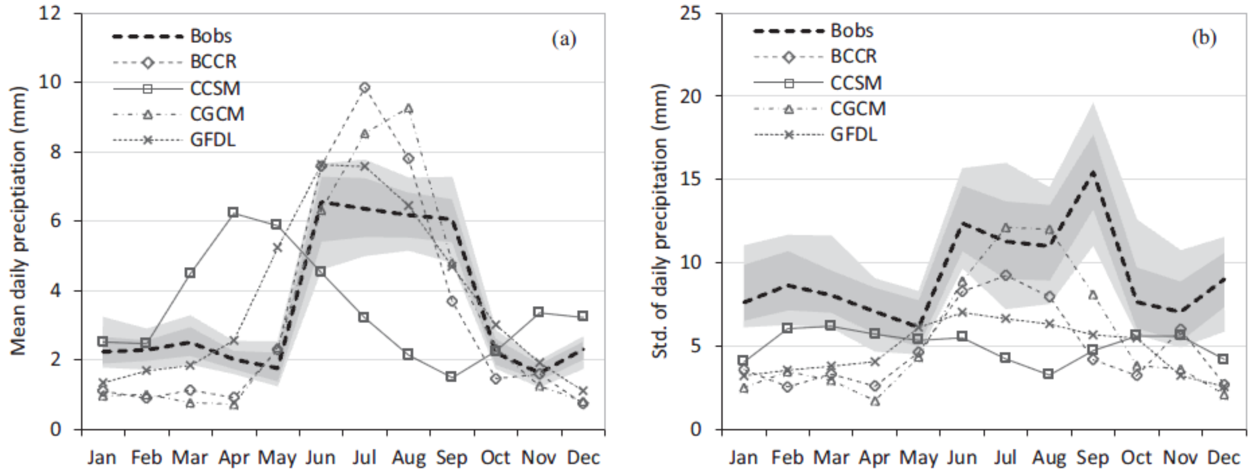
- Day 2, 3,··· : same procedure is repeated

4 GCMs (CMIP3) used in the practice

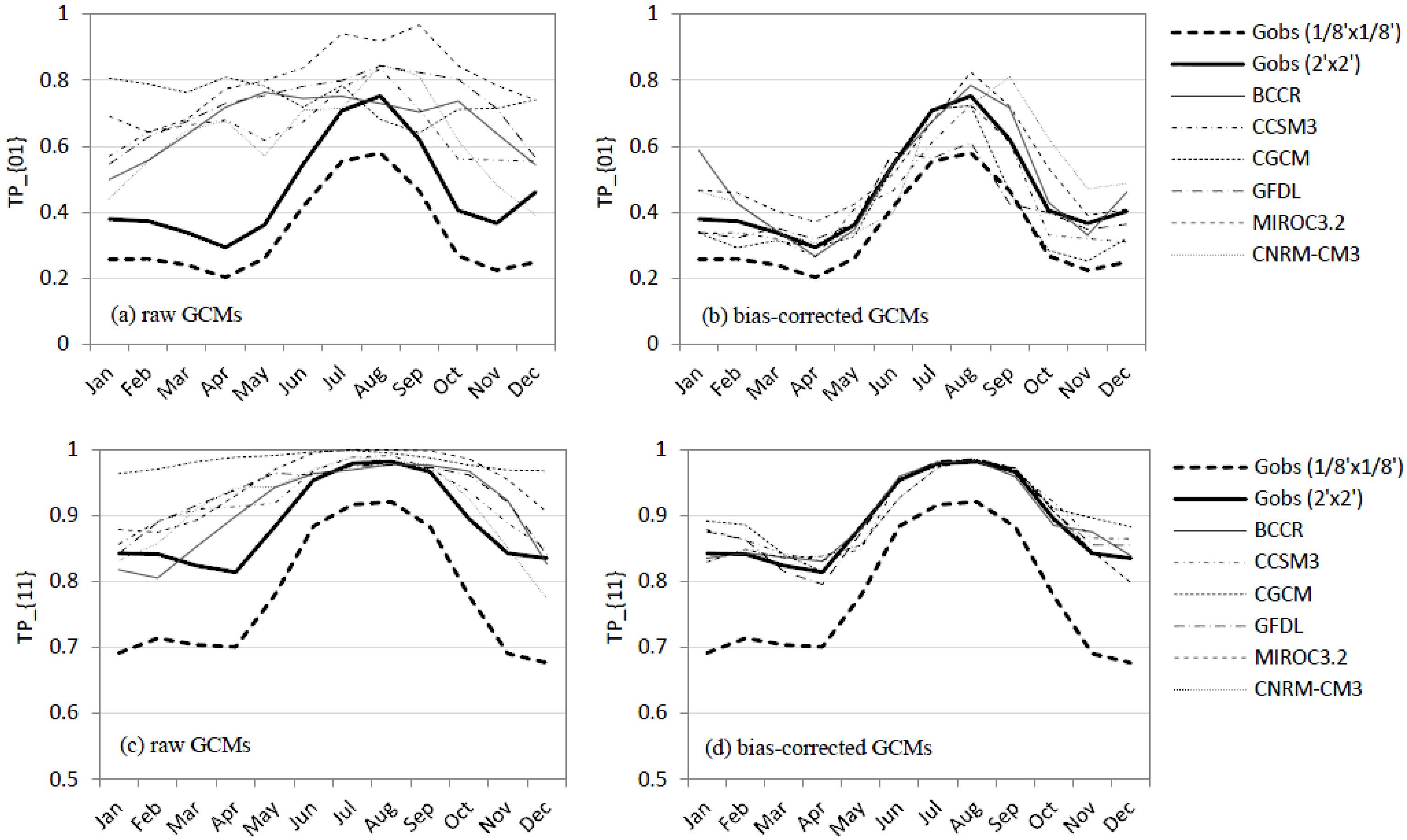
Modeling Group, Country	WCRP CMIP3* I.D.	Primary Reference
Bjerknes Centre for Climate Research, Norway	BCCR-BCM2.0	Furevik et al., 2003
US Dept. of Commerce/NOAA/Geophysical Fluid Dynamics Laboratory, USA	GFDL-CM2.0	Delworth et al., 2006
Canadian Centre for Climate Modeling & Analysis, Canada	CGCM3.1	Flato and Boer, 2001
National Center for Atmospheric Research, USA	CCSM	Collins et al., 2006



* WCRP CMIP3: World Climate Research Programme's Coupled Model Inter-comparison Project phase 3



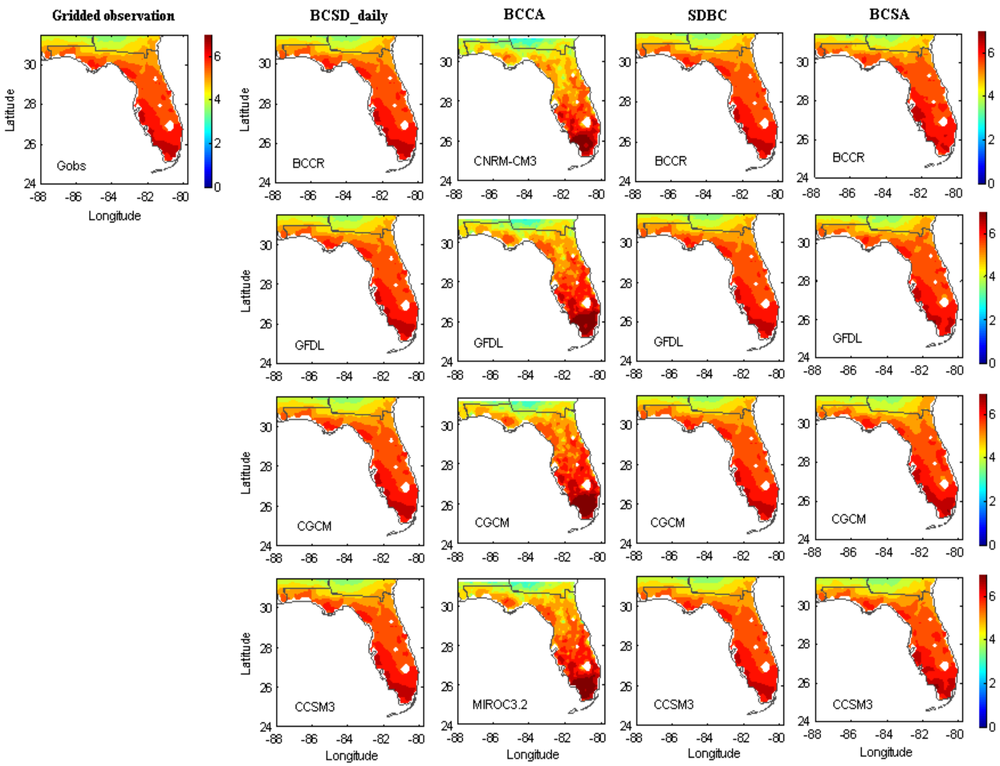
Raw GCM data vs. bias-corrected GCM results



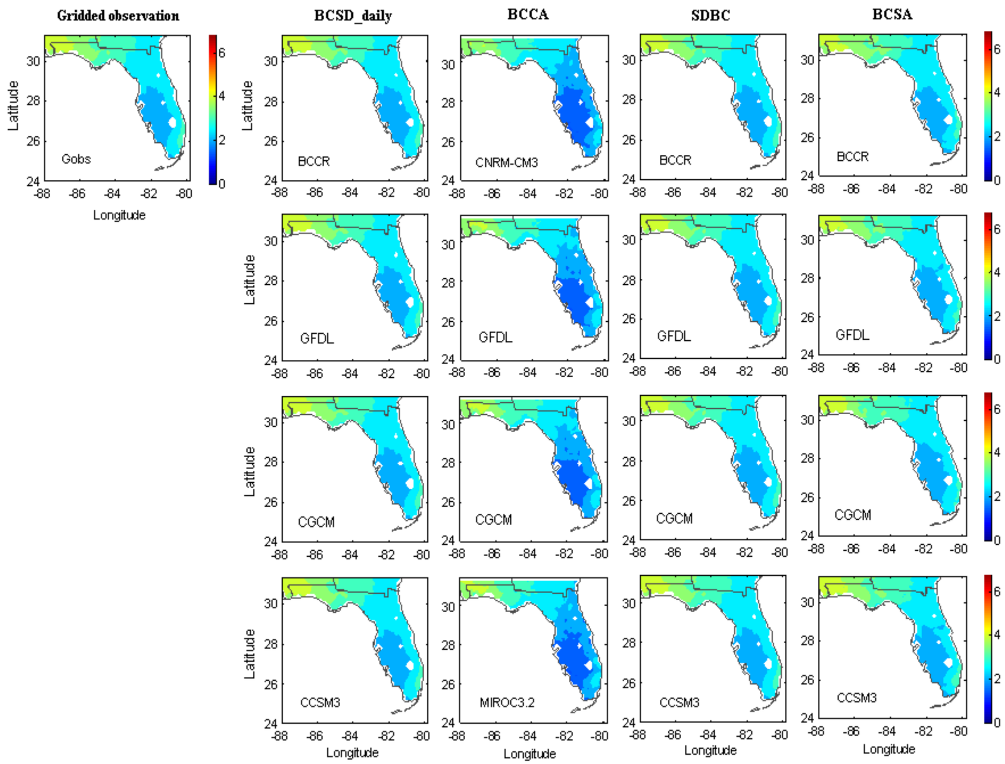
Comparison of monthly first-order dry to wet (TP_{01}, upper raw) and wet to wet (TP_{11}, bottom row) transition probabilities for raw GCM data (first column) and bias-corrected GCM results (second column). Averaged transition probabilities for all grids over the study area (i.e., the state of Florida) were plotted for each GCM.

Spatial distribution of the daily mean precipitation

for wet season



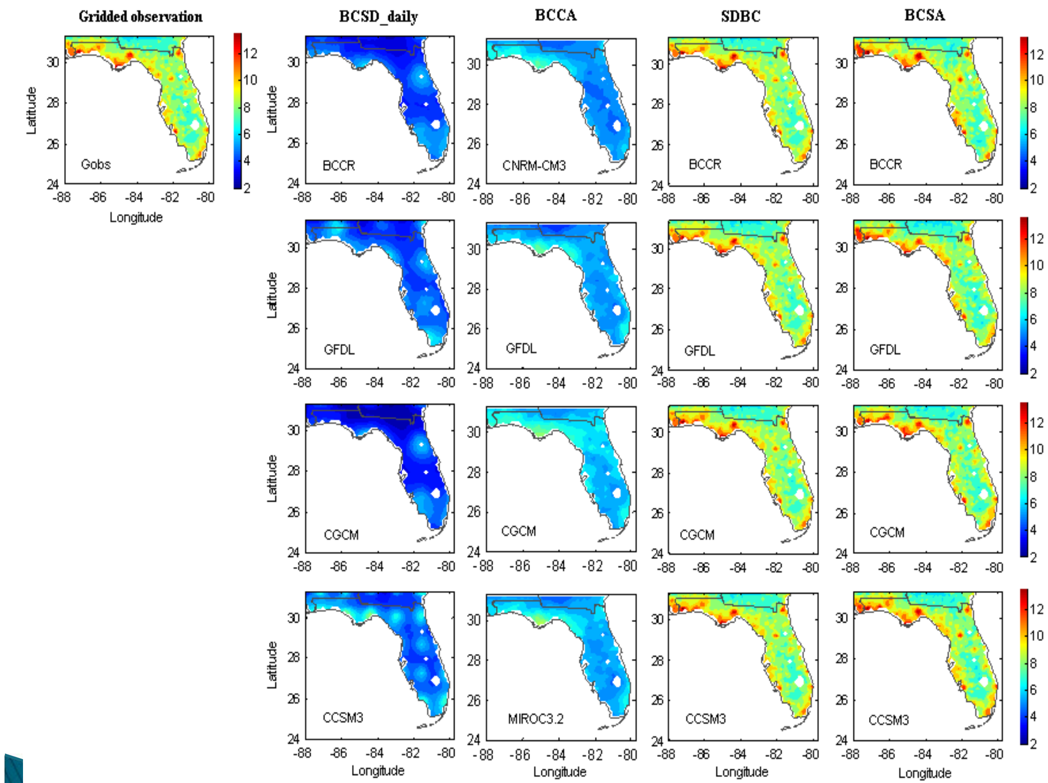
for dry season



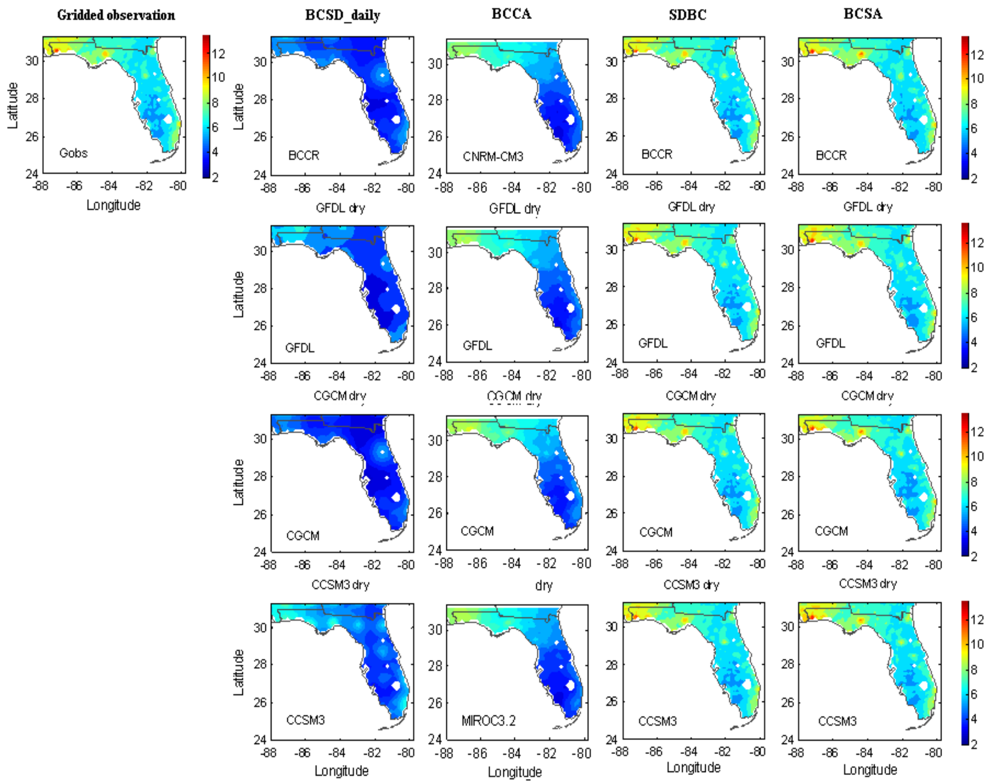
APCC

Spatial distribution of the temporal standard deviation

for wet season

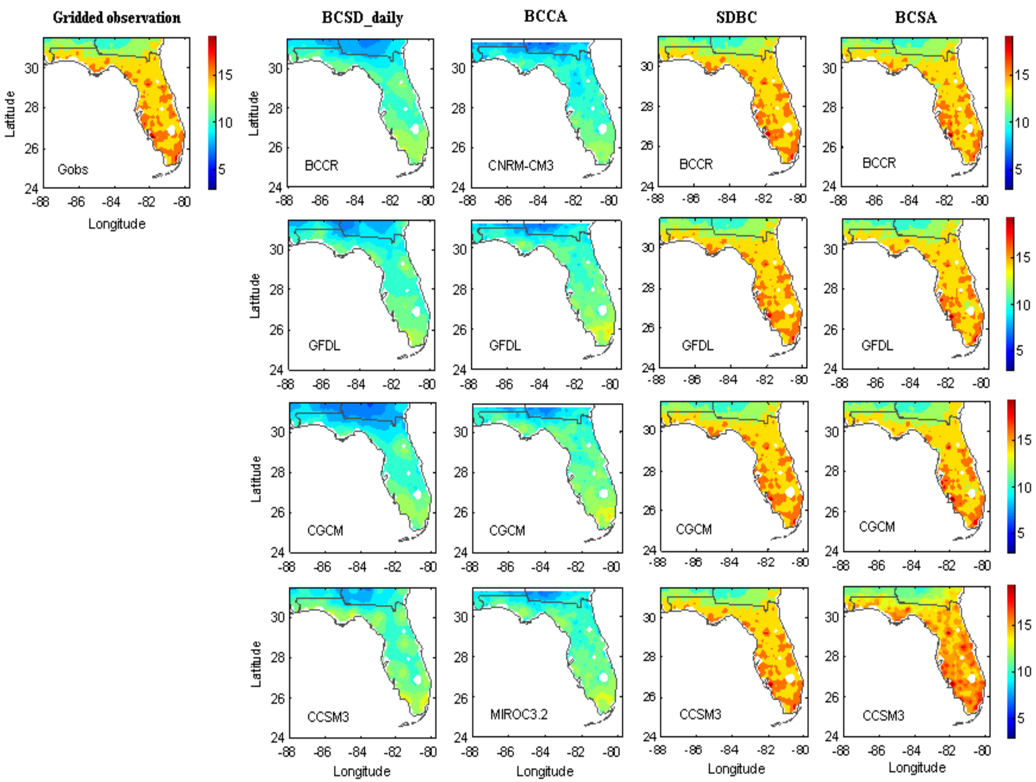


for dry season

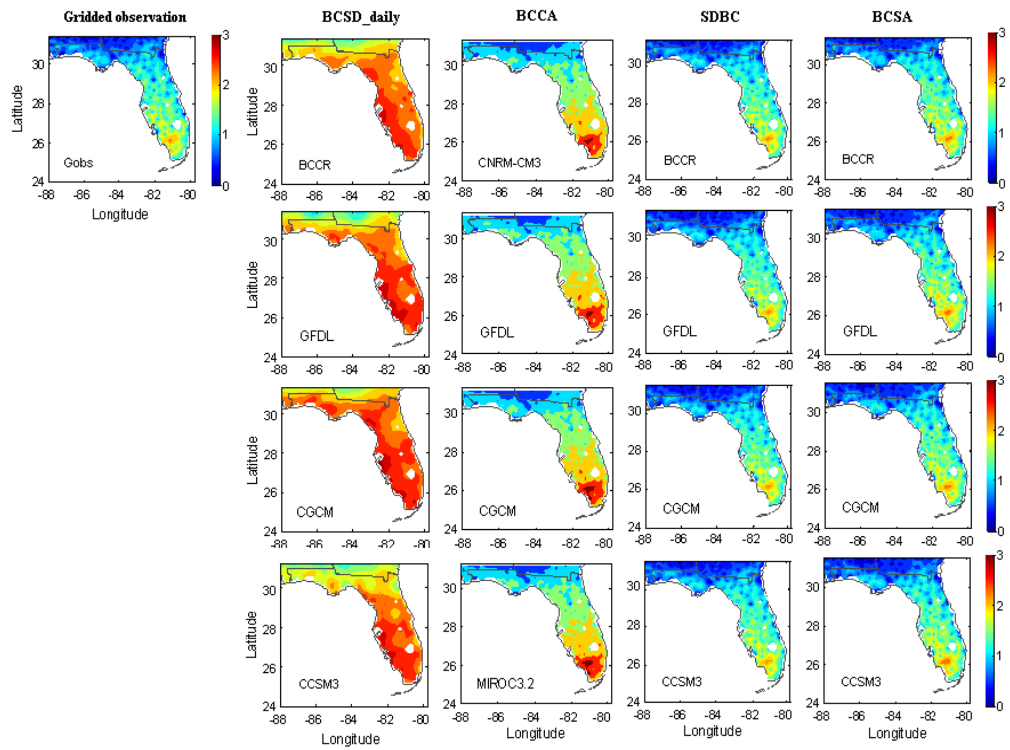


Spatial distribution of the 90th and 50th percentile daily precipitation

the 90th percentile

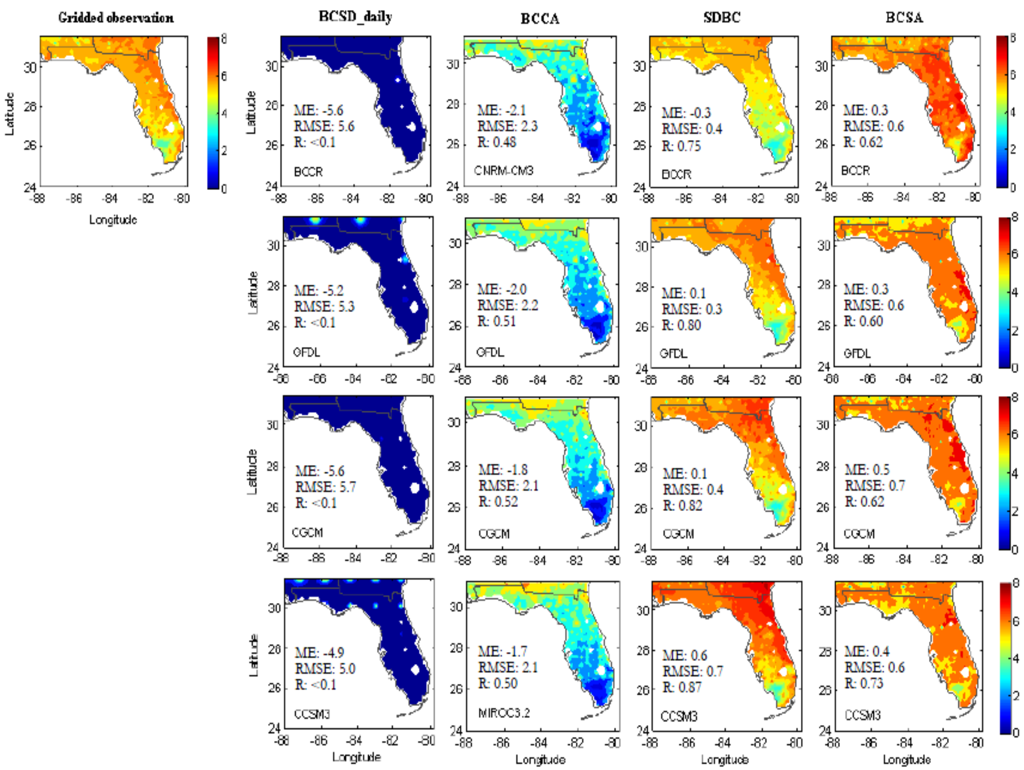


the 50th percentile

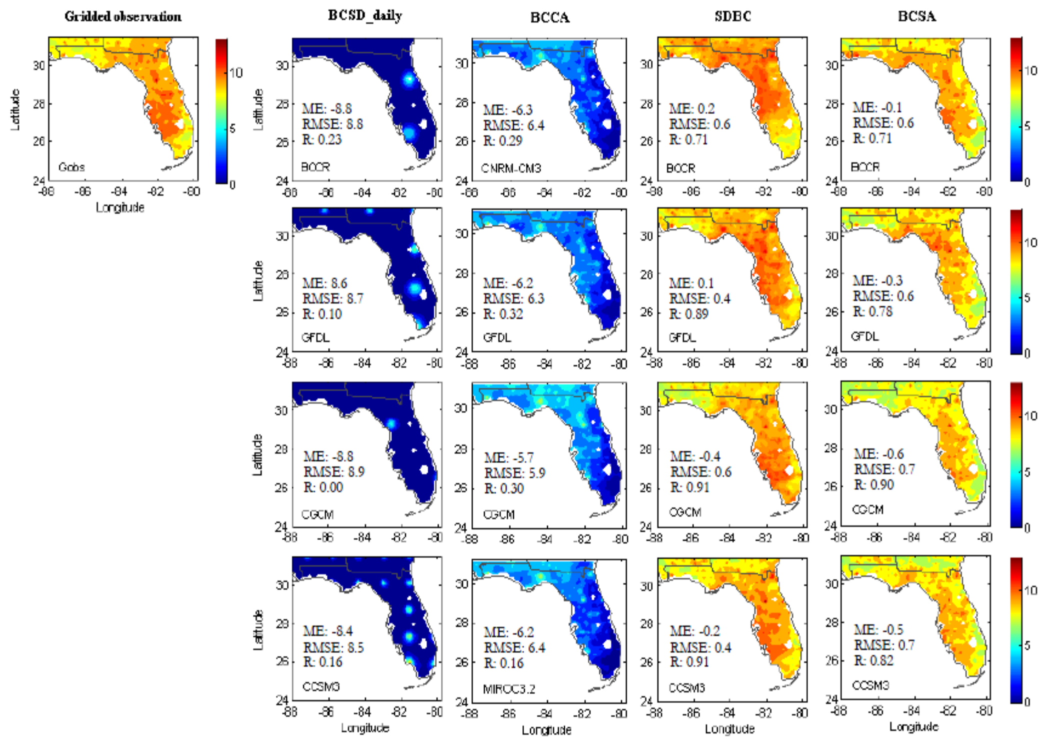


Spatial distribution of the frequency of wet spell length (〉 5 days) events.

for wet season



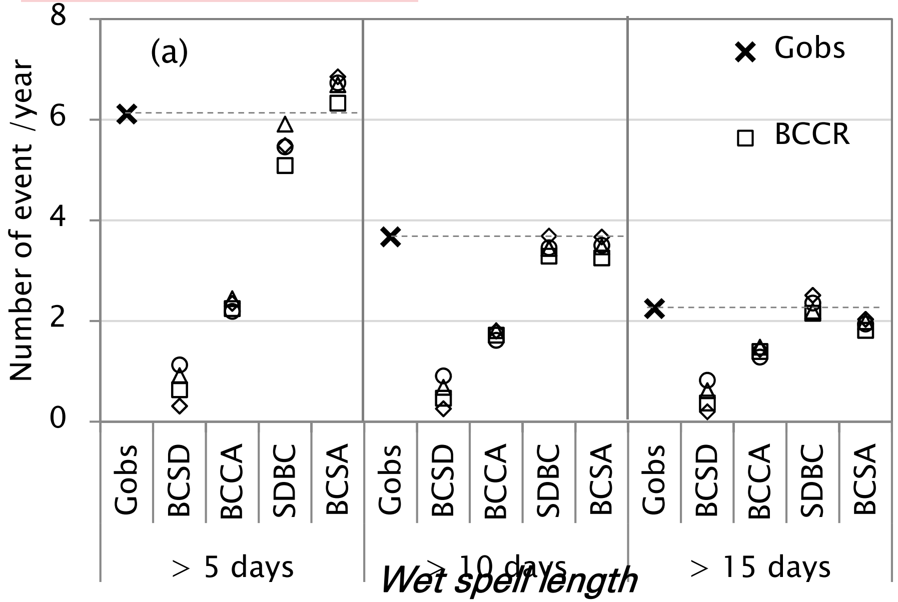
for dry season

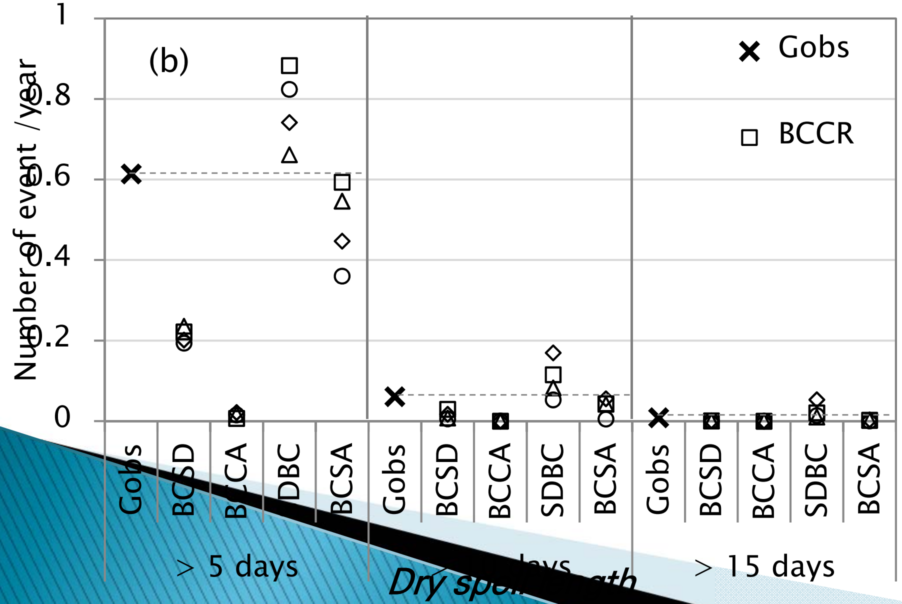


Units in "number of events/year. ME, RMSE, and R calculated for the downscaled predictions are reported on each map.

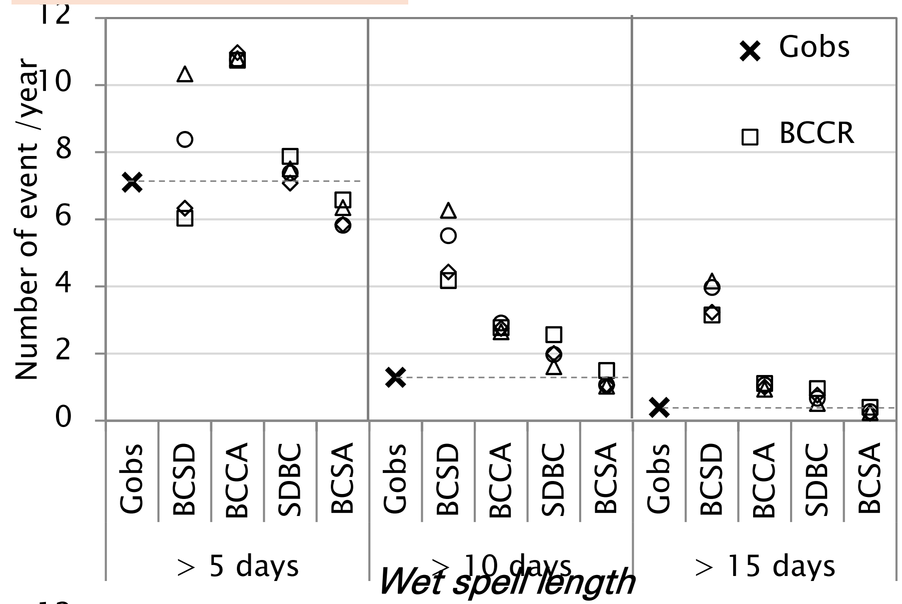
Number of the events
for given (a) wet (≥0.1mm) and (b) dry (<0.1mm) spell lengths

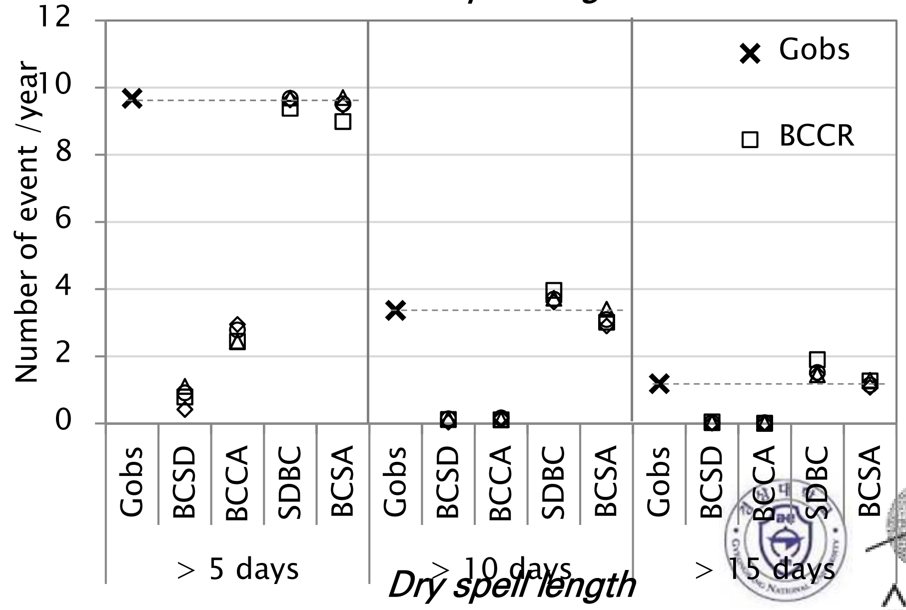
Wet season





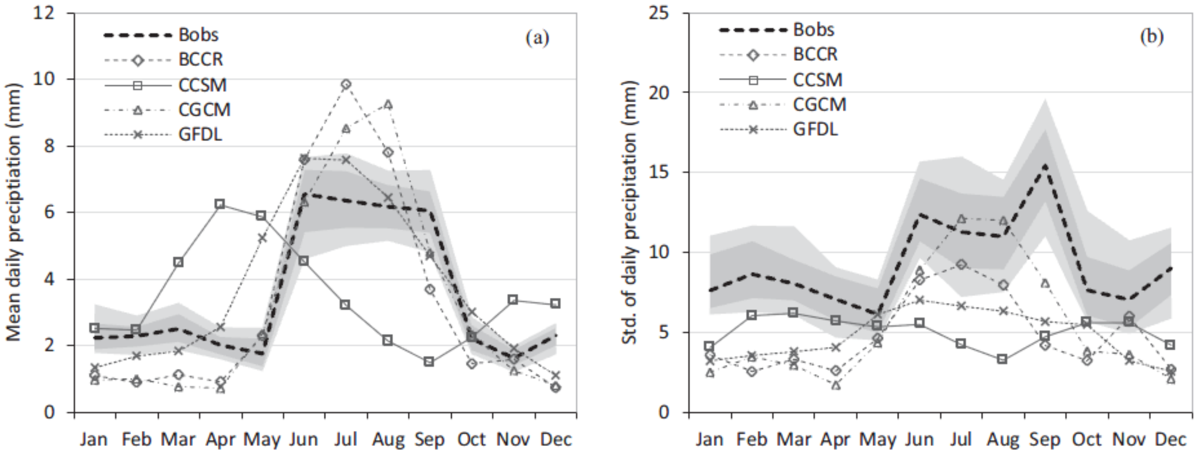
Dry season



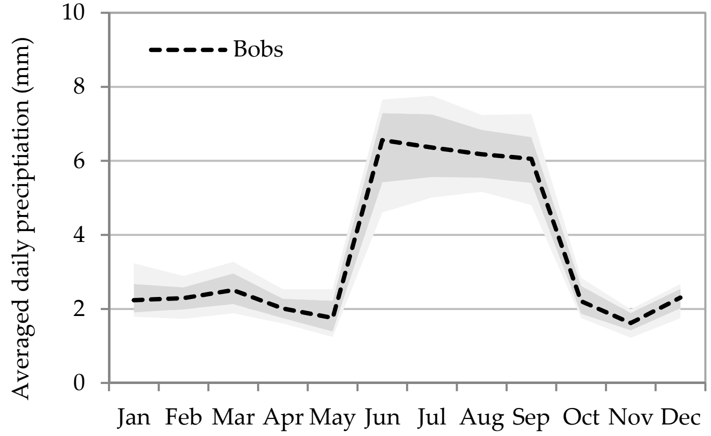


Daily precipitation Predictions

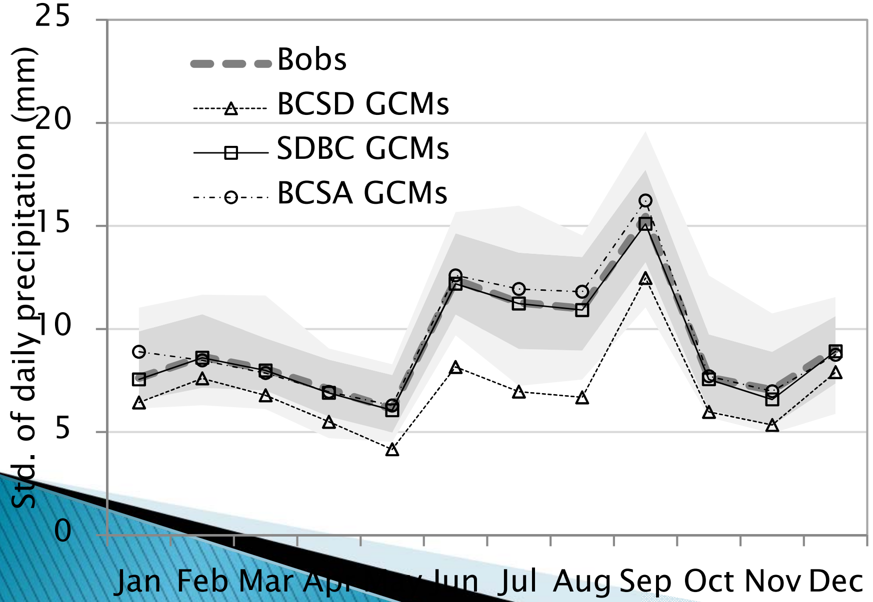
Raw GCM data vs. observation



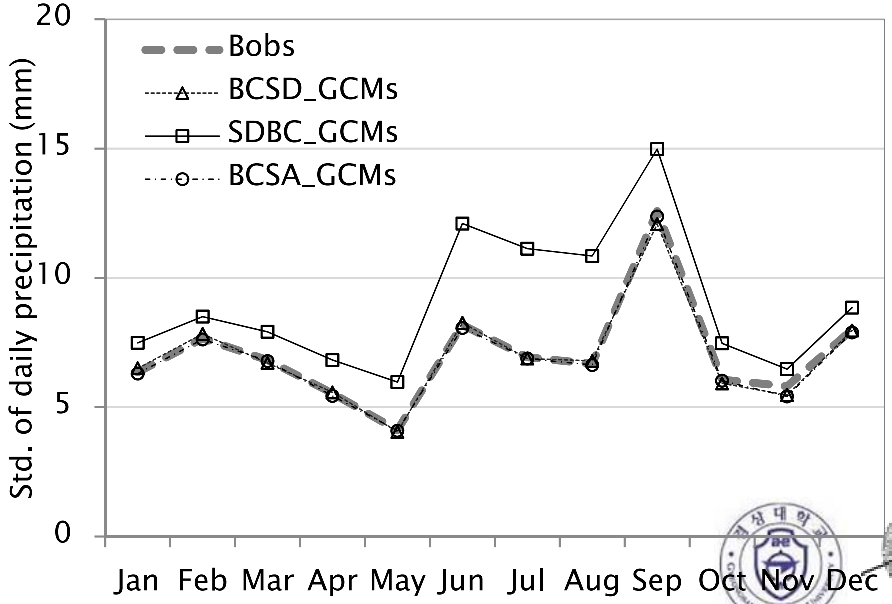
Averaged mean daily precipitation



Averaged standard deviations of daily precipitation

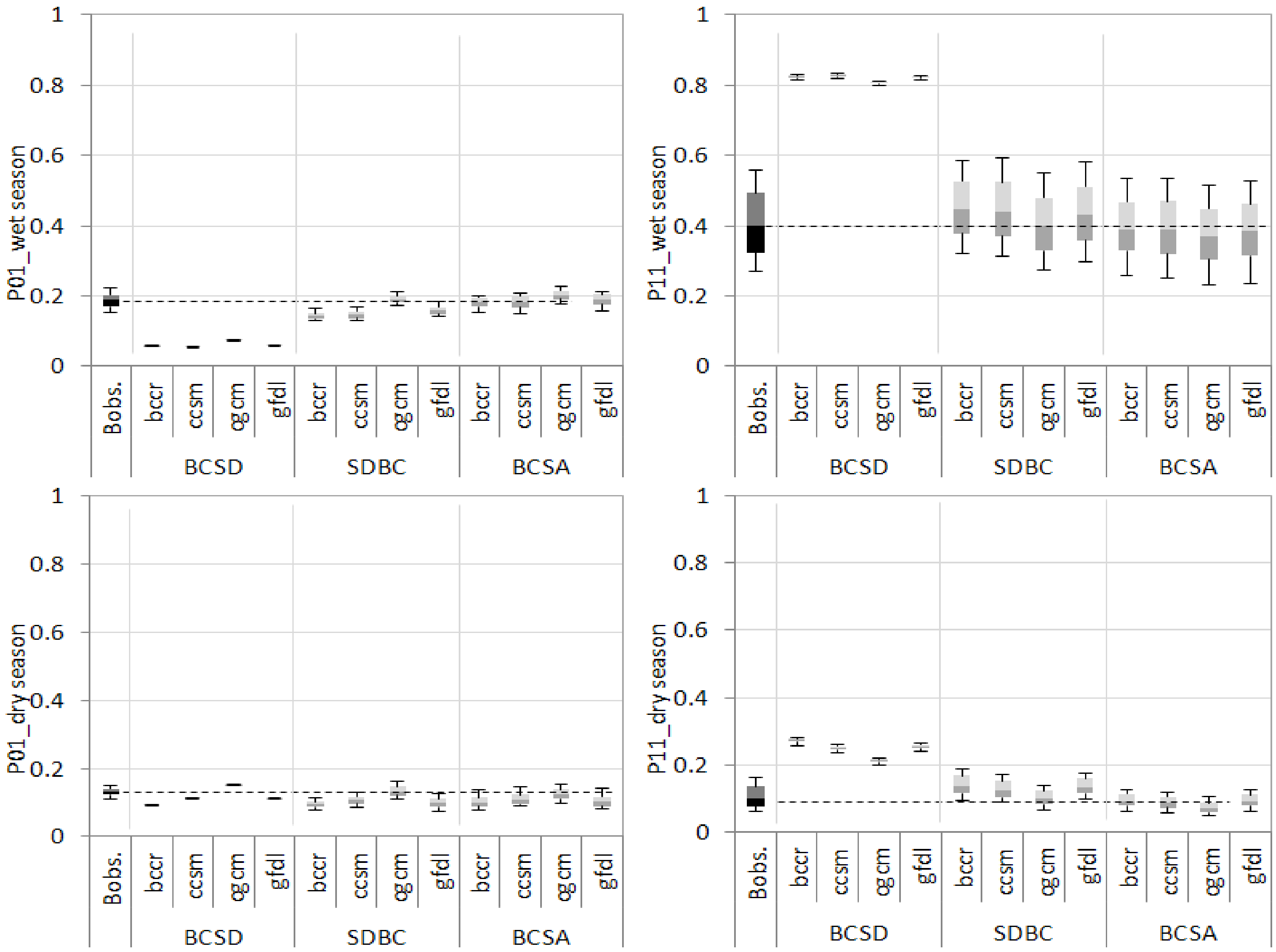


Standard deviation of spatially averaged daily precipitation



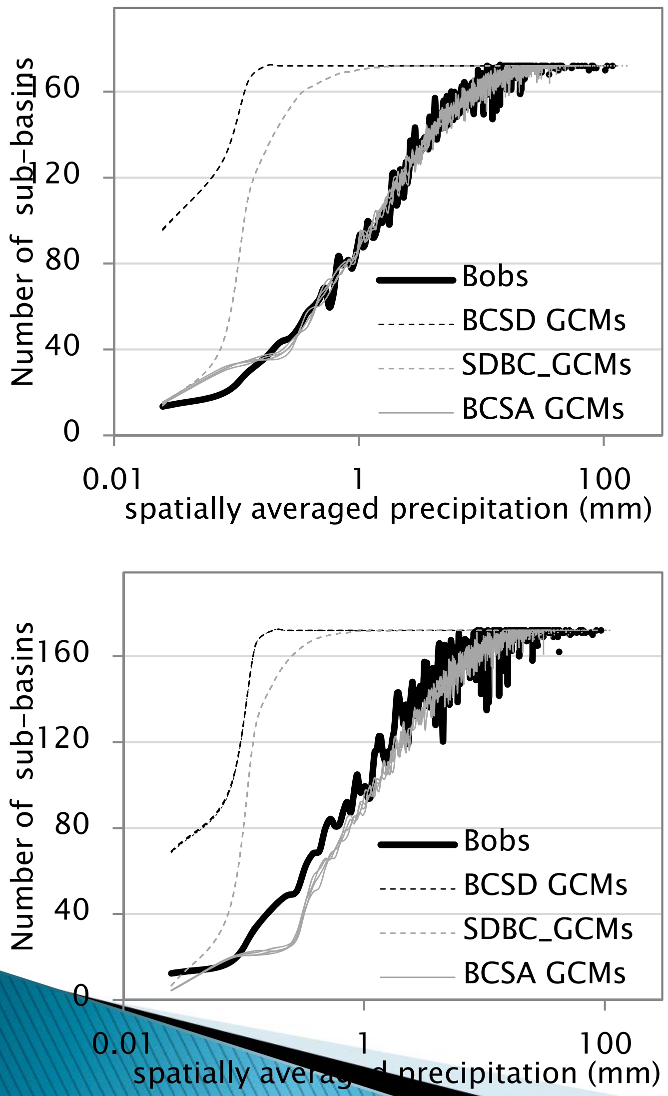
Transition probabilities

Dry to wet day (P_01, left column) and wet to wet day (P_11, right column)

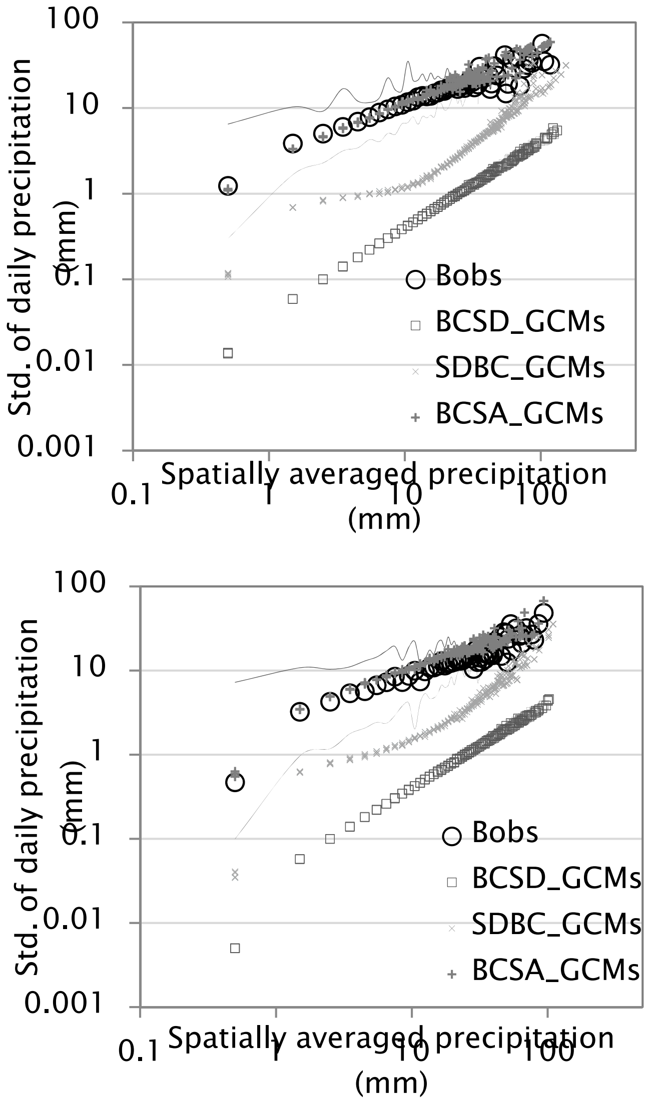


Spatial Variability of Daily Precipitation

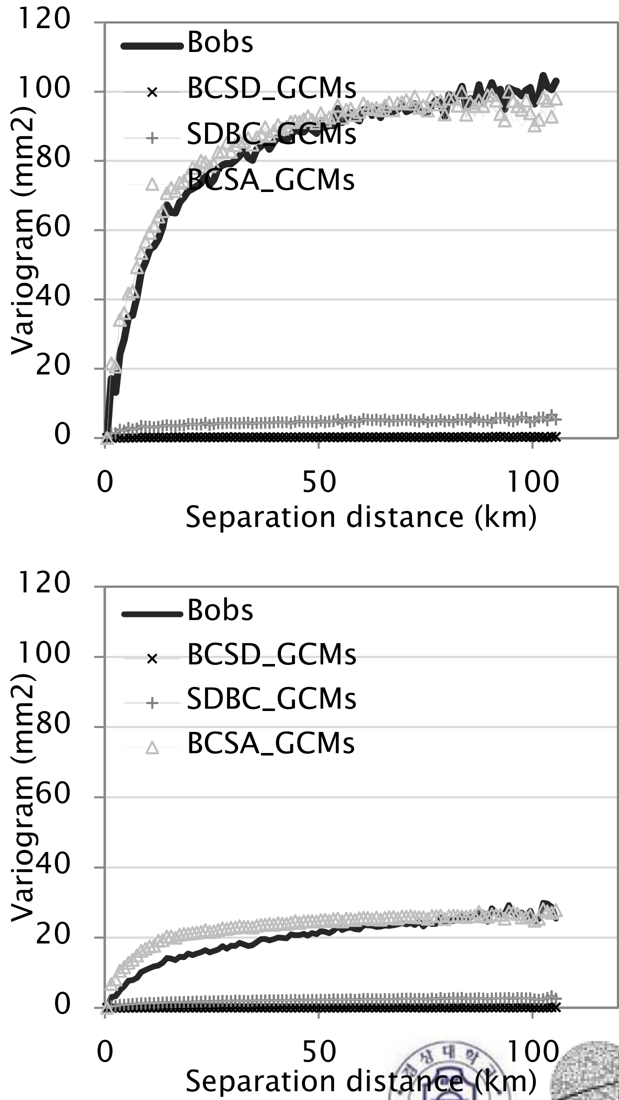
Number of rainy sub-basins



Spatial standard deviations of daily precipitation



Variograms



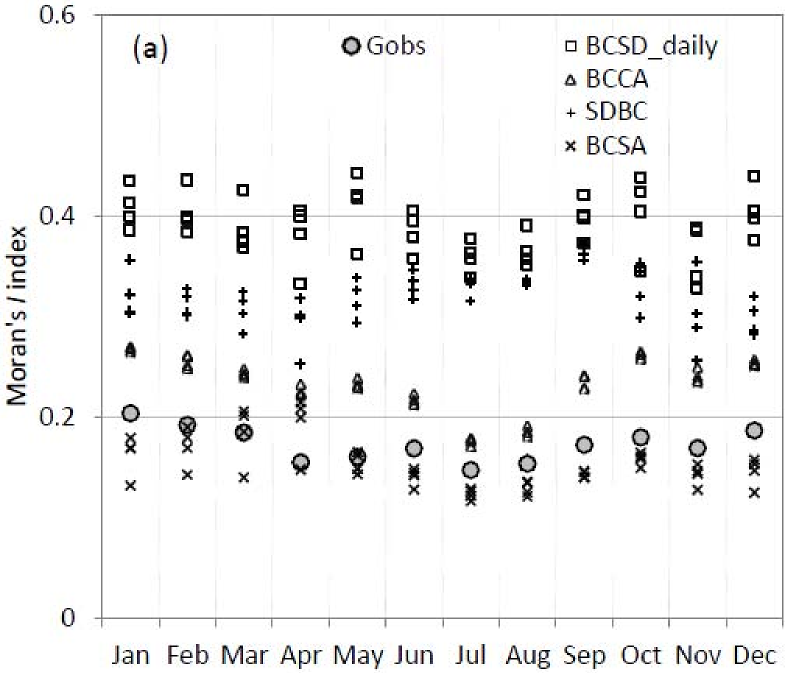
APCC

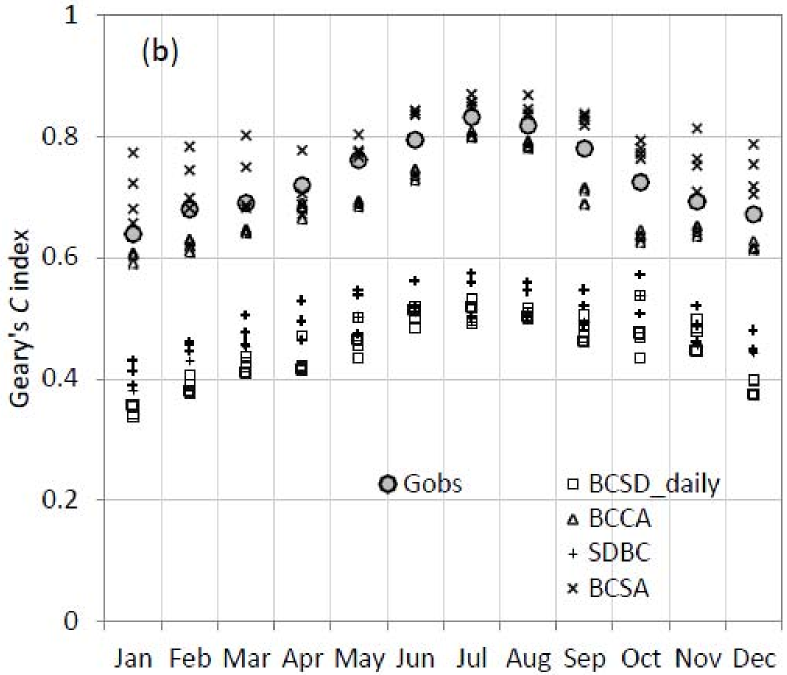
observed vs. simulated mean daily spatial correlation indices

(a) Moran's I and spatial variance indices (b) Geary's C for each month. 4 GCMs are not separately represented but are indicated by the same marker for each downscaling method.

$$I_t = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij} \left(x_{t,i} - \bar{x_t}\right)\left(x_{t,j} - \bar{x_t}\right)}{\sum_i \left(x_{t,i} - \bar{x_t}\right)^2}$$

$$C_t = \frac{(N-1)}{2\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij} \left(x_{t,i} - x_{t,j}\right)^2}{\sum_i \left(x_{t,i} - \bar{x_t}\right)^2}$$



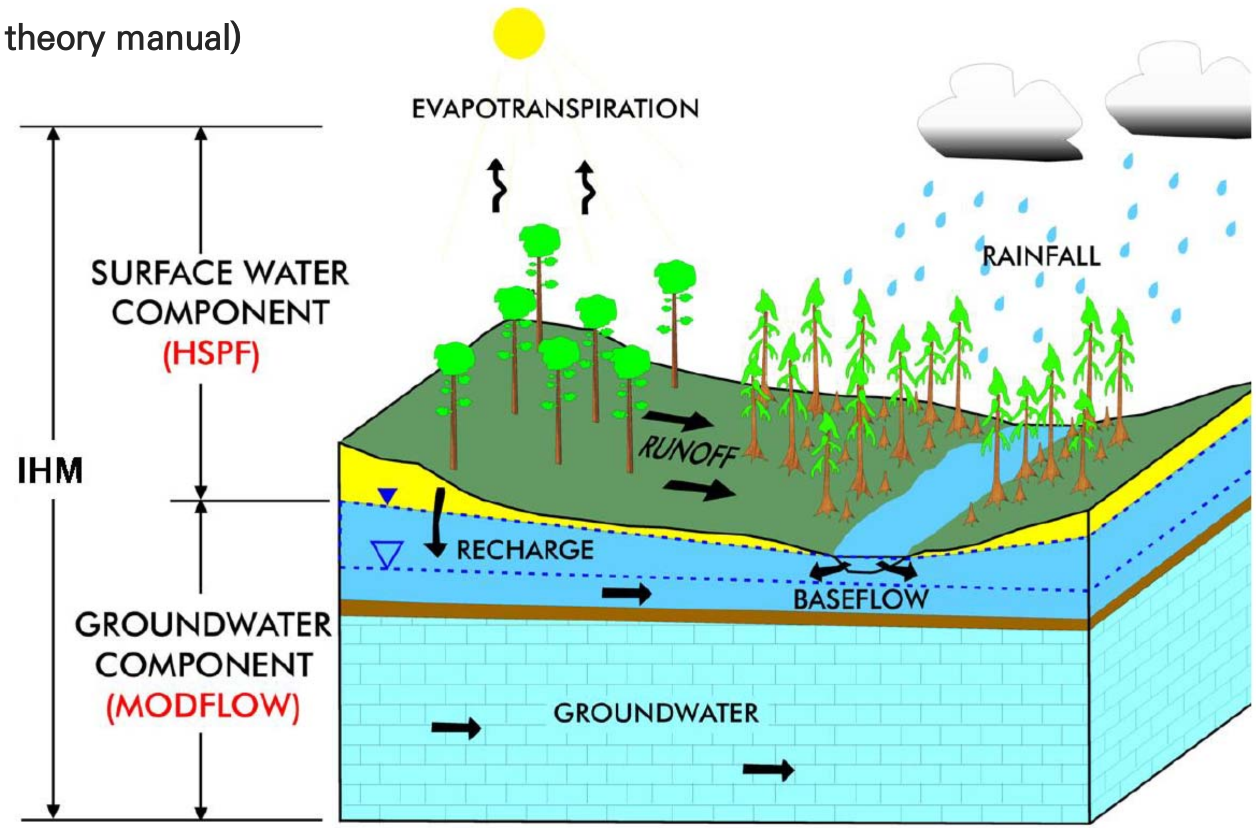


Hydrologic implication of BCSA

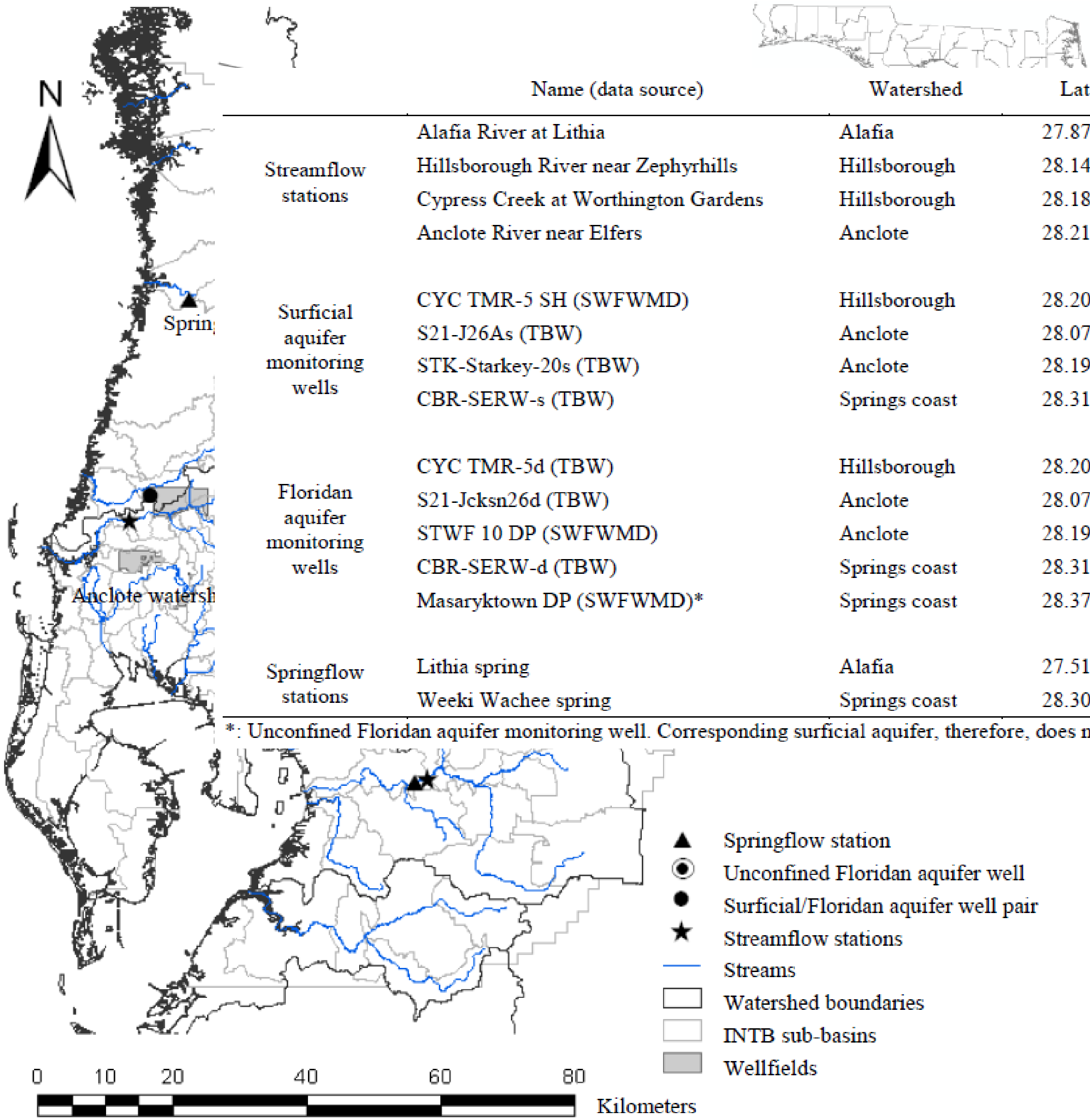
Integrated Hydrologic Model

- TBW and SWFWMD commissioned the development and application of an integrated surface water/groundwater model to gain an increased understanding of the surface and groundwater flow systems in the Tampa Bay Region.
- The Integrated Hydrologic Model (IHM) was developed which integrates the EPA Hydrologic Simulation Program–Fortran for surface-water modeling with the US Geological Survey MODFLOW96 for groundwater modeling.

Ross et al., 2004 (IHM theory manual)



Study domain

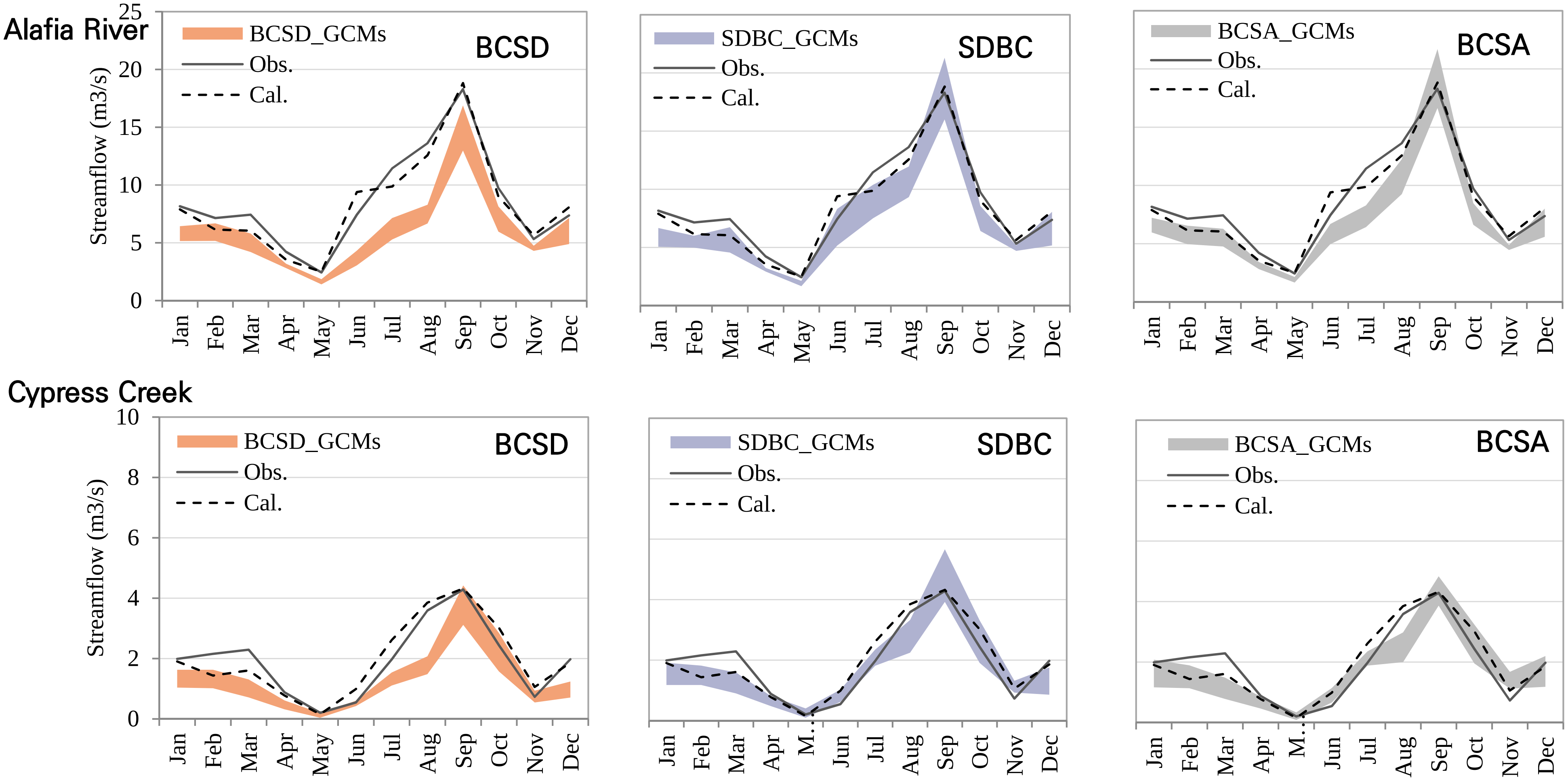


	Name (data source)	Watershed	Lat.	Lon.	Drainage area, (km^2)
Streamflow stations	Alafia River at Lithia	Alafia	27.8719	-82.2114	867.3
	Hillsborough River near Zephyrhills	Hillsborough	28.1497	-82.2325	569.6
	Cypress Creek at Worthington Gardens	Hillsborough	28.1856	-82.4008	302.9
	Anclote River near Elfers	Anclote	28.2139	-82.6667	187.7
Surficial aquifer monitoring wells	CYC TMR-5 SH (SWFWMD)	Hillsborough	28.2057	-82.4680	-
	S21-J26As (TBW)	Anclote	28.0730	-82.5800	
	STK-Starkey-20s (TBW)	Anclote	28.1956	-82.6953	
	CBR-SERW-s (TBW)	Springs coast	28.3151	-82.5146	
Floridan aquifer monitoring wells	CYC TMR-5d (TBW)	Hillsborough	28.2053	-82.4680	-
	S21-Jcksn26d (TBW)	Anclote	28.0730	-82.5800	
	STWF 10 DP (SWFWMD)	Anclote	28.1963	-82.6951	
	CBR-SERW-d (TBW)	Springs coast	28.3151	-82.5146	
	Masaryktown DP (SWFWMD)*	Springs coast	28.3740	-82.5262	
Springflow stations	Lithia spring	Alafia	27.5159	-82.1353	-
	Weeki Wachee spring	Springs coast	28.3048	-82.4680	

*: Unconfined Floridan aquifer monitoring well. Corresponding surficial aquifer, therefore, does not exist.

Hydrologic implication (Streamflow)

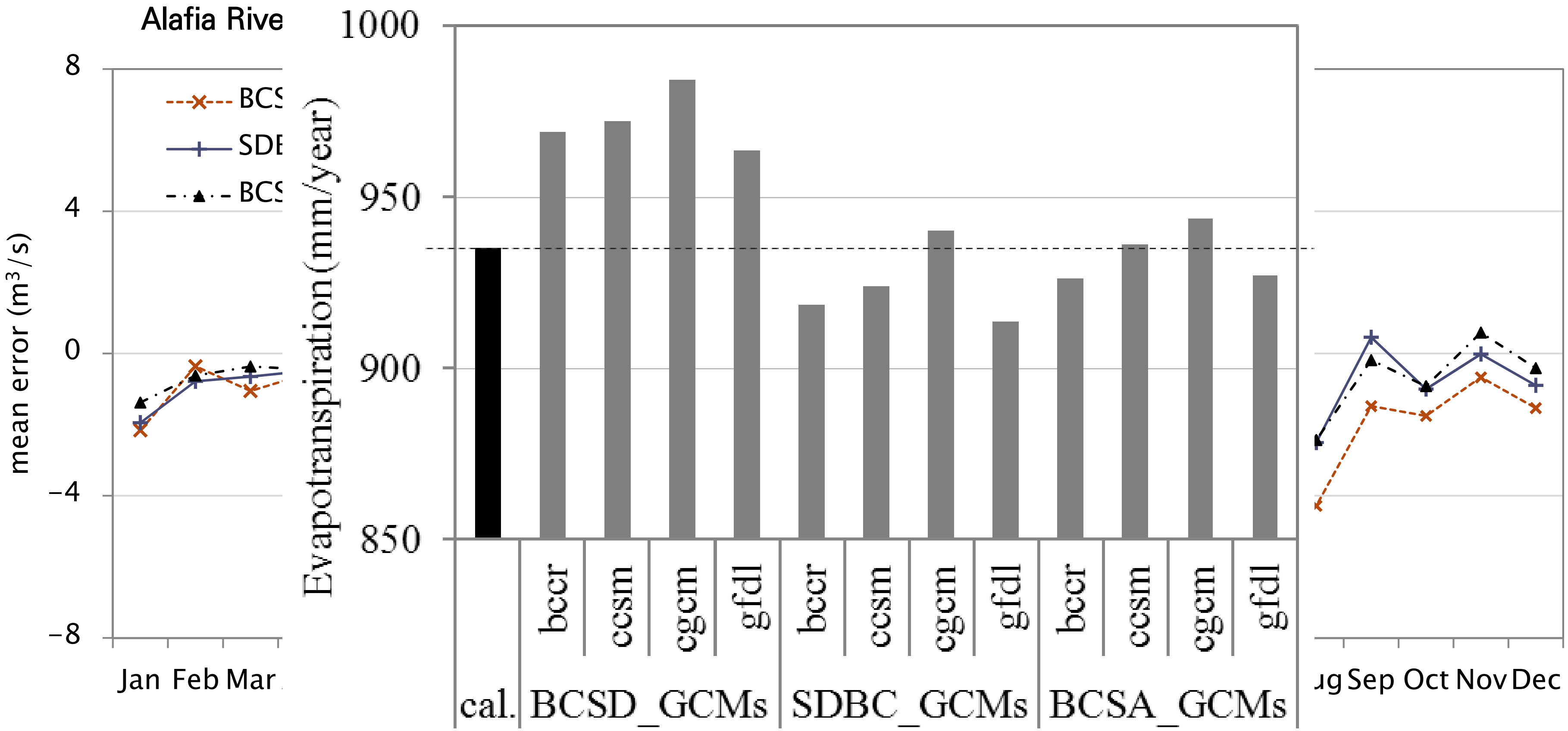
Monthly average stramflow



- The BCSD method tends to underestimate streamflow for the wet season more than the SDBC and BCSA methods at all stations due to the high spatial correlation of the BCSD daily precipitation fields and higher frequency of low precipitation events resulting in higher evapotranspiration
- The monthly average streamflow predicted by the SDBC results are reasonably close to calibrated results and similar to the BCSA results.

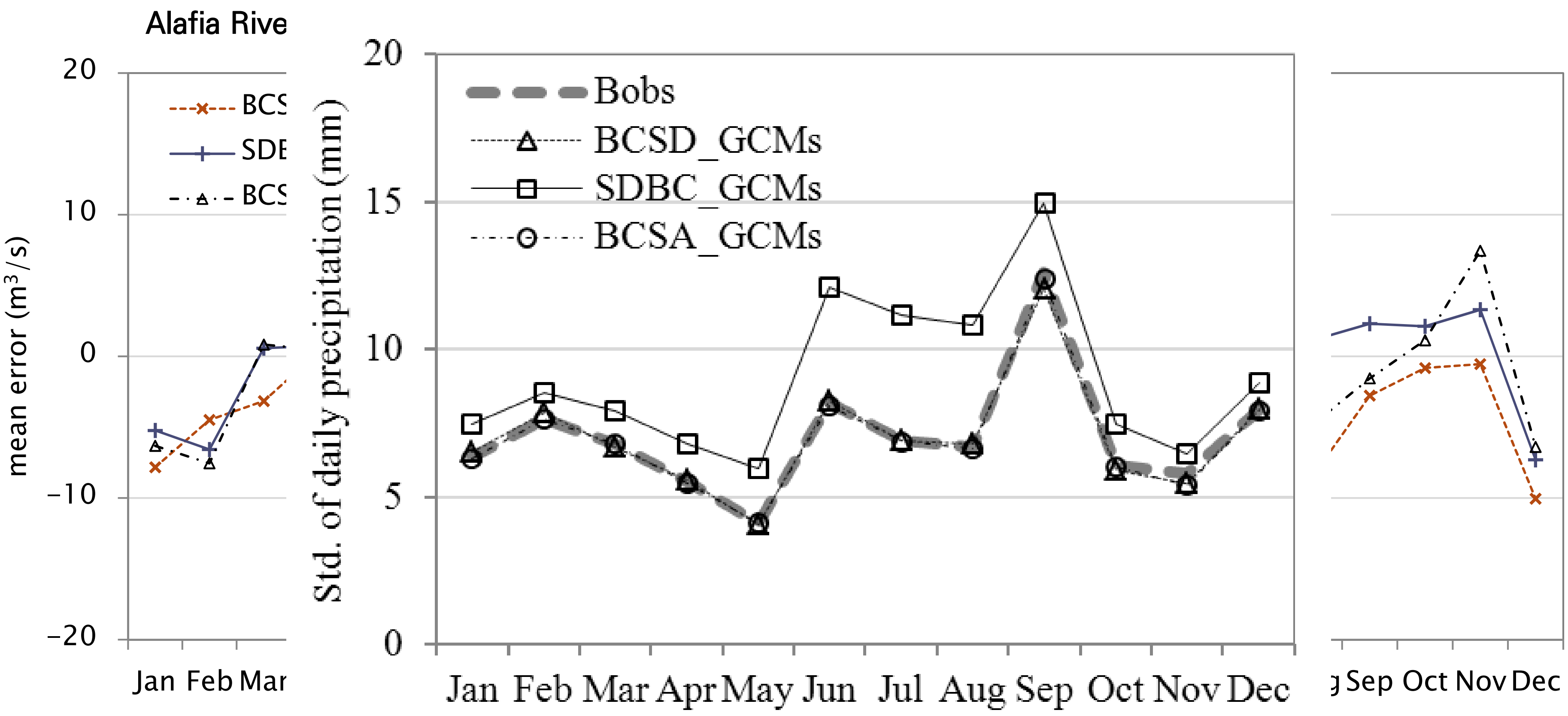
Mean of errors in streamflow simulation

Mean of errors (simulated−calibrated) of monthly average streamflow over four GCM results for each target station

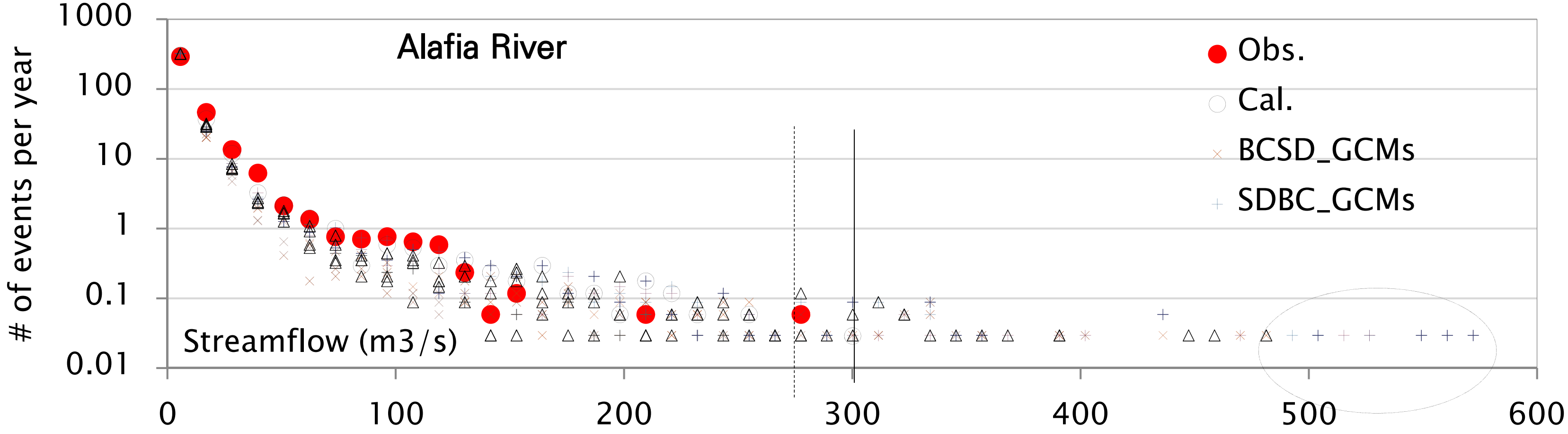


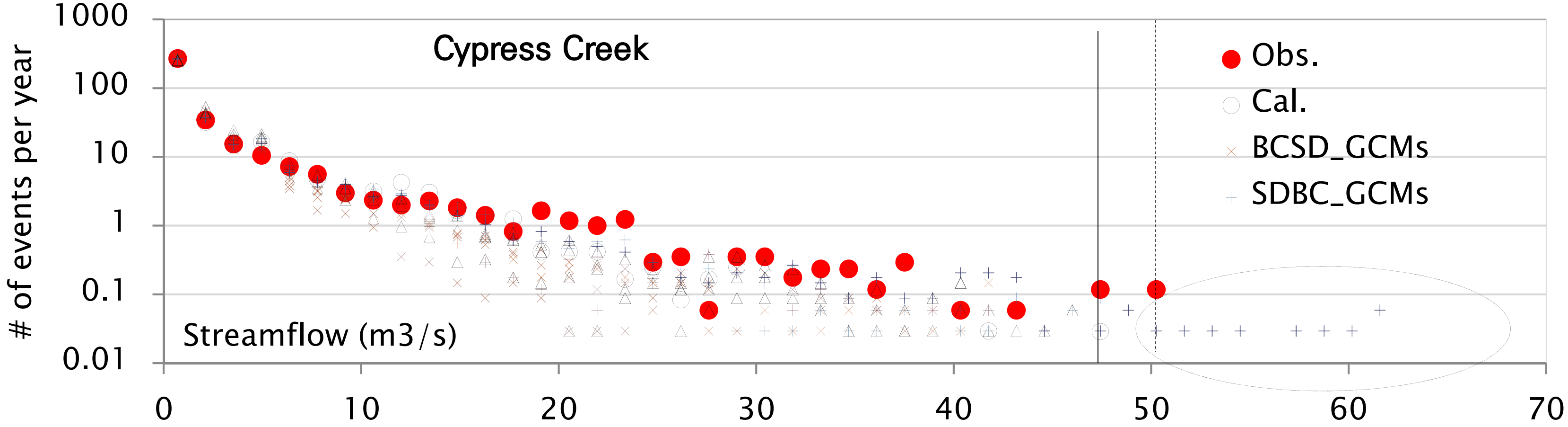
Mean of errors in streamflow simulation

Mean of errors (simulated-calibrated) of temporal standard deviation of daily streamlfow over four GCM results for each target station



Frequency of daily streamflow events

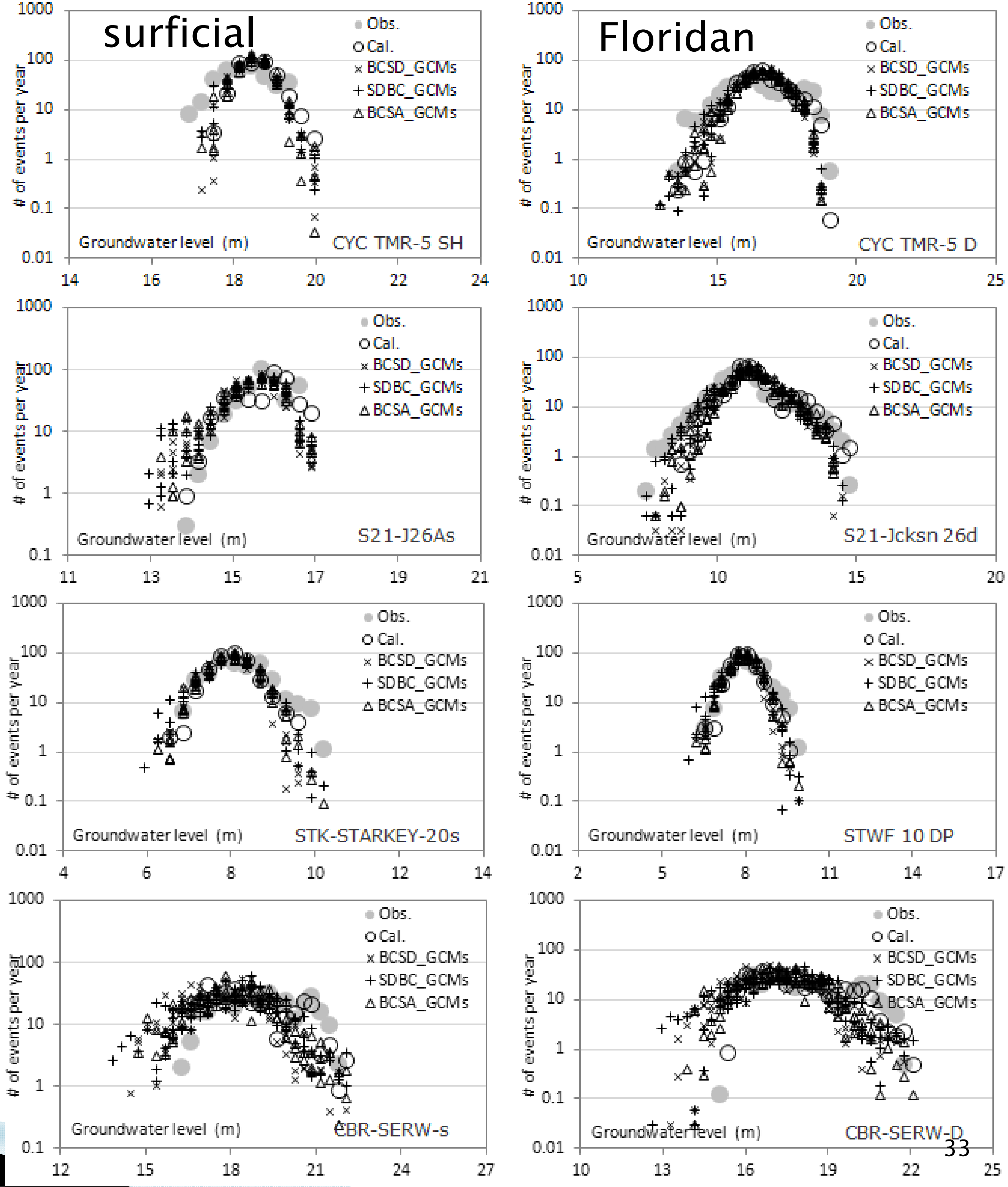




- The frequency of daily streamflow was not reproduced by SDBC as closely as for the BCSA results.
- Comparing the , it is evident that the under/overestimations of extreme events is canceled out when evaluating only the monthly mean streamflow.

Frequency of groundwater level per year

- No substantial difference of skill in reproducing the frequency of groundwater level was found among the various downscaling techniques.
- The SDBC showed some overestimation of the frequency of lower and higher groundwater level at the CBR-SERW and S21 stations compared to the calibrated results.
- This may be due to the same mechanism that resulted in overestimating the frequency of extreme streamflow events and peak flow in the wet season by the SDBC.



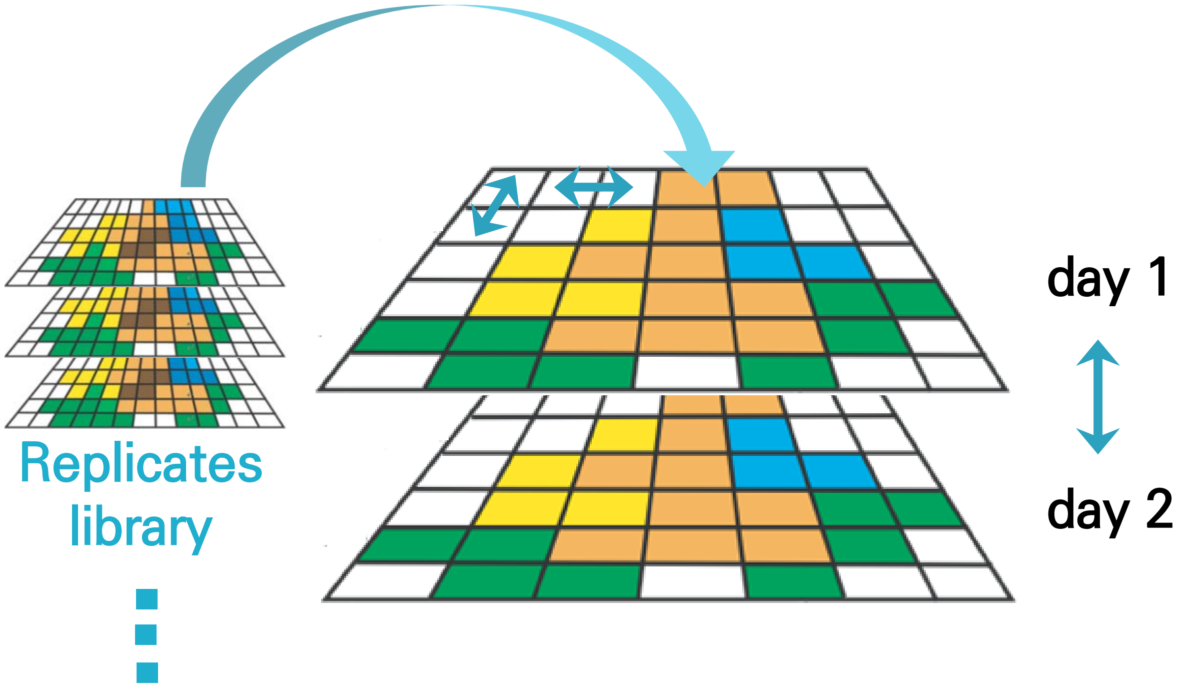
Summary

cf. SQM, SDQDM

	BCSD	SDBC	BCSA
• *Precipitation prediction*			
• Annual mean cycle	O	O	O
• Temporal mean	O	O	O
• Transition probability	X	O	O
• Frequency of events	△	X	O
• Wet & dry spell length	X	△	O
• Temporal variance	△	△	O
• Spatial variability	X	△	O
• *Hydrologic simulation*			
• Annual mean cycle	X	O	O
• Temporal variability	X	X	O
• Frequency of event	O	X	O

Drawbacks of BCSA

- Conducted independently
  - on a daily basis and
  - At each GCM grid
- Stationary covariance



- Advantages:
  - Can downscale into any temporal (hourly, daily, monthly) and spatial scale (e.g., gridded, irregularly distributed points)
  - Generate Ensemble of possible local scale precipitation patterns
  - Uncertainty due to the downscaling process could be examined using collection of equally probably downscaled climate fields

Evaluation and selection of Downscaling methods

Screening the method to use for application?

GCMs

Future climate info.
(AR5, RCP scenario)

– PCMDI (CMIP5)

GCM evaluation

not OK

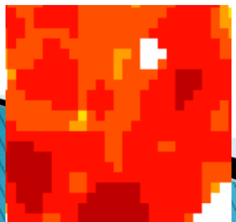
Screening

OK

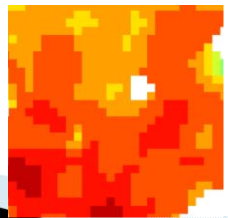
Screening GCM

Model weighting

- Physical probability
- Global scale
- Climatology
- Purpose:



vs.



Downscaling methodologies

Spatially detailed climate info.

– BCSD, BCCA, SDBC, BCSA, etc.

Method evaluation

not OK

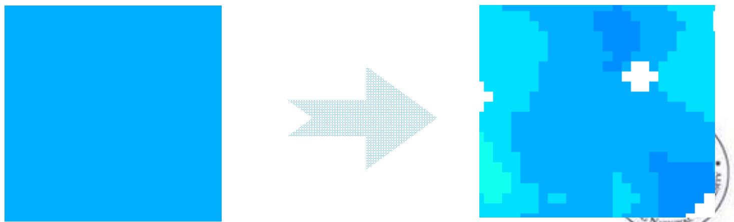
Selecting

OK

Method selection

intercomparison

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



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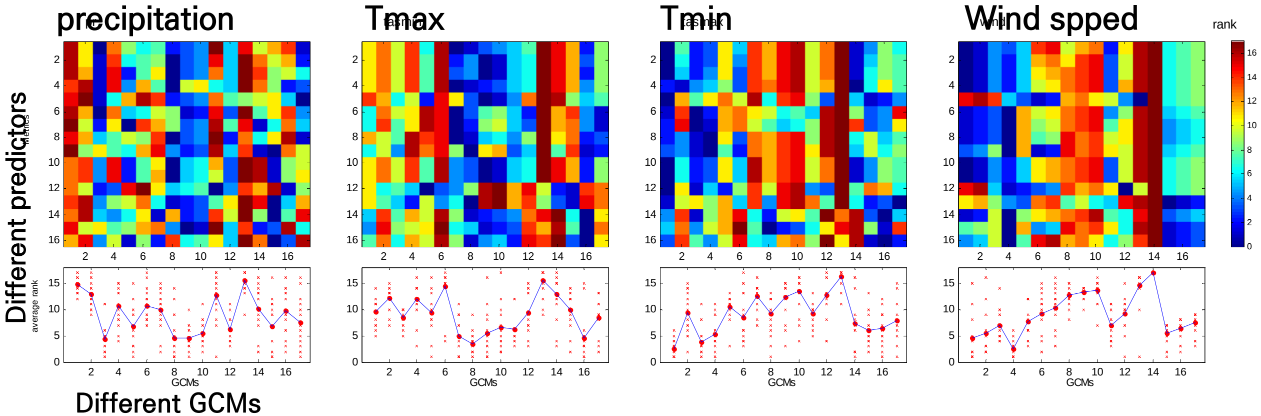
GCM skill evaluation

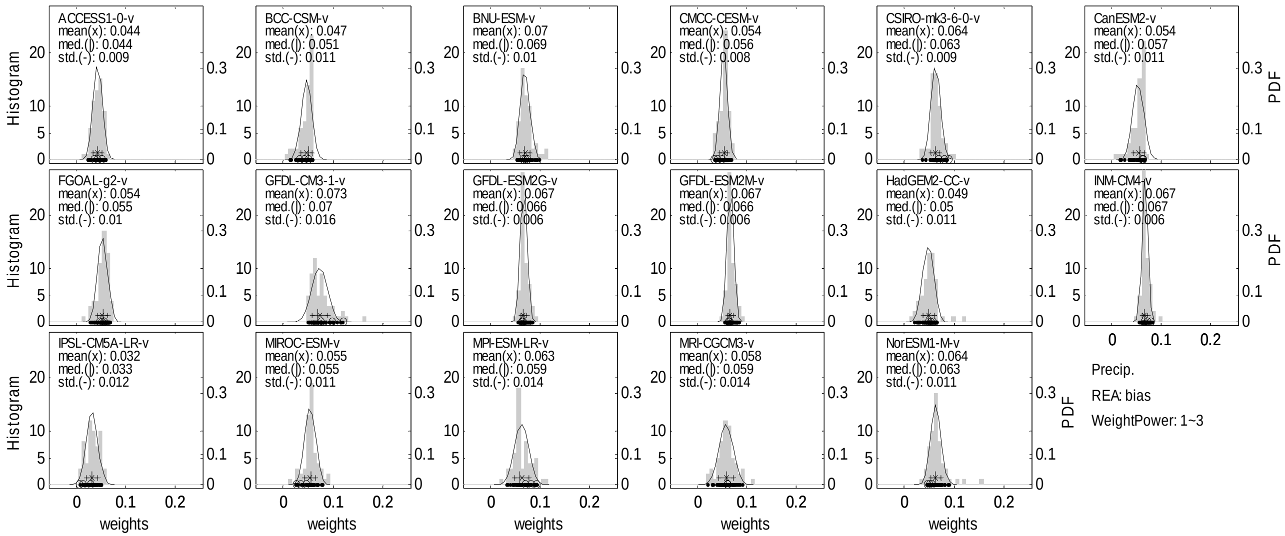


Different observations
1 Maurer's data (Maurer et al., 2002)
2 NLDAS data
3 USGS data
4 Reanalysis data?

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?

Distribution of weights for each GCM (precipitation)

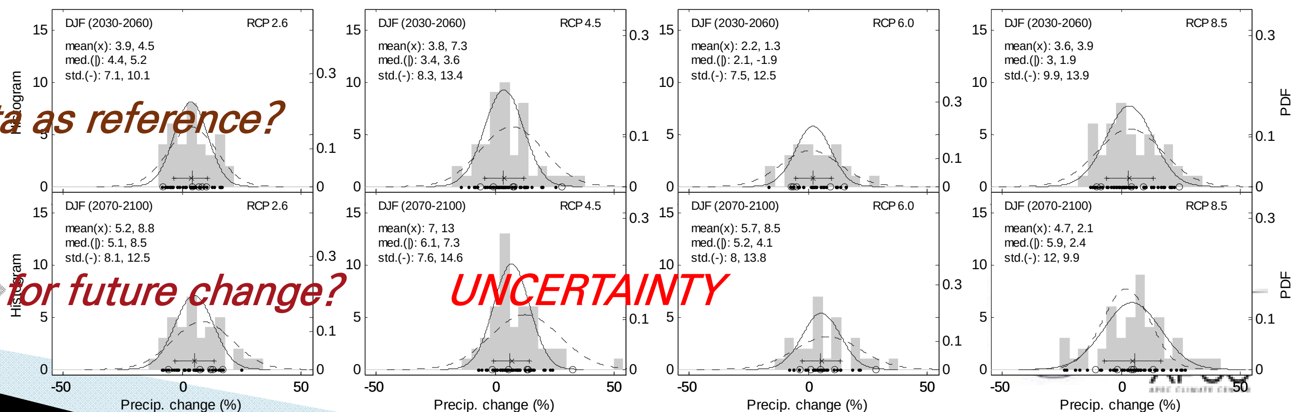


Different indicators
1 d10TS';
2 monthlyTS';
3 4seasonalTS';
4 annualTS';
5 annualCVTS';
6 annualQ95TS';
7 annualQ99TS';
8 monthlyQ95';
9 monthlyQ99';
10 d10mean';
11 monthlymean';
12 monthlyCV_daily';
13 monthlyCV_monthly';
14 d10std';
15 monthlystd_dailydata';
16 monthlystd_monthlydata';

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?



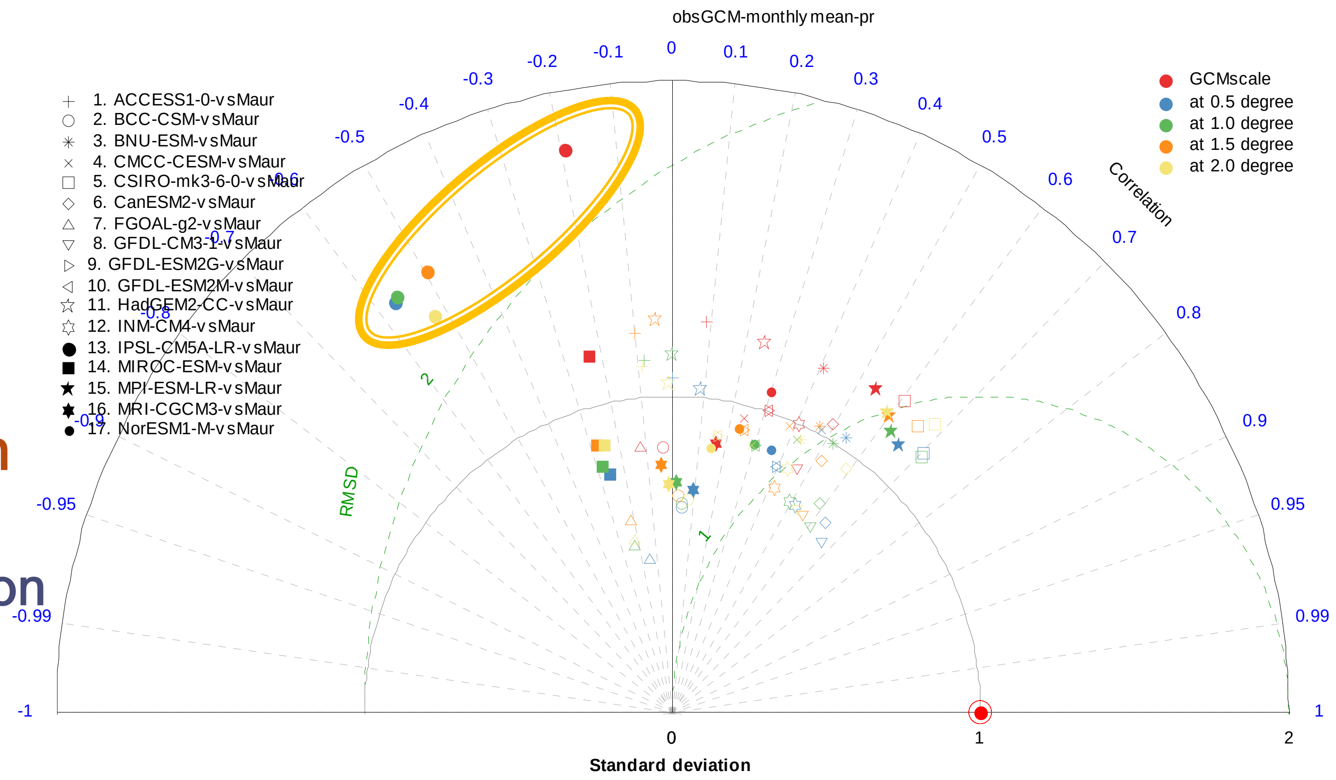
What if we have different inferences for future change?

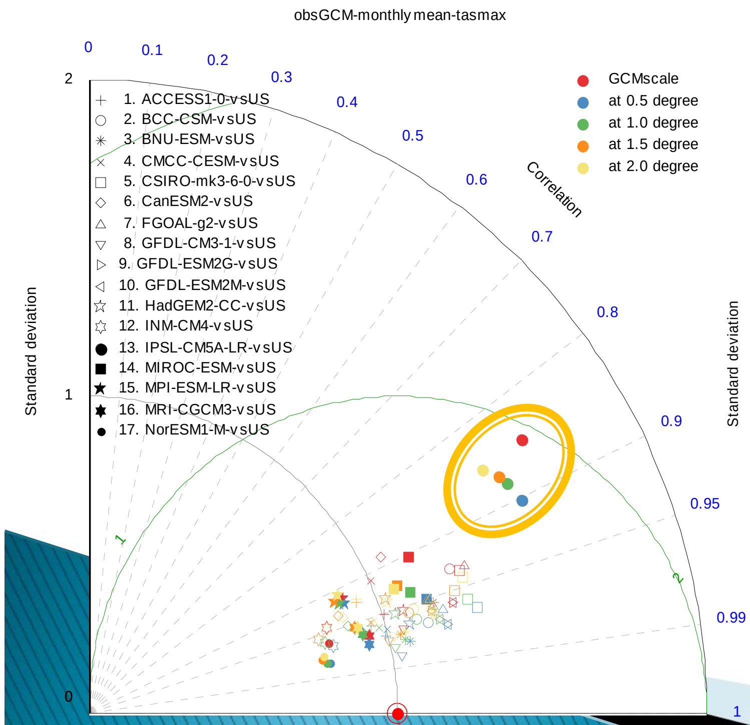
UNCERTAINTY

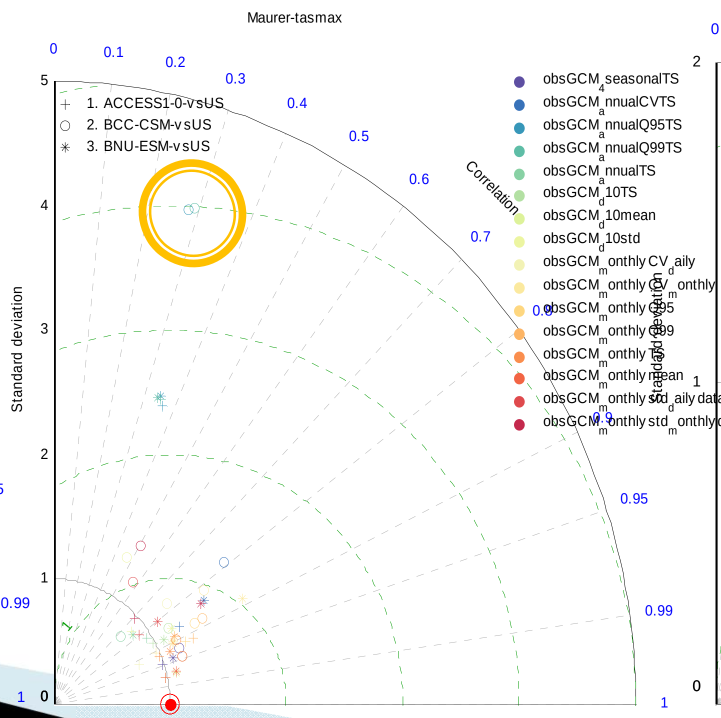
How GCMs work?

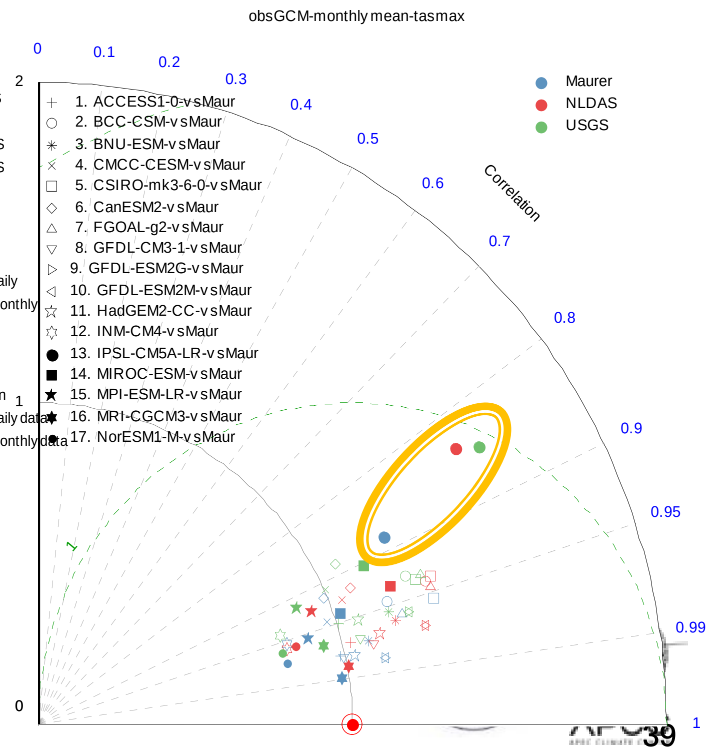
Performance evaluation

at different resolution
with different observation
For different criteria

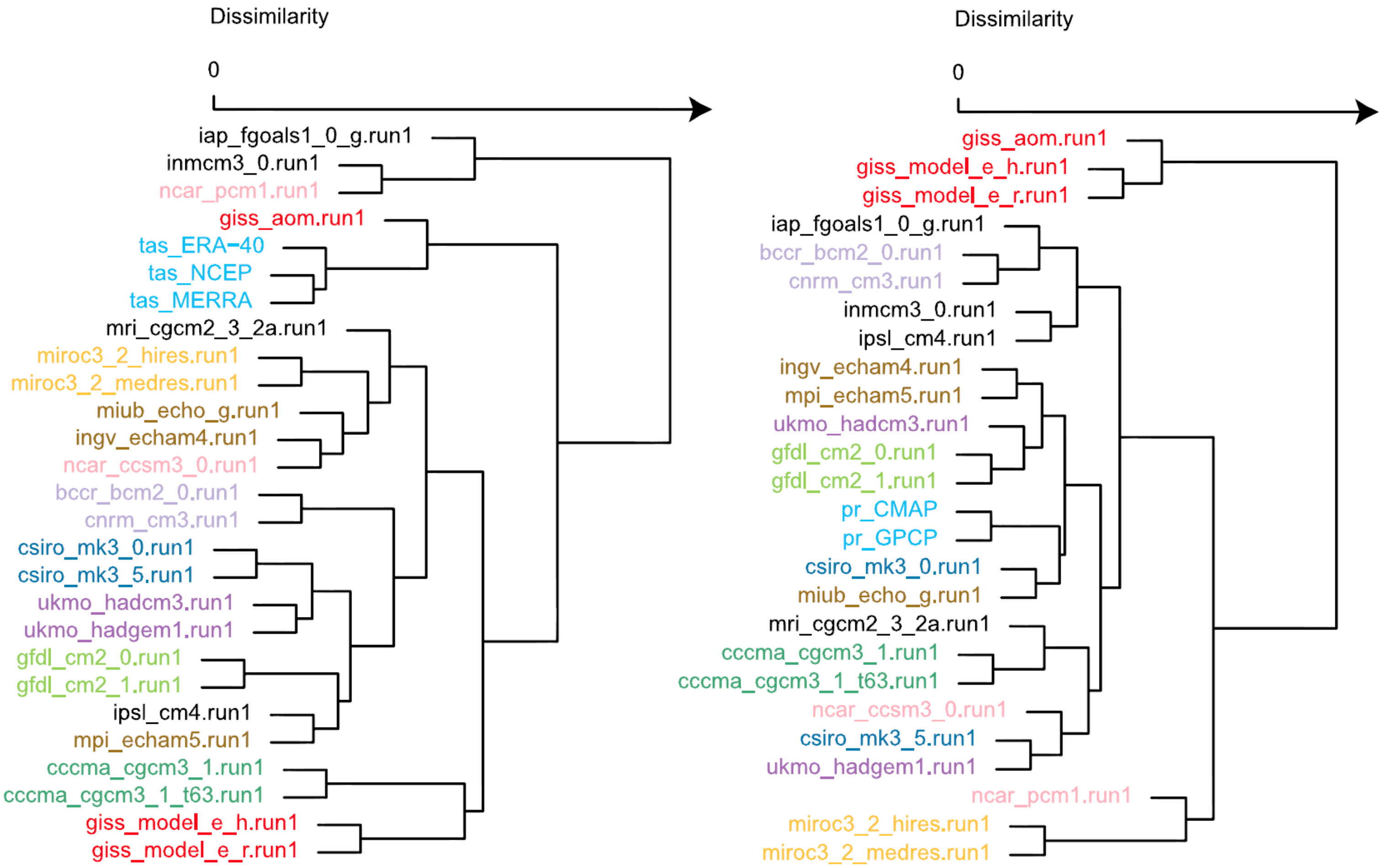








How different Models are…



(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.

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

- 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)

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Thank you!

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