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The Impacts of Model Weighting on Quantifying Hydrological Responses to Climate Change

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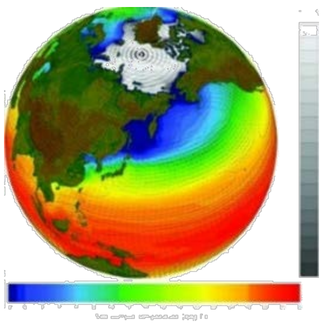
Content

1 Research Purpose

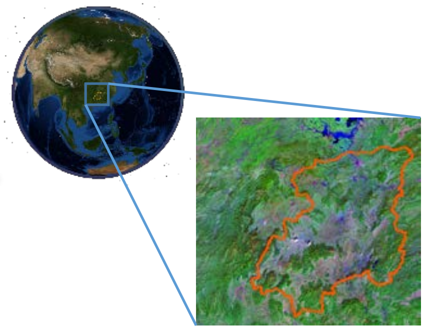
Common way to investigate the climate change impacts:

(1) Downscale outputs of global climate model (GCM) into watershed scale; and

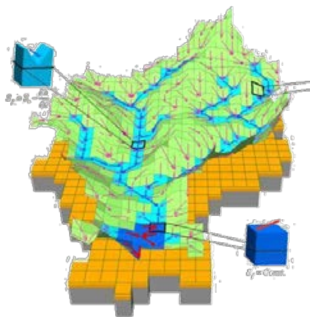
(2) Input downscaled data into hydrological model to project streamflow.



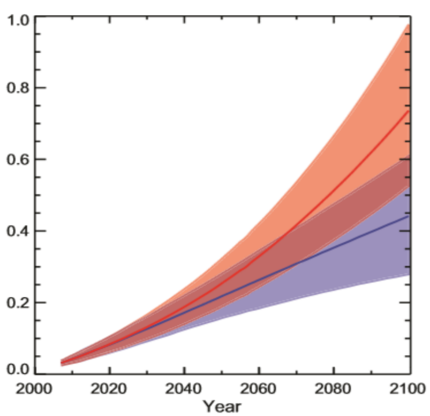
GCM Outputs
Multiple GCMs
（ Multi-model ensemble）



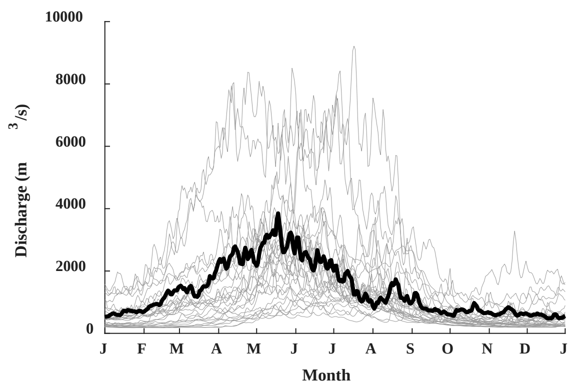
Downscaling



Hydrological Model



Climate Simulation



Hydrological Simulation

- **How to deal with multi-model ensembles?**

Common strategy:

equal weighting (model democracy)

- **Problems of equal weighting**

[1] Different performances among GCMs

[2] Interdependence between GCMs

Research Purpose

Two problems in model weighting for impact studies:

- The impact variable is related to multiple climate variables

  A trade-off among different climate variables needs to be decided in order to obtain a single set of weights for impact studies.

- There is a non-linear relationship between the climate and impact variables

  The weights calculated based on climate variables may be ineffective in the hydrological impacts.

Objectives:

- Assign weights to GCM simulations according to their ability to represent hydrological observations;
- Investigate the impacts of unequal weighting methods on the quantification of hydrological responses to climate change; and
- Assess the influences of the bias correction to GCMs on the performances of model weighting.

Study Area

Xiangjiang Watershed (China)

Xiangjiang
watershed

Annual Runoff: 2212 m^3/s
Average Temperature: 17 ℃

Flow regime is hardly affected by the snow accumulation and snowmelt.

Manicouagan-5 Watershed (Canada)

Pacific
Ocean

Area： 24610 km^2
Annual Runoff: 1020 m^3/s
Average Temperature: -1 ℃

Flow regime is significantly affected by the snow accumulation and snowmelt.

GCMs

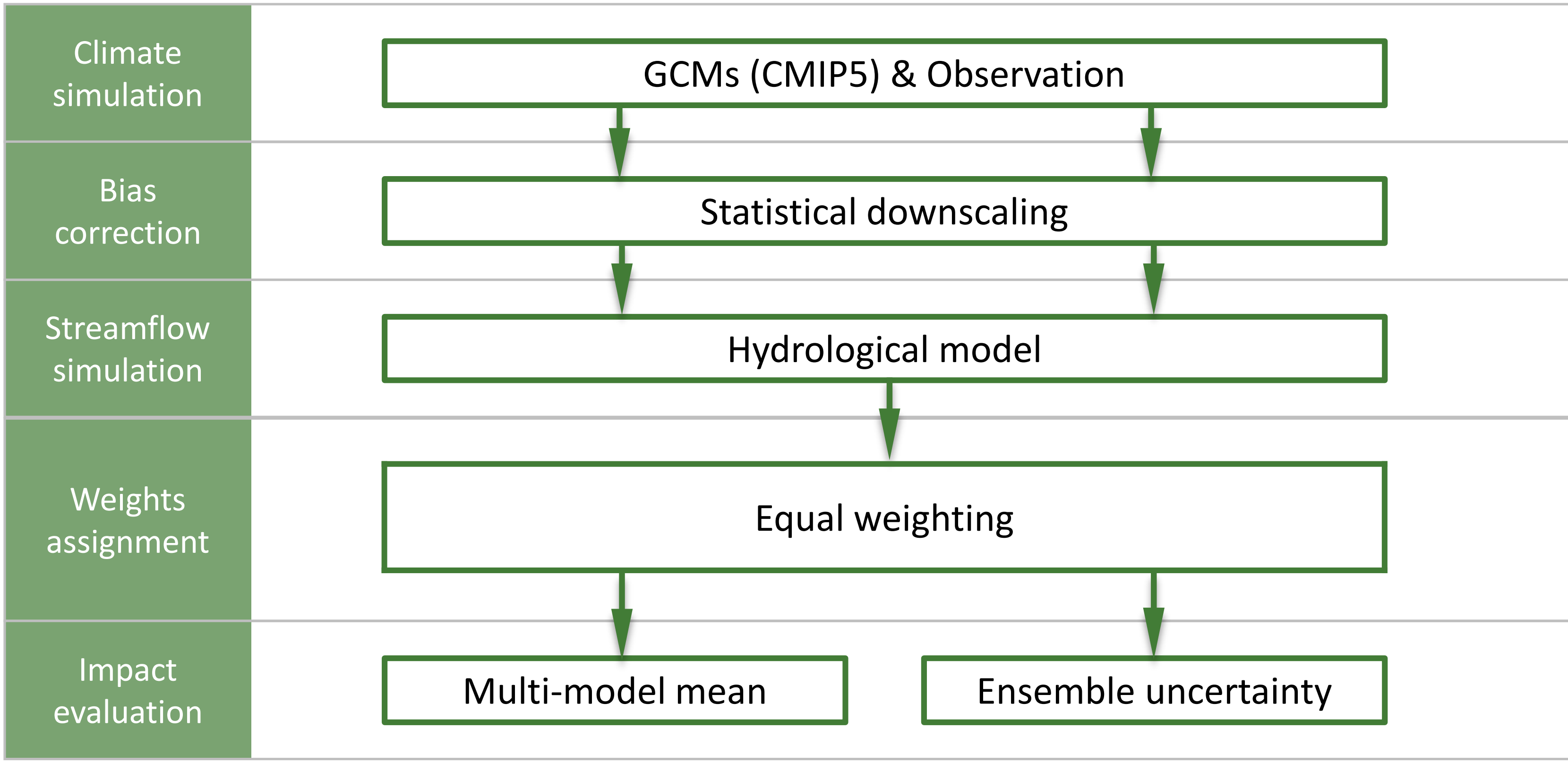
Outputs of 29 GCMs taken from CMIP5 dataset

- Reference period: 1970-1999; Future Period: 2070-2099
- Emission scenario: RCP8.5

Modeling center	Model name	Resolution (Lon. × Lat.)	Modeling center	Model name	Resolution (Lon. × Lat.)
CSIRO-BOM	ACCESS1.0	1.875° × 1.25°	MOHC	HadGEM2-CC	1.875° × 1.25°
	ACCESS1.3	1.875° × 1.25°		HadGEM2-ES	1.875° × 1.25°
BCC	BCC-CSM1.1	2.8° × 2.8°	INM	INM-CM4	2.0° × 1.5°
	BCC-CSM1.1(m)	1.125° × 1.125°	IPSL	IPSL-CM5A-LR	3.75° × 1.9°
GCESS	BNU-ESM	2.8° × 2.8°		IPSL-CM5A-MR	2.5° × 1.25°
CCCMA	CanESM2	2.8° × 2.8°		IPSL-CM5B-LR	3.75° × 1.9°
NCAR	CCSM4	1.25° × 0.94°	MIROC	MIROC-ESM-CHEM	2.8° × 2.8°
	CESM1(CAM5)	1.25° × 0.94°		MIROC-ESM	2.8° × 2.8°
CMCC	CMCC-CMS	1.875° × 1.875°	MIROC	MIROC5	1.4° × 1.4°
	CMCC-CM	0.75° × 0.75°	MPI	MPI-ESM-LR	2.8° × 2.8°
	CMCC-CESM	3.75° × 3.7°		MPI-ESM-MR	1.4° × 1.4°
CNRM-CERFACS	CNRM-CM5	1.4° × 1.4°	MRI	MRI-ESM1	1.125° × 1.125°
CSIRO-QCCCE	CSIRO-Mk3.6.0	1.8° × 1.8°		MRI-CGCM3	1.1° × 1.1°
LASG-GESS	FGOALS-g2	1.875° × 1.25°	NCC	NorESM1-M	1.875° × 1.875°
NOAA GFDL	GFDL-CM3	2.5° × 2.0°			
	GFDL-ESM2G	2.5° × 2.0°			
	GFDL-ESM2M	2.5° × 2.0°			

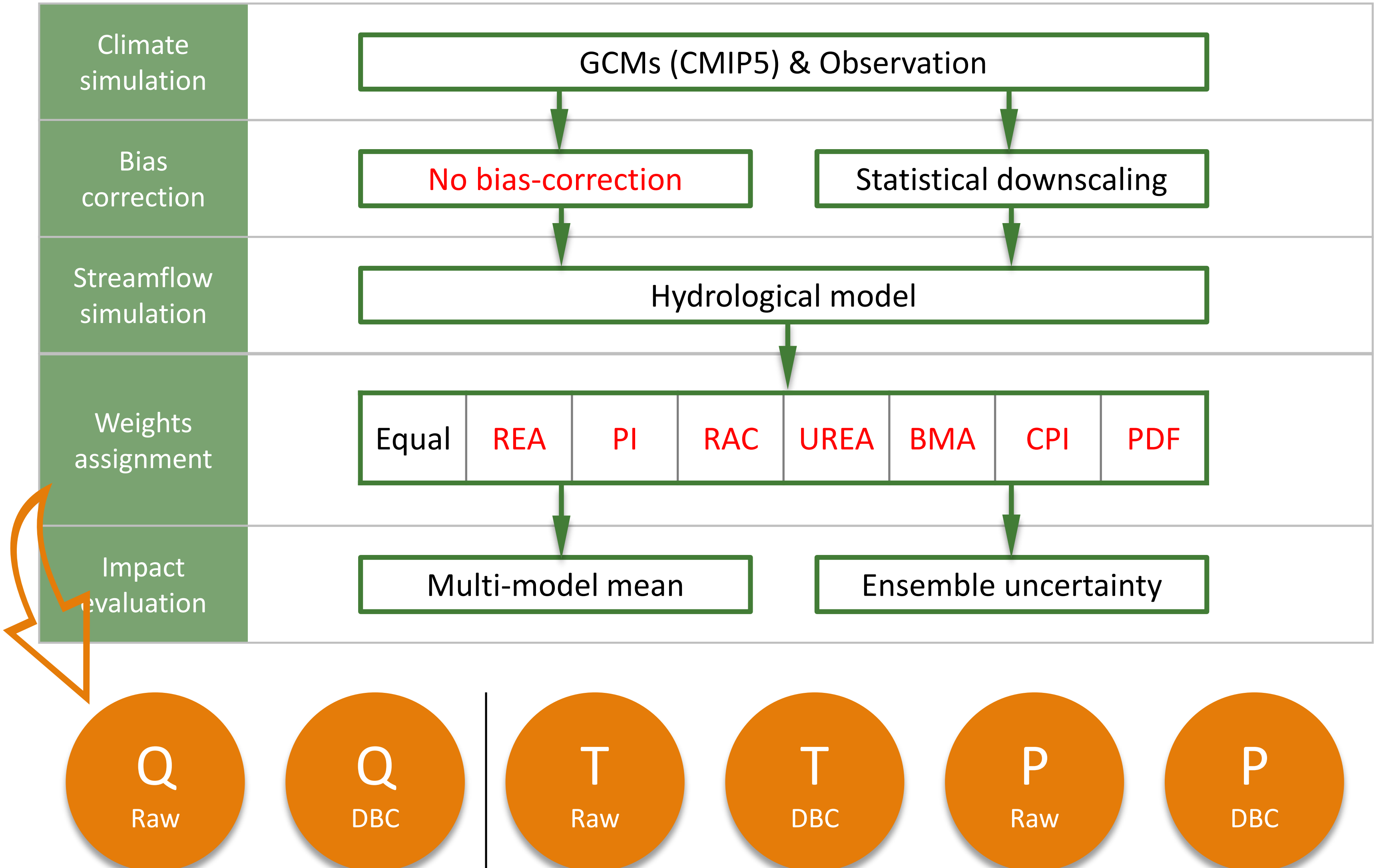
3 Methodology

Flow chart



3 Methodology

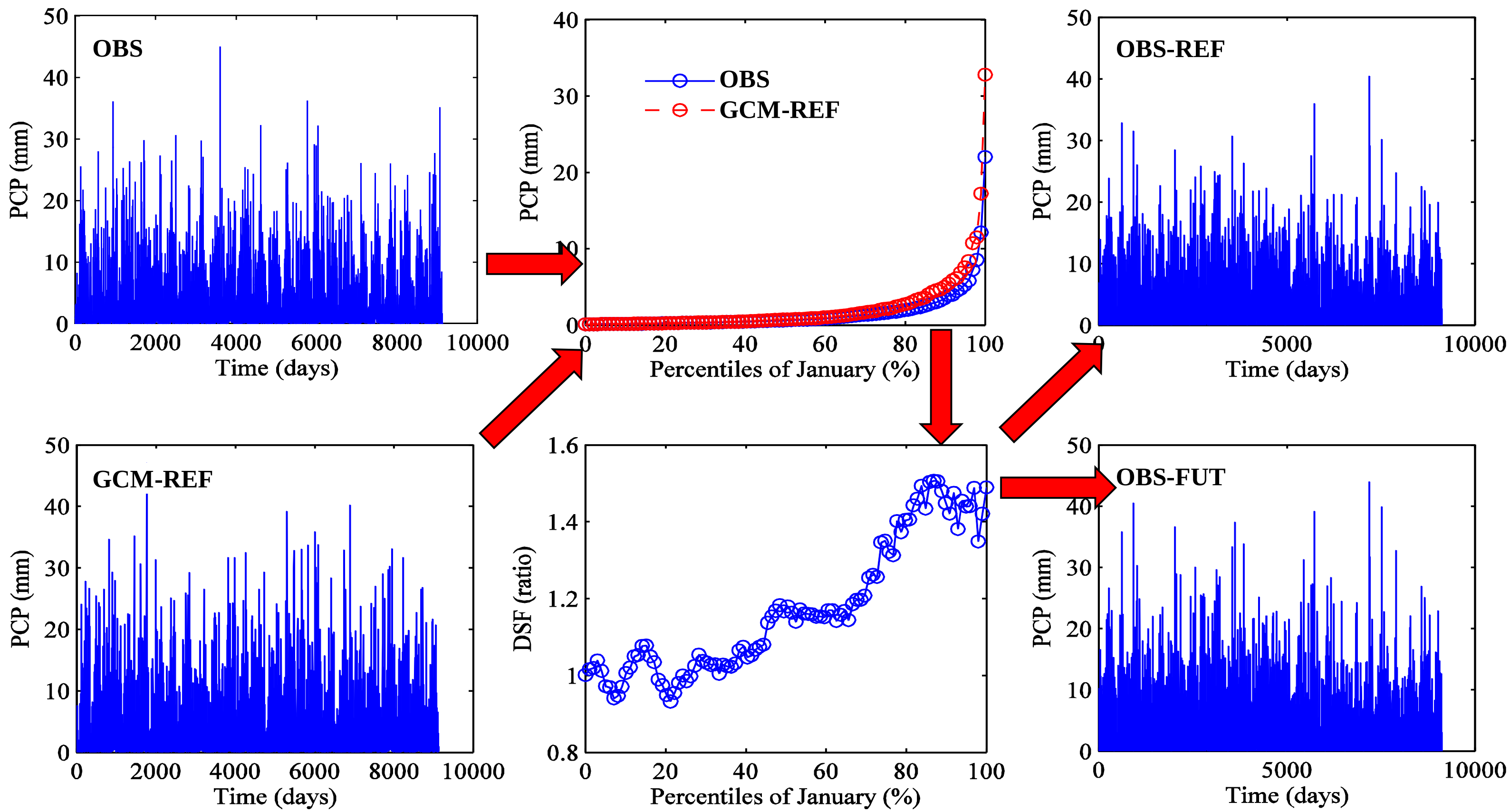
Flow chart



Downscaling Method

Daily bias correction (DBC) method consists of LOCI method and DT method

- Local intensity scaling (LOCI) adjusts the wet-day frequency of simulated precipitation
- Daily translation (DT) corrects biases in the frequency distribution of simulated precipitation amounts and temperature



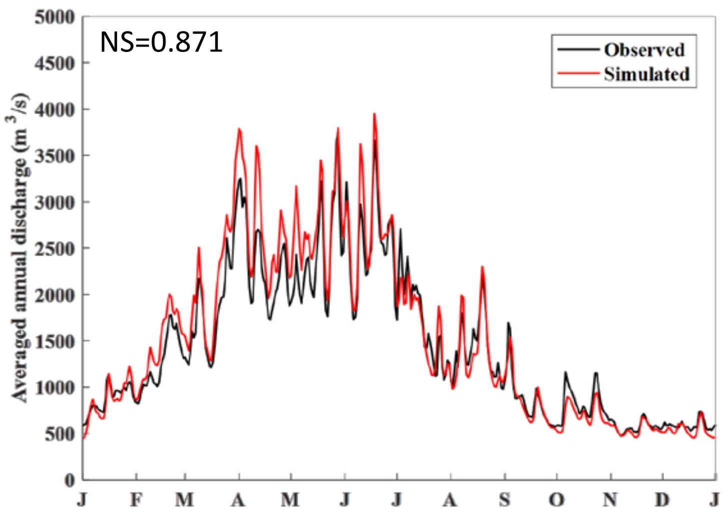
Hydrological Modeling

GR4J-6 model consists of Oudin Evaporation Formulation , GR4J rainfall-runoff model and CemaNeige snow module (6 parameters)

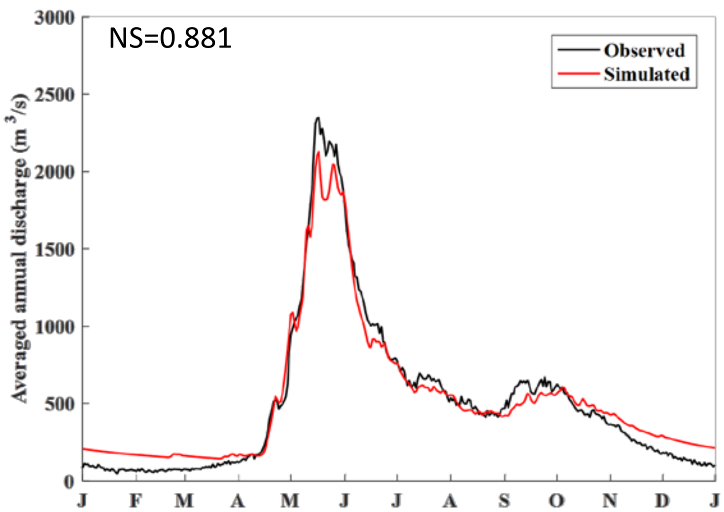
- The daily input data for the model includes Tmin, Tmax and precipitations.

Watershed Name	Calibration Period	NSE	Validation Period	NSE
Xiangjiang Watershed	1975-1987	0.916	1988-2000	0.871
Manicouagan-5 Watershed	1970-1979	0.926	1980-1989	0.881

Validation, Xiangjiang River



Validation, Manicouagan 5 River



Weighting Approaches

Equal weighting method and 7 unequal weighting methods

- Five performance-based methods
- Two methods based on multiple criteria

PI

$$PI_i = e^{-\frac{B_i^2}{\sigma_B^2}} \times \frac{1}{1 + \sum_{j \neq i}^{N} e^{-D_{ij}^2/\sigma_D^2}}$$

B_i: bias to observation in climatological mean
σ_B: skill radius of model performance
D_{ij}: distance between 2 GCMs in climatological mean
σ_D: uniqueness radius of model interdependence

Performance criterion | **Independence criterion**

REA

$$R_i = \left\{ \left[\frac{\epsilon_v}{\mathrm{abs}(B_{v,i})} \right]^m \times \left[\frac{\epsilon_v}{\mathrm{abs}(D_{v,i})} \right]^n \right\}^{1/mn}$$

ϵ_v: natural variability
$B_{v,i}$: bias to observation
$D_{v,i}$: difference to multi-model mean in future

Performance criterion | **Convergence criterion**

Weighting Approaches

RAC

$$S = \frac{4(1+R)^4}{(\sigma + 1/\sigma)^2 (1+R_0)^4}$$

R: correlation between simulation and observation
R_0: maximum correlation (=1)
σ: ratio of standard deviation

UREA

$$R_i = \left[\frac{\epsilon_a}{\mathrm{abs}(B_{a,i})}\right]^{m_1} \times \left[\frac{\epsilon_v}{\mathrm{abs}(B_{v,i})}\right]^{m_2}$$

$B_{a,i}$: bias in climatological mean
$B_{v,i}$: bias in variation

BMA

$$E[y|D] = \sum_{i=1}^{N} p(f_i|D) \cdot E[p_i(y|f_i, D)]$$

D: observation series
f_i: simulation series
p: weight

CPI

$$\mathrm{CPI}_i = \exp\left[-0.5 \frac{(s_i - o_i)^2}{\sigma_{ANN}^2}\right]$$

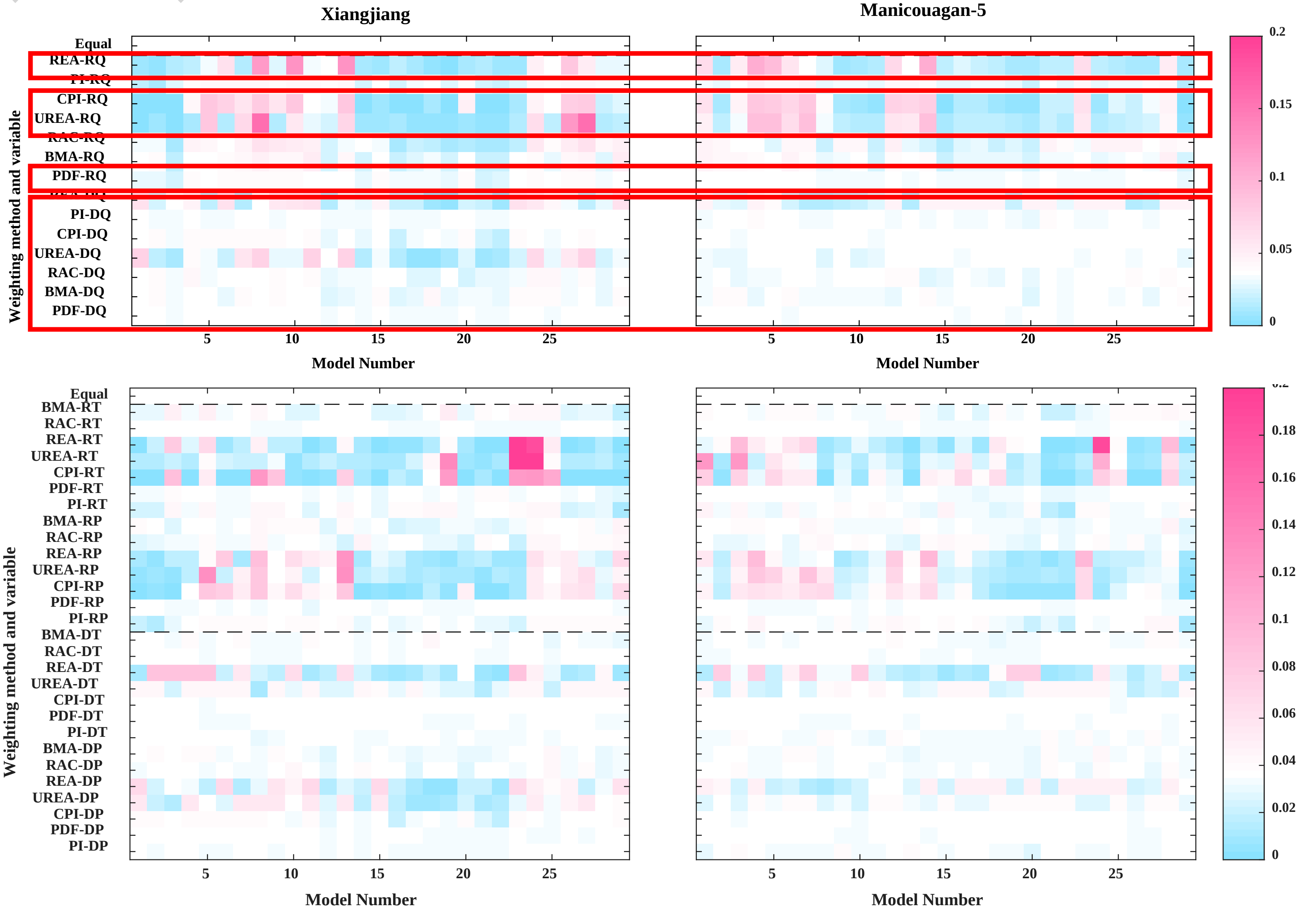
s_i: simulated climatological mean
o_i: observed climatological mean
σ_{ANN}^2: inter-annual variance of the simulated series

PDF

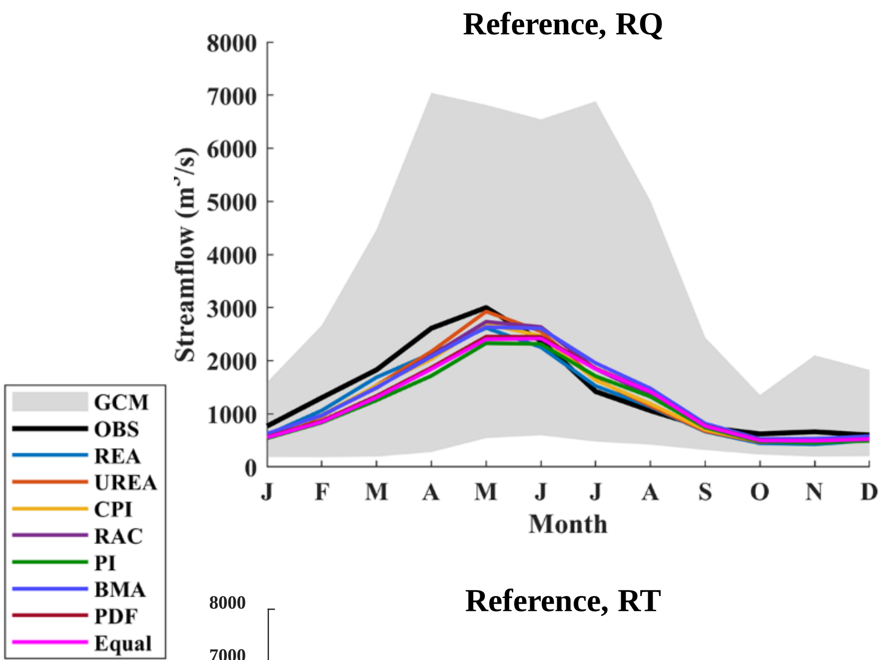
$$\mathrm{PDF}_i = \sum_{1}^{K} \mathrm{minimum}(Z_s, Z_o)$$

Z_s: simulated frequency in a given bin
Z_o: observed frequency in a given bin

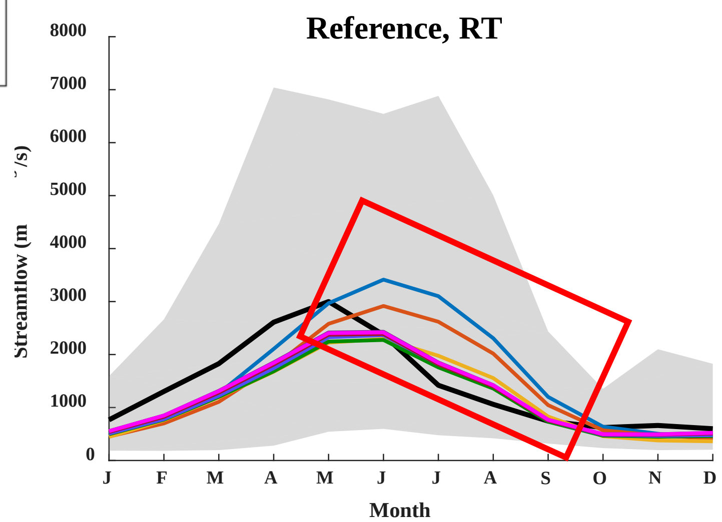
Weights

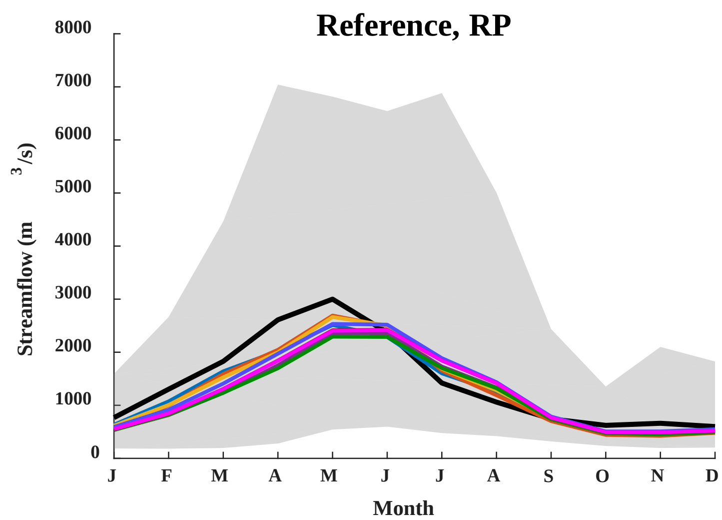

Xiangjiang
Manicouagan-5
Equal
REA-RQ
PI-RQ
CPI-RQ
UREA-RQ
RAC-RQ
BMA-RQ
PDF-RQ
PI-DQ
CPI-DQ
UREA-DQ
RAC-DQ
BMA-DQ
PDF-DQ
Weighting method and variable
Model Number
0.2
0.15
0.1
0.05
0
Equal
BMA-RT
RAC-RT
REA-RT
UREA-RT
CPI-RT
PDF-RT
PI-RT
BMA-RP
RAC-RP
REA-RP
UREA-RP
CPI-RP
PDF-RP
PI-RP
BMA-DT
RAC-DT
REA-DT
UREA-DT
CPI-DT
PDF-DT
PI-DT
BMA-DP
RAC-DP
REA-DP
UREA-DP
CPI-DP
PDF-DP
PI-DP
Weighting method and variable
Model Number
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0

Multi-model mean hydrograph (Xiangjiang, Raw)

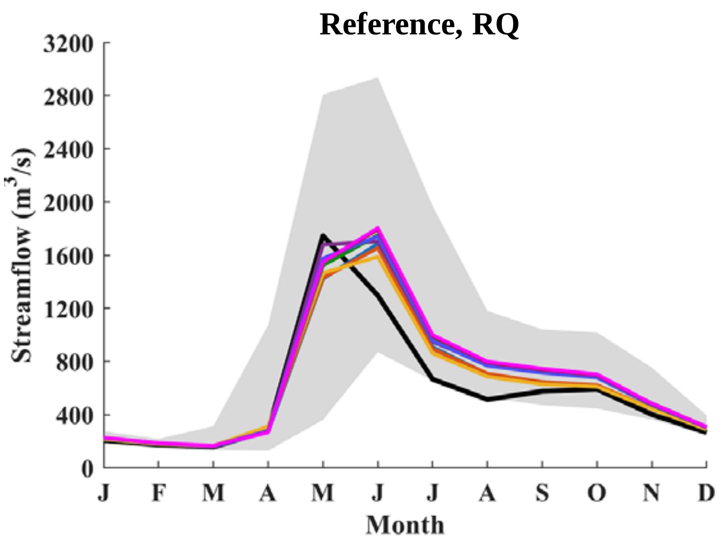


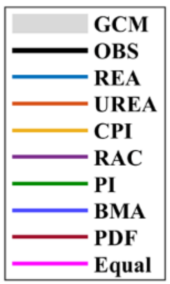
- Equal weighting underestimates streamflow before peak and overestimates streamflow after peak.
- Temperature-based weights induce to biased mean hydrograph, compared to streamflow-based weights.



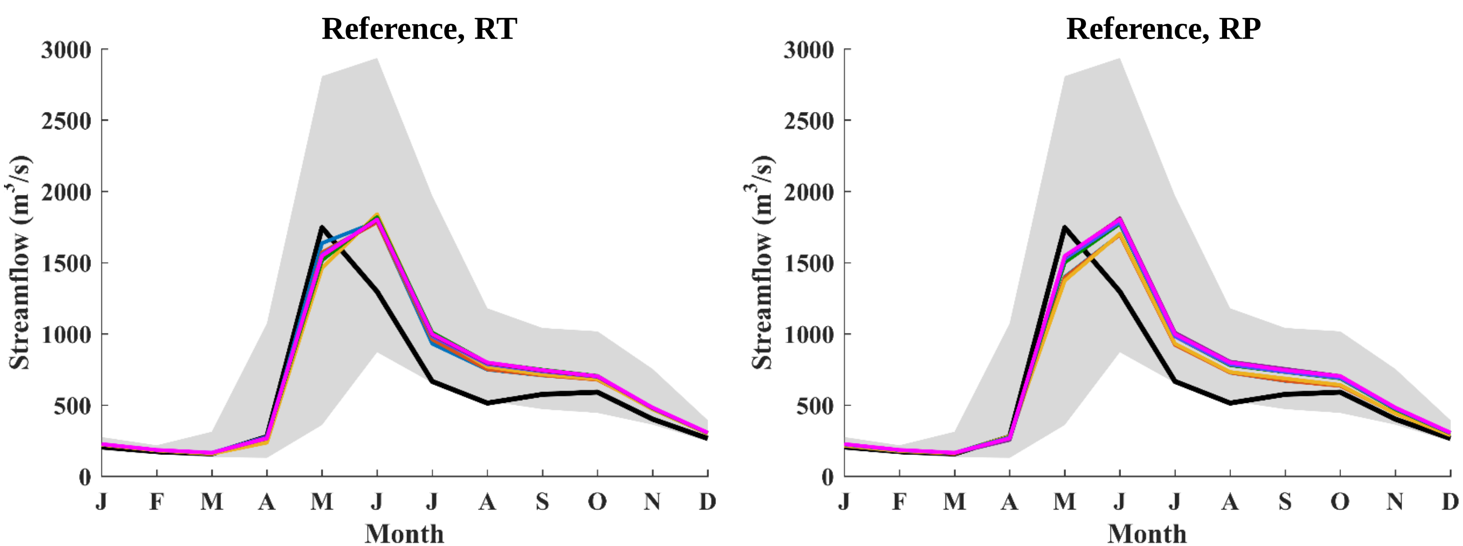


Multi-model mean hydrograph (Manicouagan-5, Raw)

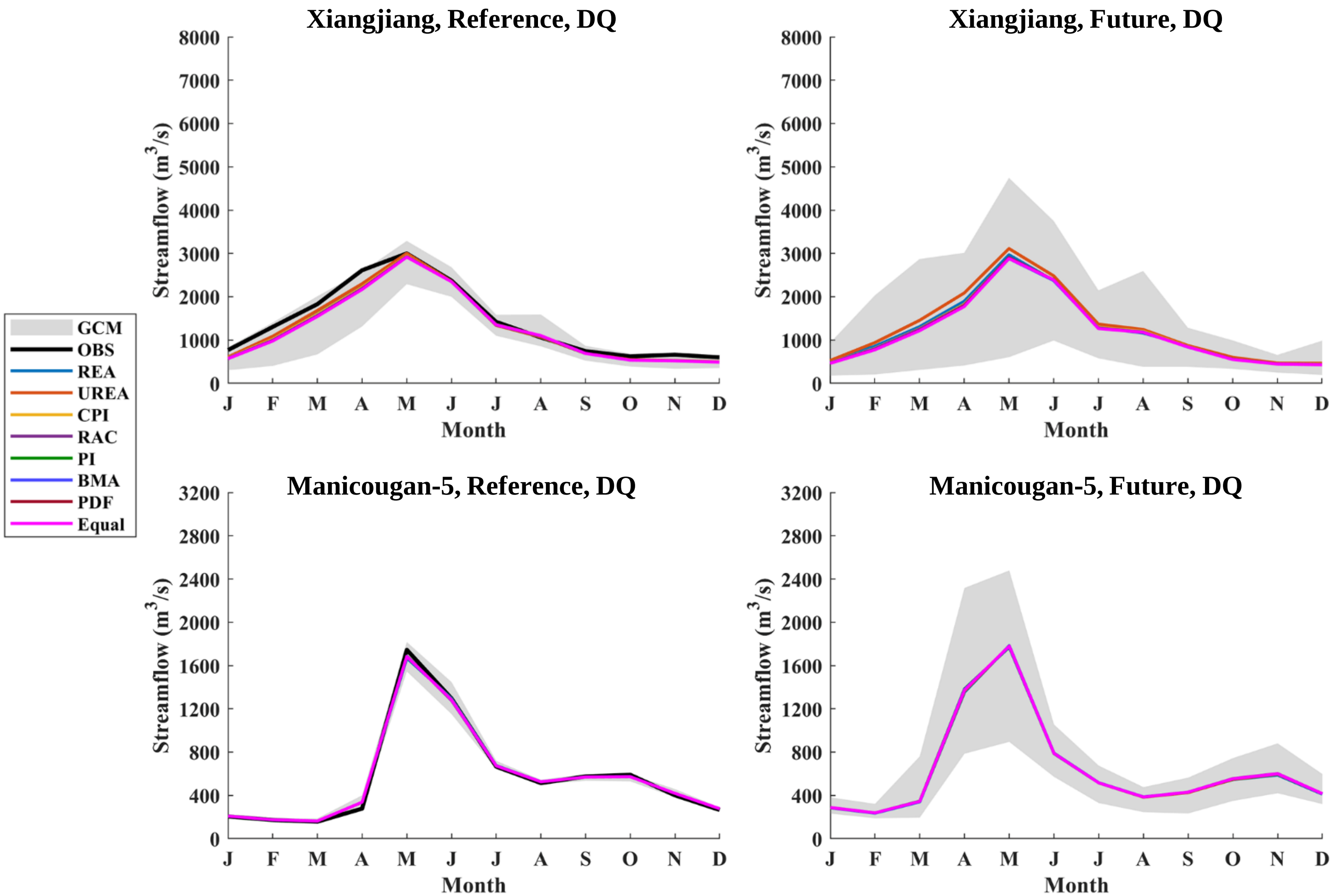




- Temperature- and precipitation-based weights do not induce to significantly biased hydrograph.
- Streamflow-based weights have slightly better performances.



Multi-model mean hydrograph (Bias-corrected streamflow)



- Although biases in the reference period are greatly reduced, there are still significant uncertainty in future period.
- Since similar weights are assigned to ensemble members, there are few differences in the multi-model mean hydrograph.

Uncertainty of changes (Xiangjiang)

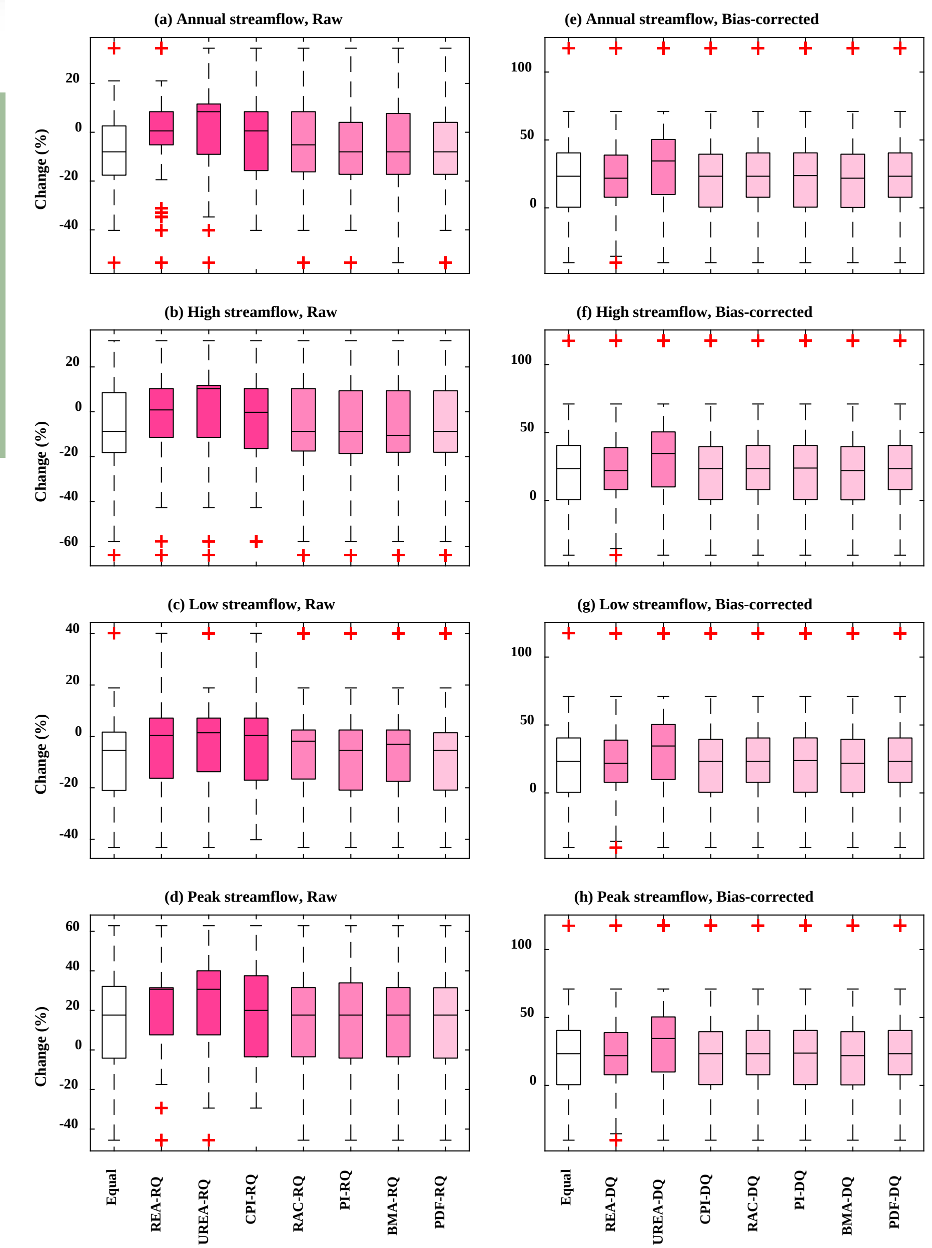
- Monte-Carlo sampling

  Uncertainty of equal weighting is directly represented by the 29 values from GCMs;

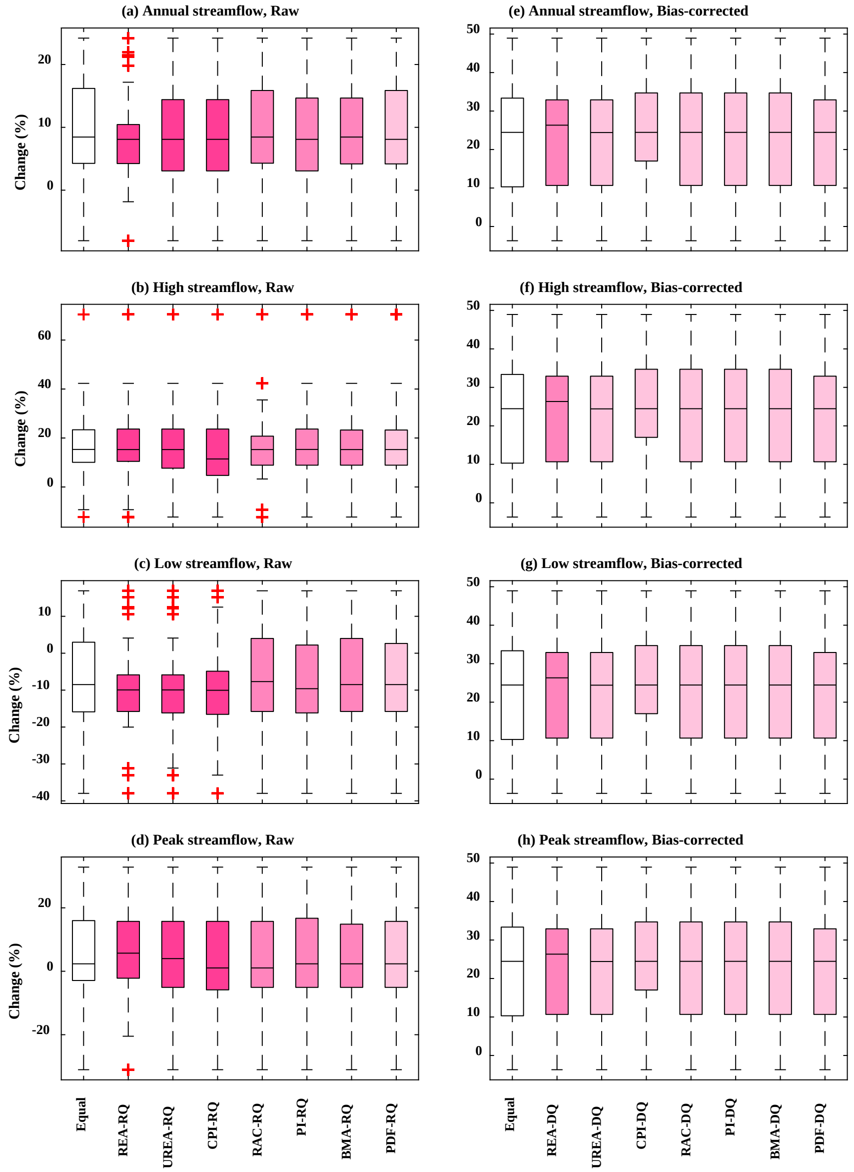
  Uncertainty of unequal weighting is represented by the 1000 samples taken from the Monte-Carlo experiment

- For streamflows simulated by raw GCMs, unequal weights present reduced or similar uncertainty, compared to that of equal weighting;

- For streamflows simulated by bias-corrected GCMs, the equal weighting and unequal weighting present similar performances in uncertainty evaluation.



Ensemble Uncertainty (Manicouagan-5)



Conclusions

- For the streamflows simulated using raw GCM outputs without bias correction, the weights calculated based on streamflows can produce better hydrographs, compared with the weights calculated based on climate variables;
- When using bias-corrected GCM outputs to simulate streamflow, similar multi-model means and uncertainty of hydrological impacts for all unequal weighting methods are observed;
- It is likely that using bias correction and equal weighting is viable and sufficient for hydrological impact studies

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