Multi-model/input hydrologic prediction uncertainties analysis by parameter optimization and Bayesian model averaging

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HydroPredict'2012, Vienna, Austria, 24-27 Sept 2012

Outline

1. Overview of Hydrological model

2. Uncertainties in Hydrological prediction

3. Uncertainties estimation method

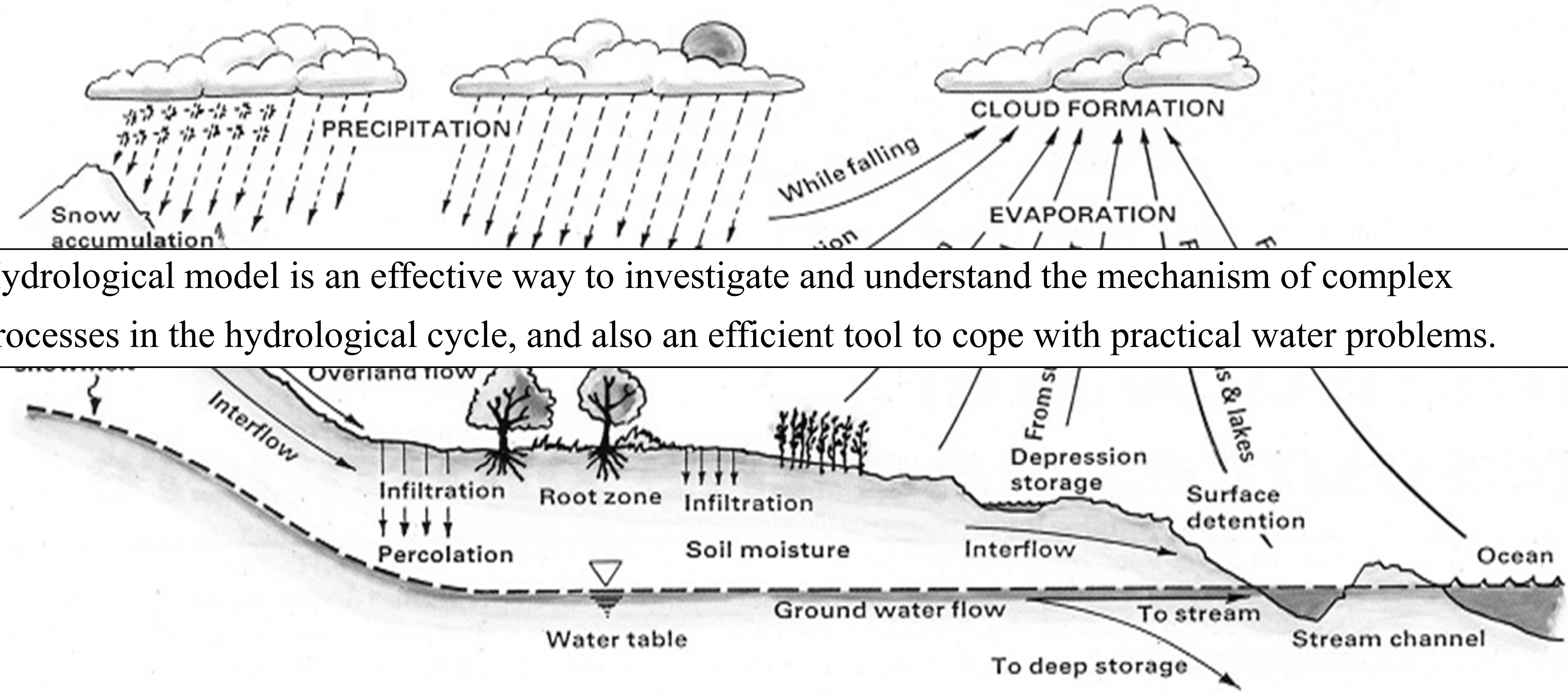
4. Case Study 1: multi-model hydrological prediction

5. Case Study 2: multi-input hydrological prediction

6. Suggestions

1. Overview of hydrological model

Upper boundary: temperature/precipitation, weather, climate [Climate Change ?]



Hydrological model is an effective way to investigate and understand the mechanism of complex processes in the hydrological cycle, and also an efficient tool to cope with practical water problems.

Lower boundary: topography, vegetation, geology, soil structure, …… [Human Activities ?]

1. Overview of hydrological model

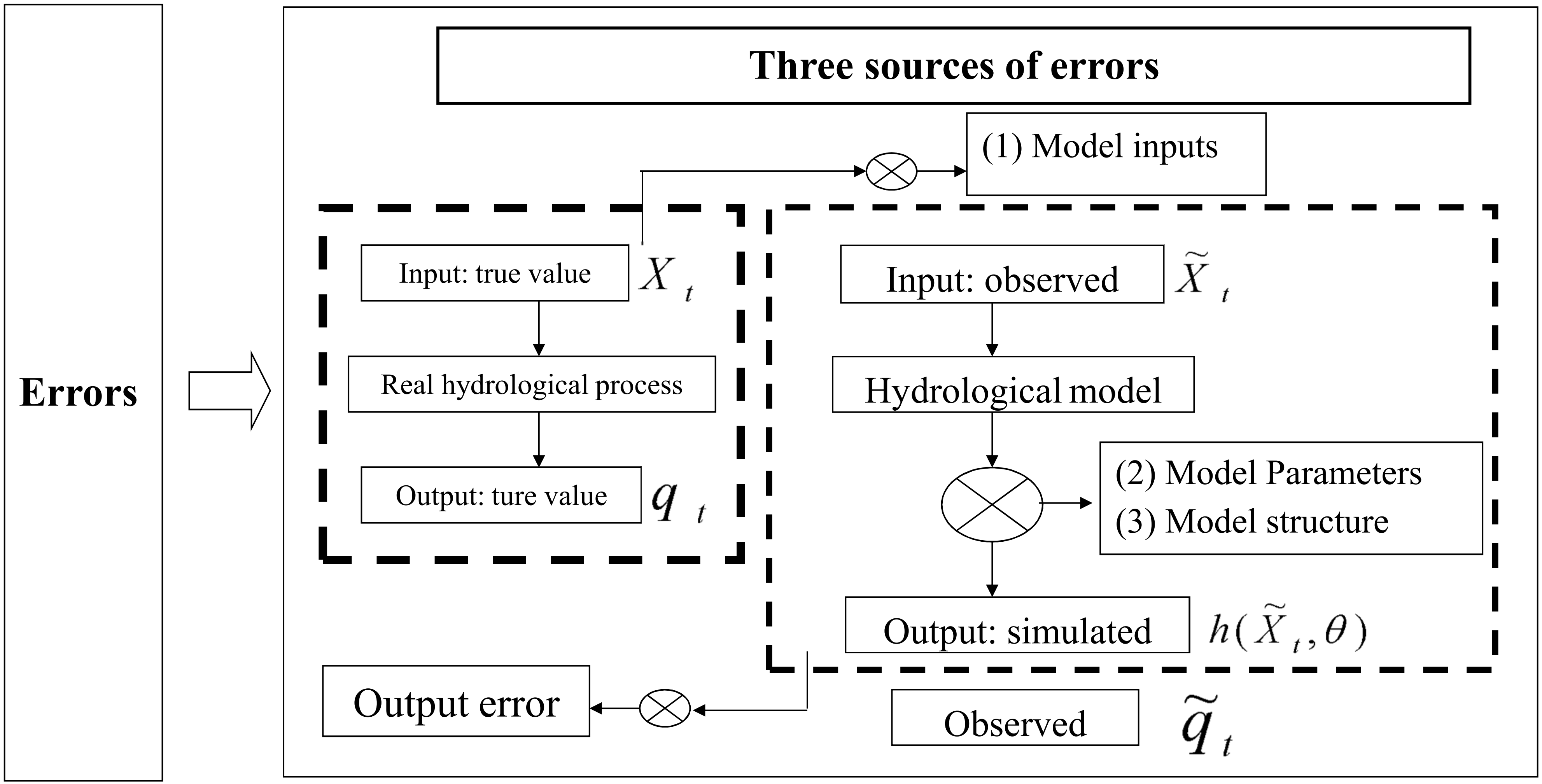
Catchment characteristics	Homogeneity	Heterogeneity
Advantage	simple structure, easily applied	clear physical meaning of the model parameters
Weakness	can't reflect the real watershed spatial variability	complex、more parameters

Lumped model → System model, Conceptual model

Distributed model → Conceptual model, Physical model

	System model	Conceptual model	Physical model
Method	regression analysis	physical concept & empirical formula	physical law & basin characteristics
Property	black-box model	grey-box model	white-box model
Model	1. Sherman unit line 2. Nonlinear system 3. Neural Network Model	1. Tank model 2. Stanford model 3. Xinanjiang model	1. SHE 2. VIC 3. SWAT

2. Uncertainties in hydrological prediction



3. Uncertainties estimation method

One way to reduce input uncertainty is using input error multiplier.

$r_t = \phi_t \tilde{r}_t$; $\phi_t \rightarrow N(m, \sigma_m^{\ 2})$

$$\begin{bmatrix} \tilde{r}_1 \\ \tilde{r}_2 \\ \tilde{r}_3 \\ \cdots \\ \tilde{r}_T \end{bmatrix} * \begin{bmatrix} \phi_1 \\ \phi_2 \\ \phi_3 \\ \cdots \\ \phi_T \end{bmatrix} = \begin{bmatrix} r_1 \\ r_2 \\ r_3 \\ \cdots \\ r_T \end{bmatrix}$$

in which， $\tilde{r}_t$ is measured rainfall；

is a ϕ_t normal multiplier， mean value

is m, variance is $\sigma_m^{\ 2}$, in this study

$m \in [0.95, 1.05]$，

$\in [1\text{e-}5, 1\text{e-}3]$。

ϕ_t

Two methods to reduce parameters uncertainty:

❖ **Method 1：**

For a given river basin and model structure, one set of optimal parameters could be found [calibration].

Representative method：

Genetic Algorithm (GA)

SCE-UA (Shuffled Complex Evolution Algorithm; Duan et al., 1992)

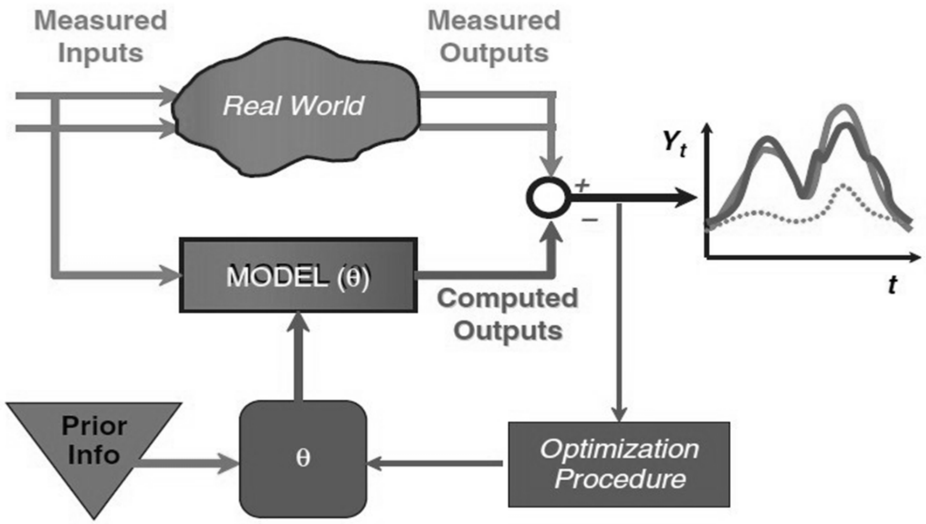
❖ **Method 2：**

For a given river basin and model structure, a series of sets of parameters obey a certain joint probability distribution.

Representative method：

GLUE (Generalized Likelihood Uncertainty Estimation; Beven et al., 2001)

SCEM-UA (Shuffled Complex Evolution Metropolis Algorithm; Vrugt et al., 2003)



Parameter calibration

The way to reduce model structure uncertainty:

Different models have different advantages. The result computed from a single model is always limited. Combining multi-model predictions can obtain better results, such as

- Weighted average method (**Bayesian model averaging, BMA**)
- Simple Average Method
- Artificial Neural Network

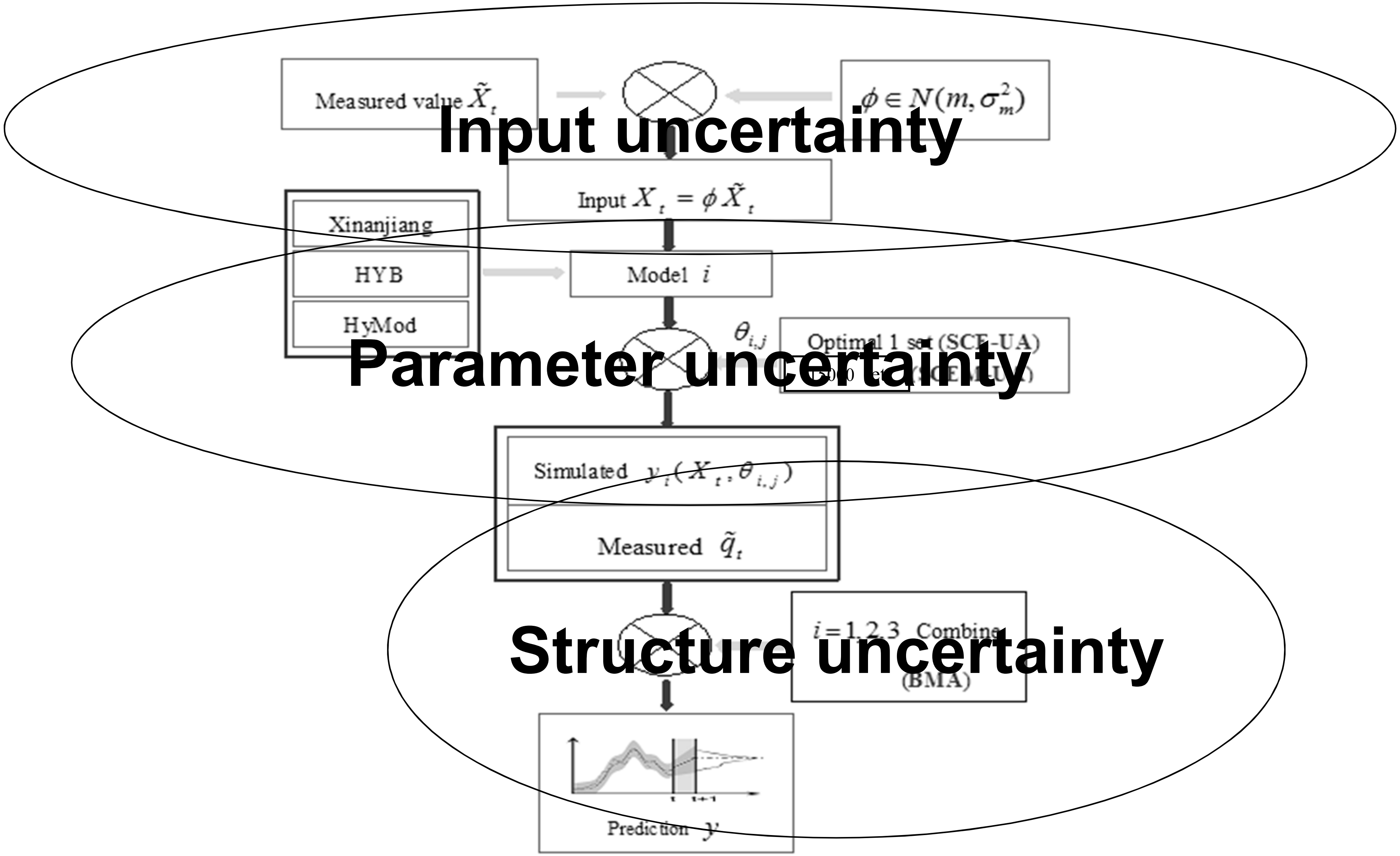
Reference:

[1] Ajami NK, Duan QY, Sorooshian S, 2006. An integrated hydrological Bayesian multimodel combination framework: Confronting input, parameter, and model structural uncertainty in hydrological prediction. *Water Resources Research*, 43, W01403.

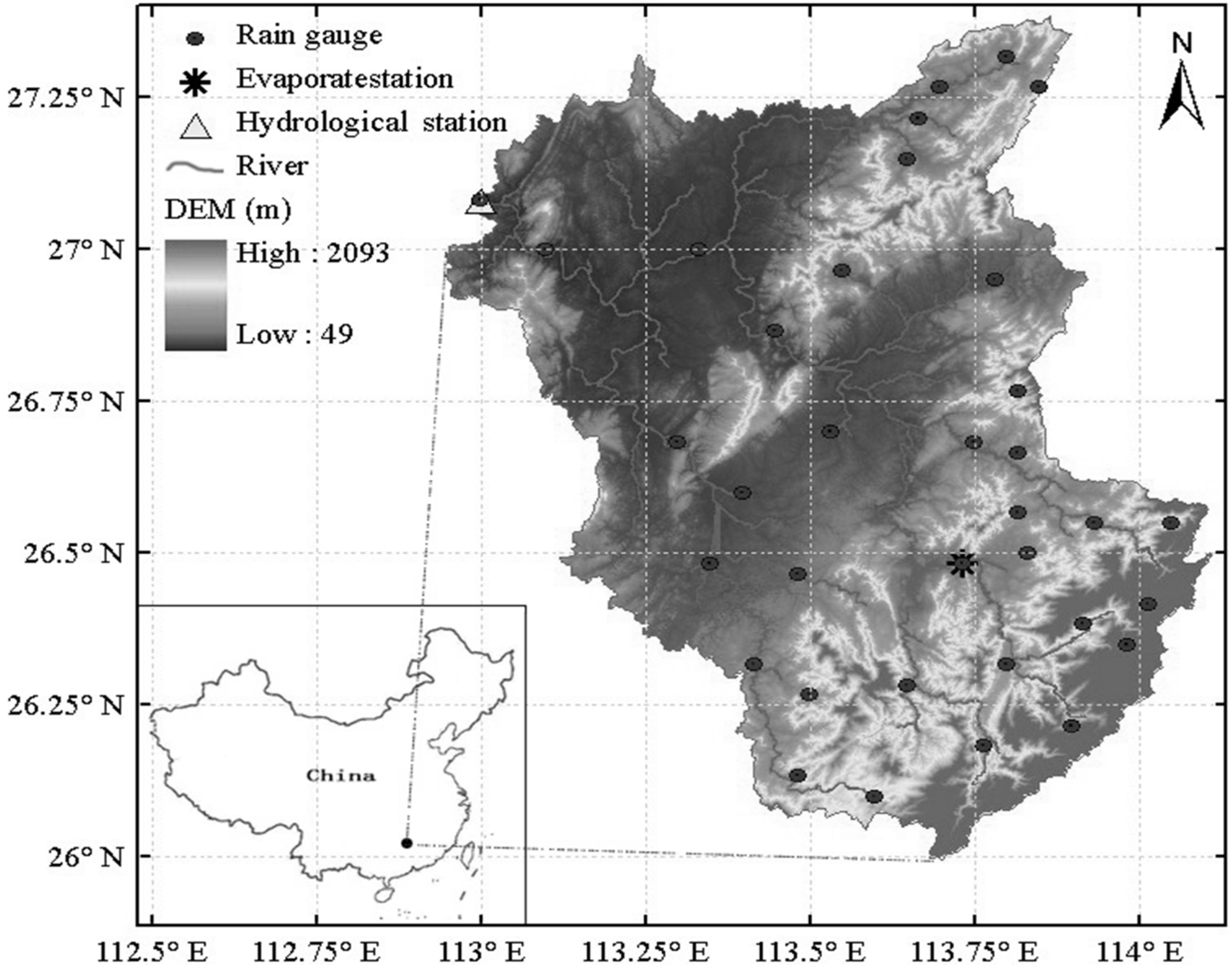
[2] Duan QY, Ajami NK, Gao XG, Sorooshian S, 2007. Multi-model ensemble hydrological prediction using Bayesian model averaging. *Advances in Water Resources*, 30, 1371-1386.

[3] Liang ZM, Wang D, Guo Y, Zhang Y, Dai R, 2012. Application of Bayesian model averaging approach to multi-model ensemble hydrologic forcasting. *Journal of Hydrologic Engineering*. Doi: 10.1061/(ASCE)HE.1943-5584.0000493.

4. Multi-model hydrologic prediction uncertainties analysis



Study Area



Mishui Basin

Tributary of:

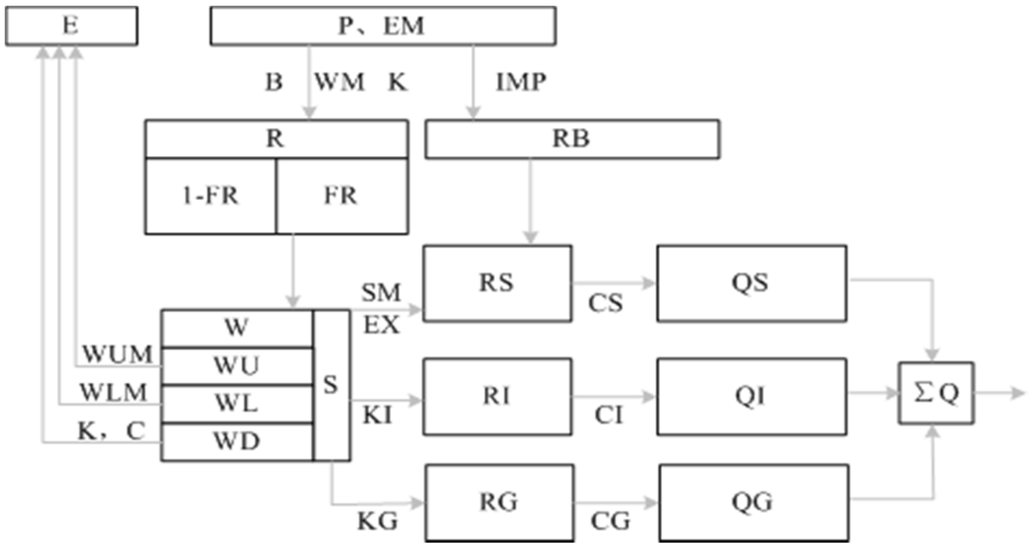
the Xiangjiang River

Rain gauge:

35 stations

Drainage area :

9 972 km^2



Xinanjaing model

Zhao et al. (1980)

Saturation excess runoff

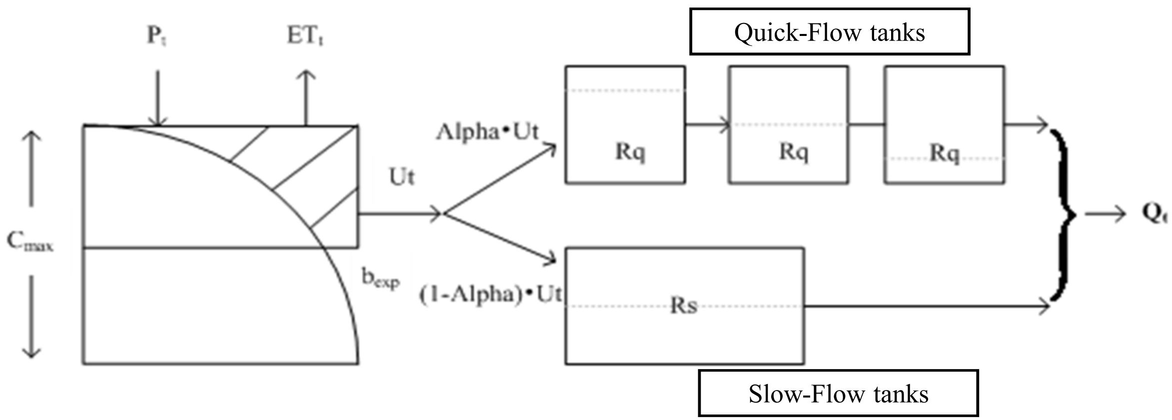
Hybrid Runoff model (HYB)

Combine the infiltration excess (Horton) runoff and saturation excess (Dunne) runoff by means of the combination of *spatial distribution curve of soil tension water storage capacity* and *that of infiltration capacity*.

HYB

Hu et al. (1993)

Two runoff mechanisms



HyMod

Moore et al. (1985)

Saturation excess runoff

15 parameters of the *XAJ* model , including their physical meanings and numeric range

Parameter	Physical meaning	Range
Kc	ratio of potential evapotranspiration to pan evaporation	0.5-1.5
WUM	water capacity in the upper soil layer	10-40
WLM	water capacity in the lower soil layer	50-90
WDM	Water capacity in the deeper soil layer	10-70
B	exponent of the tension water capacity curve	0.1-0.5
C	coefficient of deep evapotranspiration	0.1-0.3
EX	exponent of the free water capacity curve	1-1.5
SM	the free water capacity of the surface soil layer	10-60
KI0	outflow coefficients of the free water storage to interfolw	KI+KG=0.7
KG0	outflow coefficients of the free water storage to groundwater	0.1-0.5
CI0	recession constant of the lower interflow storage	0.1-0.9
CG0	daily recession constant of groundwater storage	0.9-0.999
CS0	recession constant for channel routing	0.1-0.5
KE	Slot storage coefficient	20-24
XE	Flow proportion factor	0.1-0.5

14 parameters of the *HYB* model , including their physical meanings and numeric range

Parameter	Physical meaning	Range
Kc	ratio of potential evapotranspiration to pan evaporation	0.5-1.5
WUM	water capacity in the upper soil layer	10-40
WLM	water capacity in the lower soil layer	50-90
WDM	Water capacity in the deeper soil layer	10-70
B	exponent of the tension water capacity curve	0.1-0.5
bx	Infiltration capacity distribution curve index	0.1-2
f0	The average maximum infiltration capacity	5-30
fc	The average stability infiltration capacity	0.1-10
k	Infiltration capacity attenuation coefficient	0.1-0.9
CS	recession constant for channel routing	0.1-0.5
CG	daily recession constant of groundwater storage	0.9-0.999
C	coefficient of deep evapotranspiration	0.1-0.3
KE	Slot storage coefficient	20-24
XE	Flow proportion factor	0.1-0.5

9 parameters of the HyMod , including their physical meanings and numeric range

Parameter	Physical meaning	Range
Kc	ratio of potential evapotranspiration to pan evaporation	0.5-1.5
Cmax	Max height of soil moisture accounting tank	1-1000
bexp	Distribution function shape parameter	0.1-2
Alpha	Quick-slow split parameter	0.1-0.99
Nq	Number of quickflow routing tanks	1-8
Rs	Slowflow routing tanks rate parameter	0.001-0.1
Rq	Quickflow routing tanks rate parameter	0.1-0.99
KE	Slot storage coefficient	20-24
XE	Flow proportion factor	0.1-0.5

Validation statistical indices

$$\mathrm{NSCE} = 1 - \frac{\sum_{i=1}^{n} (Q_{oi} - Q_{si})^2}{\sum_{i=1}^{n} (Q_{oi} - \overline{Q_o})^2}$$

$$BIAS = \frac{\sum_{i=1}^{n} Q_{si} - \sum_{i=1}^{n} Q_{oi}}{\sum_{i=1}^{n} Q_{oi}} \times 100\%$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (Q_{si} - Q_{oi})^2}$$

Indices for evaluating the prediction series

$$CR = \frac{n_c}{n} \times 100\%$$

Containing rate

$$B = \frac{1}{n} \sum_{i=1}^{n} (q_{ui} - q_{li})$$

Average bandwidth

$$D = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{2} \left| (q_{ui} + q_{li}) - Q_{oi} \right|$$

Average deviation amplitude

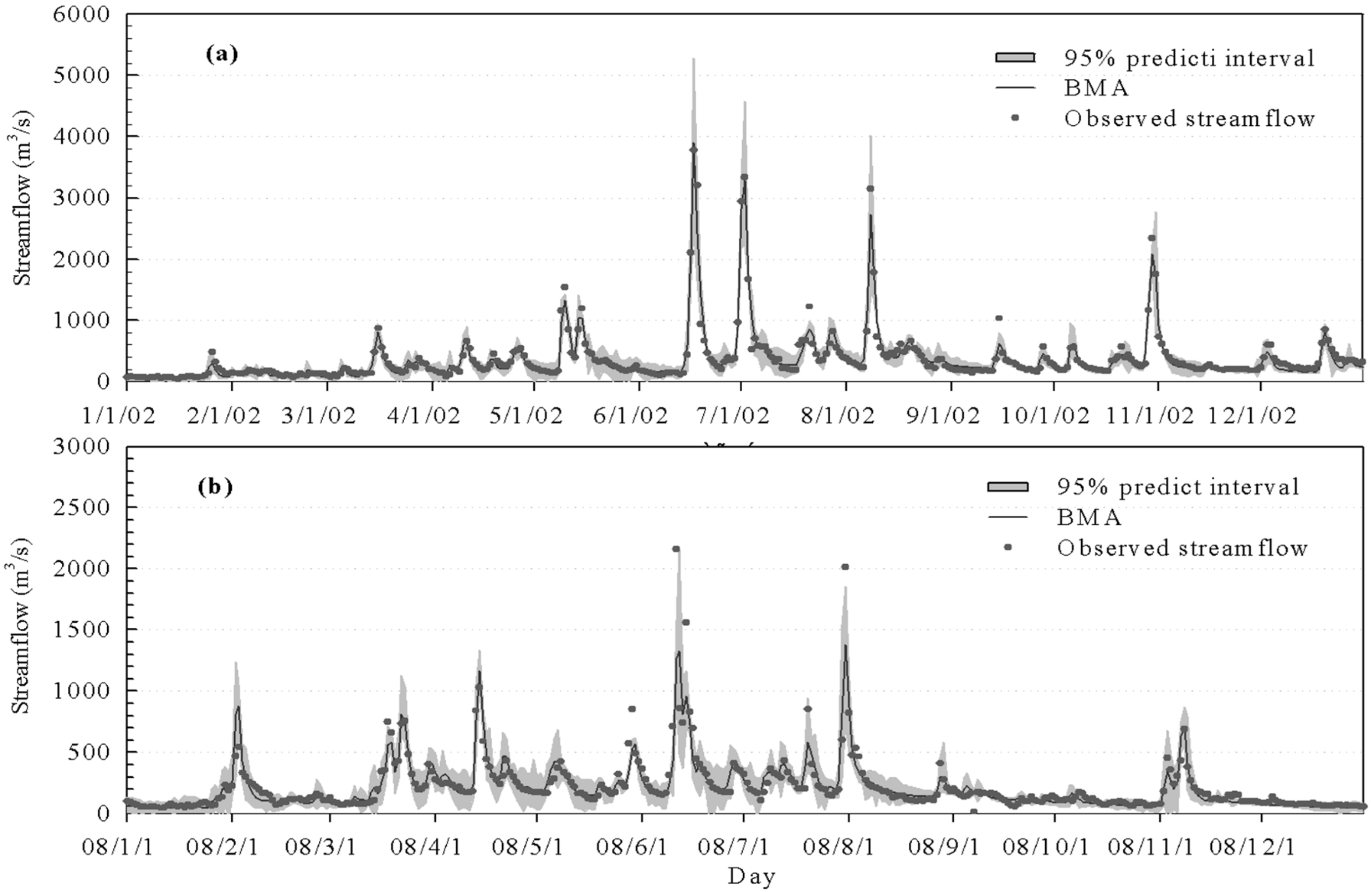
Indices for evaluating the prediction interval

15

SCE-UA:

MCMC

100 sampling



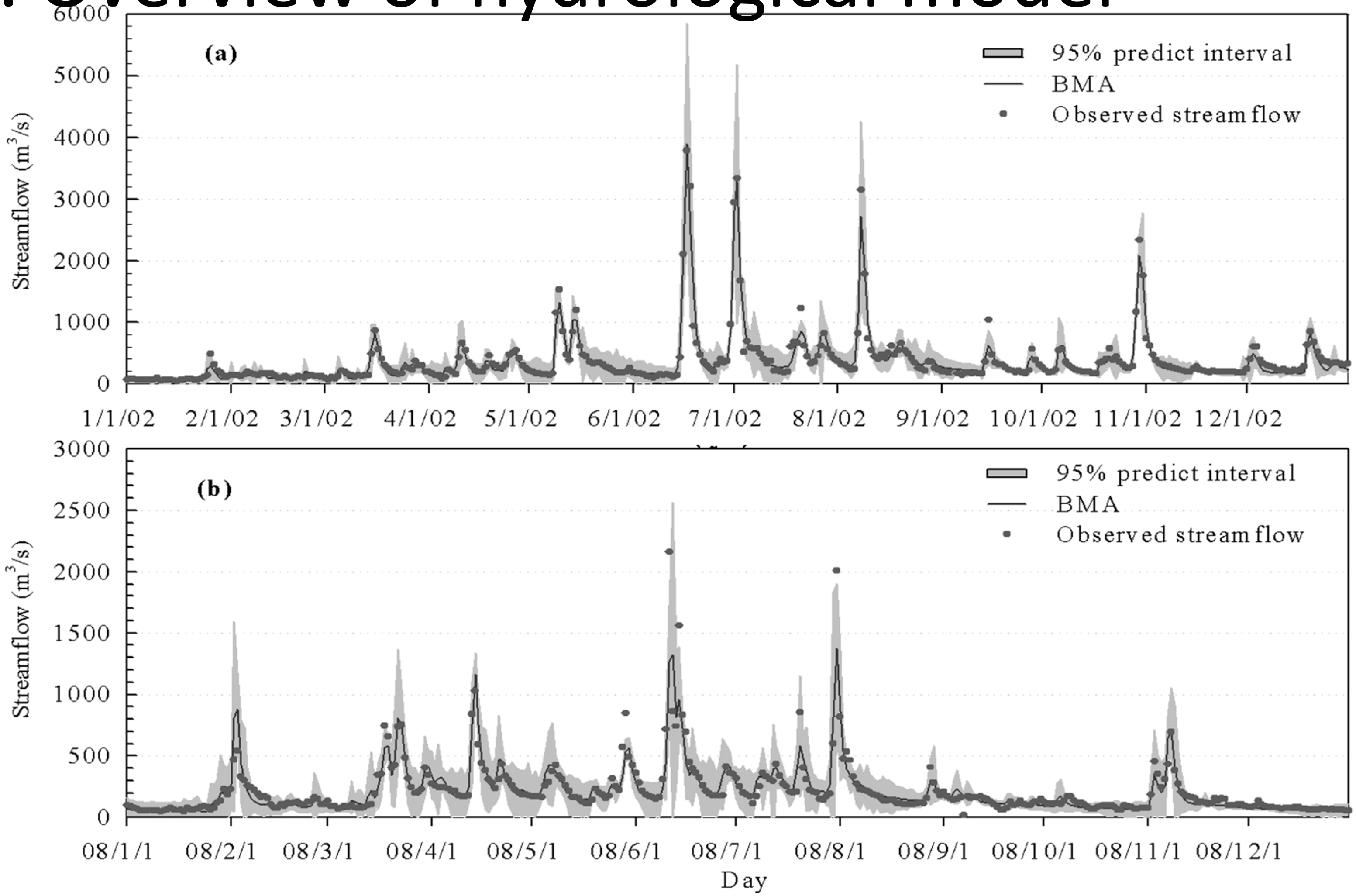
The BMA-combined streamflow shows a good agreement with observed series. The 95% of prediction interval contains most of the observed values.

4. Overview of hydrological model

SCE-UA:

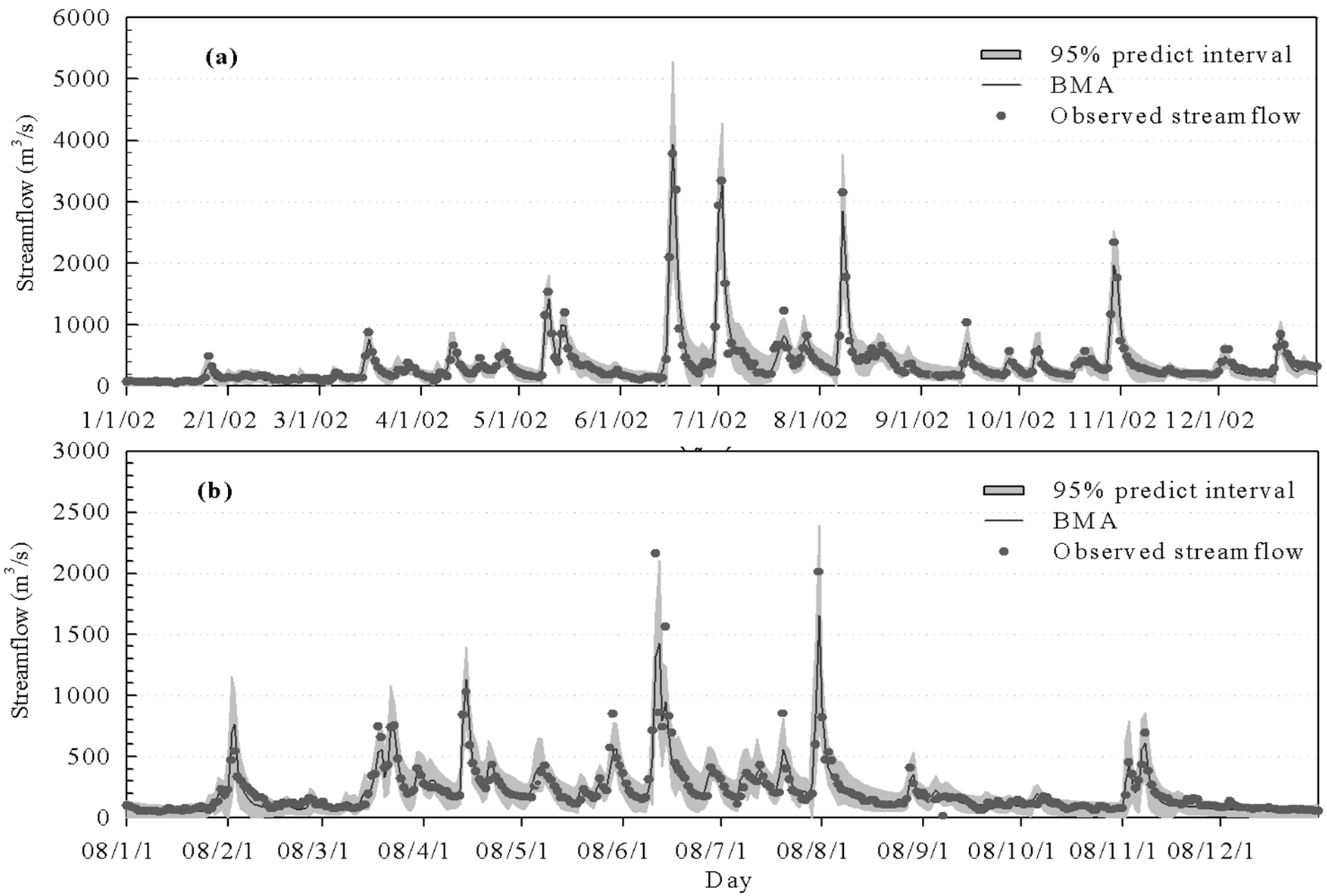
MCMC

1000 sampling



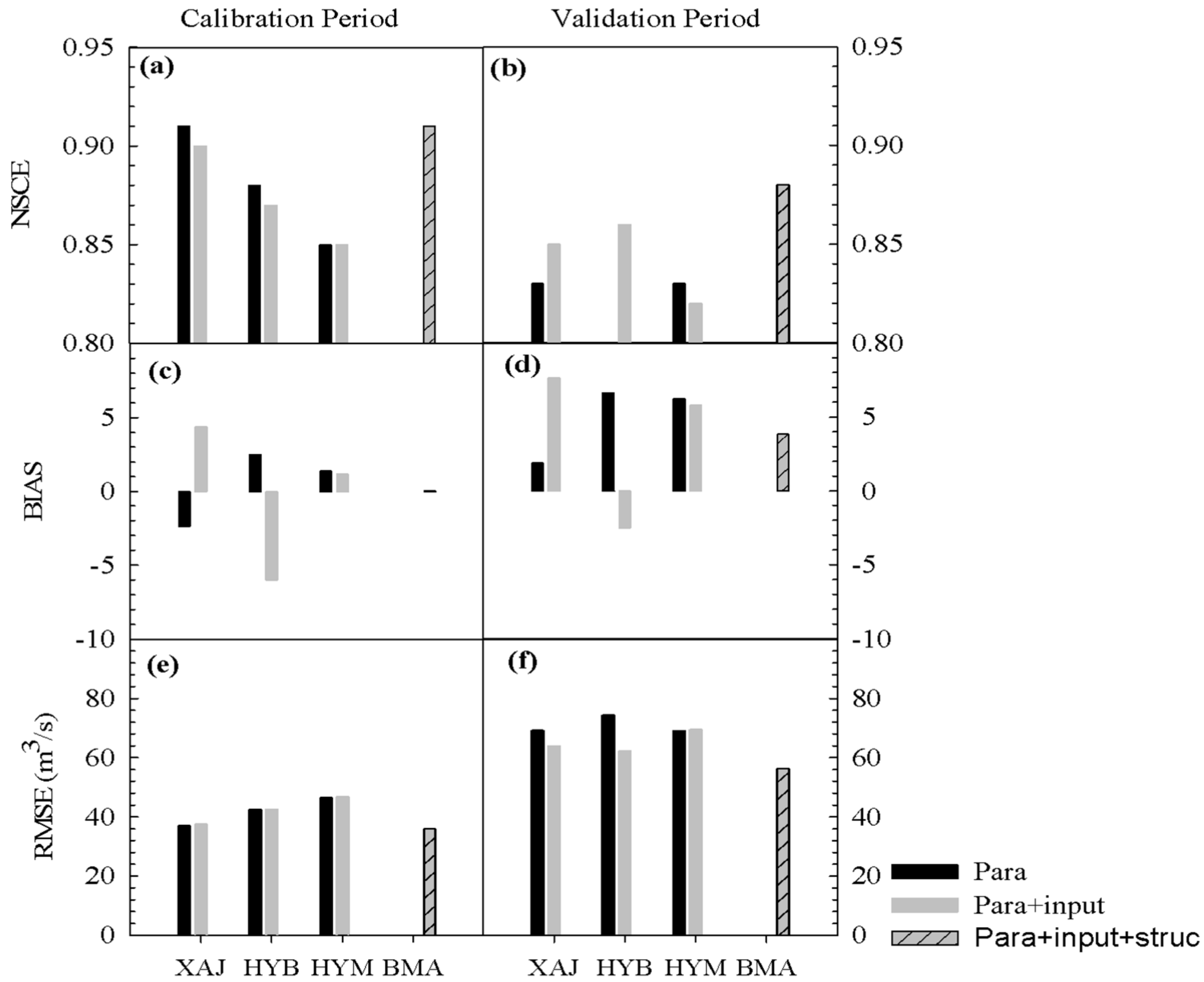
The average bandwidth of 1000 sampling prediction interval is wider than that of 100 sampling. The 1000 sampling prediction interval has a higher containing rate.

SCEM-UA:



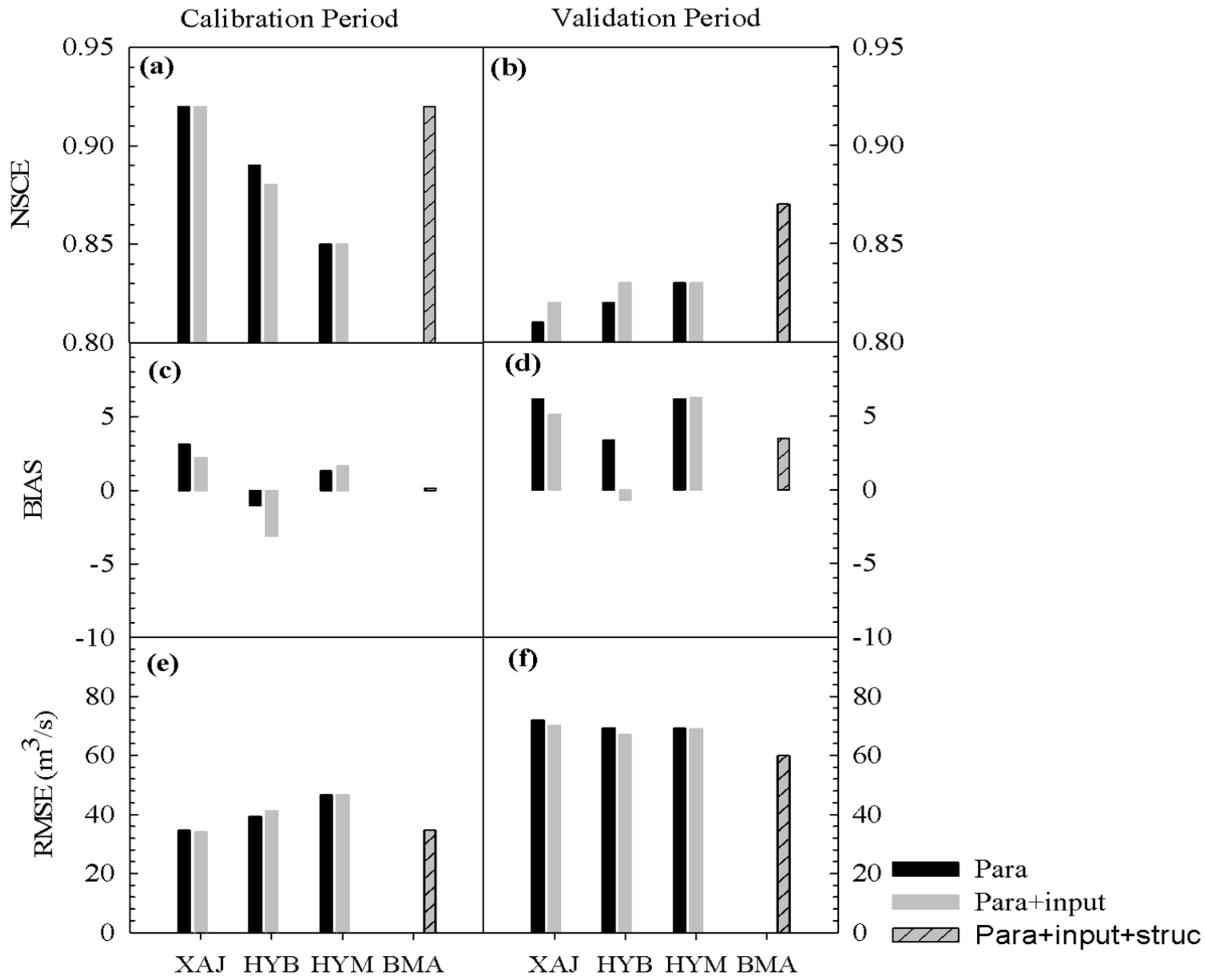
The prediction interval by SCEM-UA is better than that by SCE-UA.

SCE-UA Simulation



The BMA-combined streamflow series is superior to that of the best individual predictions, with a larger NSCE, comparable BIAS and smaller RMSE, especially in validation period.

SCEM-UA Simulation



The performance of the SCEM-UA simulation is equivalent to that of the SCE-UA simulation in terms of NSCE, BIAS and RMSE . The BMA-combination method get the optimal streamflow simulation.

Validation statistical indices of the 95% prediction interval

	Model	SCE-UA(100 sampling)			SCE-UA (1000 sampling)			SCEM-UA		
		CR%	B(m^3/s)	D(m3/s)	CR%	B(m^3/s)	D(m3/s)	CR%	B(m^3/s)	D(m3/s)
CP	XAJ (Para)	51.73	**118.73**	58.99	59.31	**152.87**	58.20	78.65	**169.17**	52.31
	XAJ (Para+input)	65.37	154.45	60.58	74.86	200.15	60.78	79.06	169.78	**51.79**
	HYB (Para)	64.46	201.11	74.75	75.05	258.66	74.08	80.34	222.25	64.41
	HYB (Para+input)	72.63	217.23	67.92	81.07	273.01	65.39	78.97	225.23	67.60
	HYM (Para)	63.46	175.11	63.25	71.40	225.70	63.08	85.26	237.97	62.91
	HYM (Para+input)	60.26	165.34	63.91	68.57	212.49	63.29	87.68	254.06	64.01
	BMA (Para+input+struc)	**84.35**	241.23	**56.44**	**90.19**	315.60	**56.70**	**95.62**	271.15	55.03
VP	XAJ (Para)	52.28	**142.38**	72.00	62.32	**183.64**	71.21	80.47	**188.68**	64.41
	XAJ (Para+input)	65.78	172.59	74.13	73.81	220.50	74.63	81.48	190.31	**63.07**
	HYB (Para)	64.51	227.50	84.61	71.99	289.95	82.84	80.66	244.40	74.13
	HYB (Para+input)	74.36	225.05	71.46	82.66	285.44	71.71	80.38	249.24	77.14
	HYM (Para)	60.68	210.54	79.68	68.61	270.26	77.88	86.77	261.23	76.62
	HYM (Para+input)	61.50	197.37	77.99	69.16	252.23	76.84	88.96	278.24	77.31
	BMA (Para+input+struc)	**83.76**	265.11	**66.23**	**90.97**	348.56	**69.74**	**95.17**	303.04	66.06

The red one means the best value in the column. The performance of the SCEM-UA based prediction interval is superior to that of the SCE-UA based prediction interval in terms of Containing rate (*CR*) and Average deviation amplitude (*D*).

Notation: *CP* is Calibration Period, *VP* is Validation Period

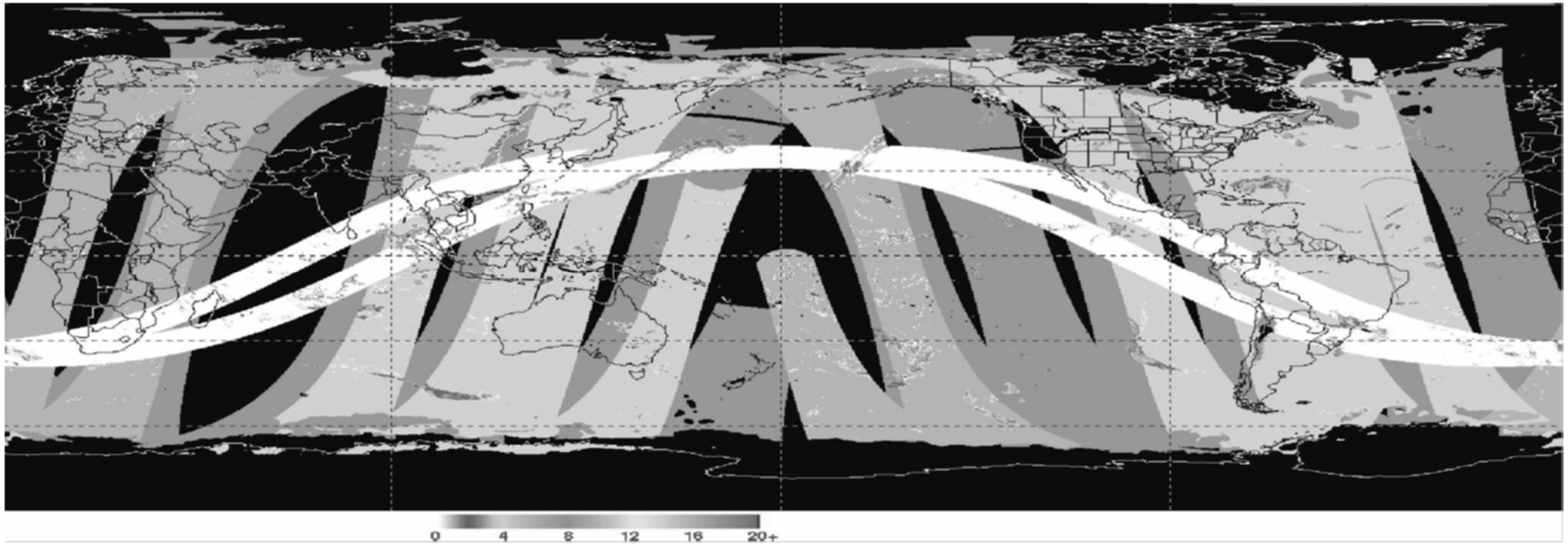
Conclusion 1

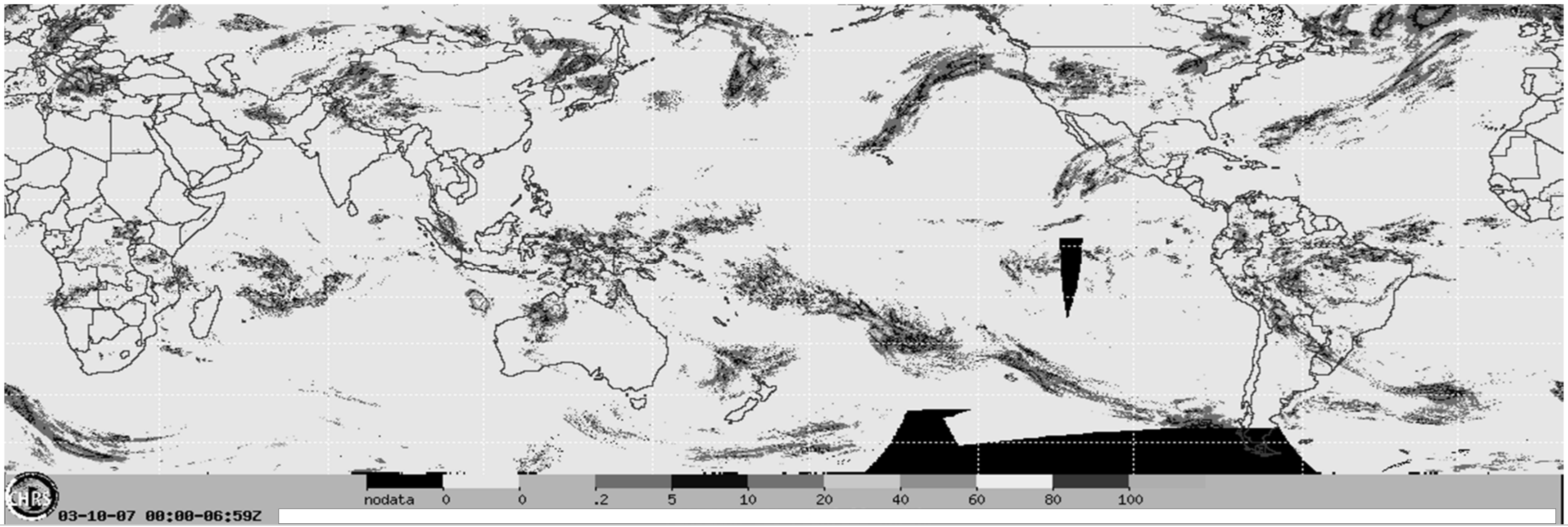
1. Two parameter optimization algorithms (SCE-UA & SCEM-UA) generate good streamflow simulations;

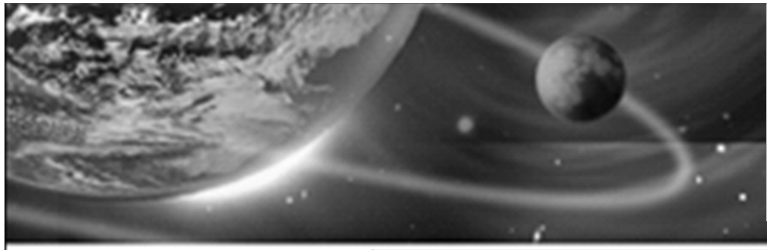
2. SCEM-UA algorithm results in better estimation for the prediction interval than SCE-UA algorithm;

3. The Bayesian Model Averaging (BMA) method can improve the streamflow prediction efficiency and quantitatively give the uncertainty bounds for simulation, as applied for reducing model structure uncertainty.

5. *Using multi-satellite real-time precipitation estimation for ensemble streamflow simulation*



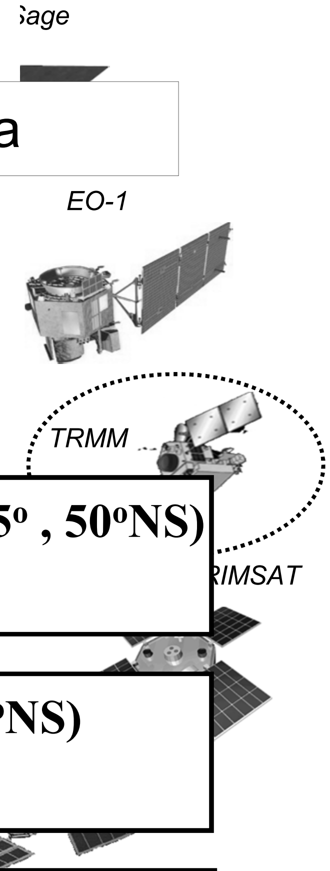




NASA Earth Observing System EOS

Data Source	Type	Resolution	Frequency	Coverage	Period
NLDAS	gauge+radar	0.125°	1 hr	CONUS	1996/10~
NARR	regional reanalysis	32km	3 hr	N. America	1979~
ERA-Interim	global reanalysis	T255	6 hr	Global	1989~
TRMM 3B42V6	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
TMI	MW	0.25°	2 per day	40°S~40°N	1998~2002
CMORPH	MW+IR	0.08~0.25°	0.5, 3 hr	60°S~60°N	2002/12~
PERSIANN	MW+IR	0.25°	3, 6 hr	50°S~50°N	2000/03~
GPCP-1DD	MW+IR+gauge	1°	1 day	Global	1996/10~
ERA-40	global reanalysis	T159	6 hr	Global	1957~2002

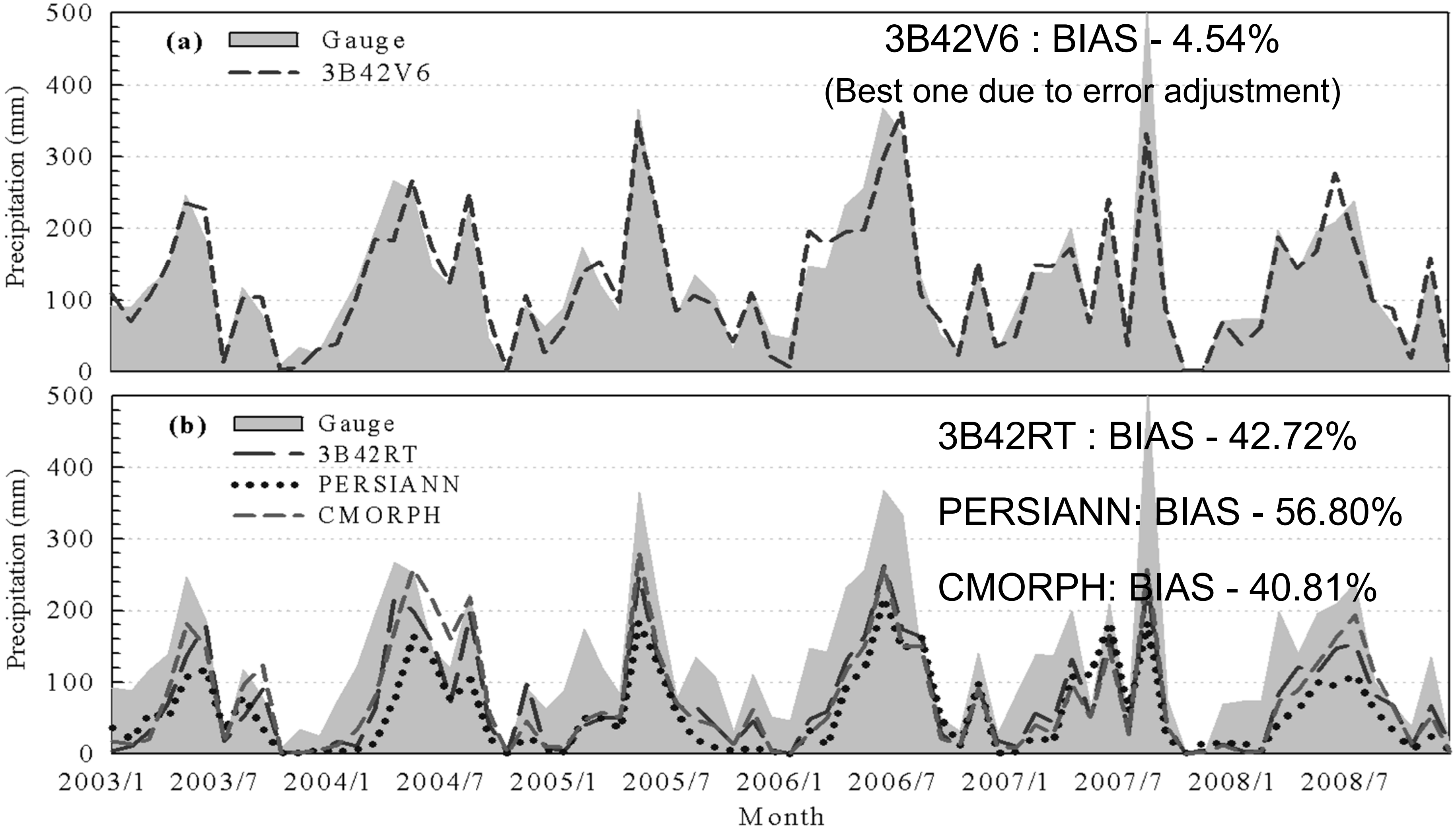
Commonly used 10 kinds global satellite precipitation data



1) The near Real-Time product(i.e. TRMM 3B42RT , 3 hourly, $0.25^o \times 0.25^o$, 50^oNS) about 3-9 hours after real-time, Jan 2002 to present;

2) The near Real-Time product(i.e. PERSIANN, 3-hourly, $0.25^o \times 0.25^o$, 60^oNS) about 18 hours after real-time, Dec 2002 to present.

3) The near Real-Time product(i.e. CPC CMORPH, 3-hourly, $0.25^o \times 0.25^o$, 60^oNS) about 18 hours after real-time, Dec 2002 to present.



Monthly basin averaged precipitation time series

❖Parameter uncertainty:

SCEM-UA algorithm (Shuffled Complex Evolution Metropolis, Vrugt et al., 2003)

❖Model:

Grid Xinanjiang model

❖Input bias and uncertainty (simple error model):

Error model 1.

$$P_e = \phi_t \bullet P \longrightarrow \phi_t = N(m, \sigma_m^2)$$

3B42RT $\longrightarrow m \in [1.73, 1.77]$

PERSIANN $\longrightarrow m \in [2.29, 2.33]$ $\quad \sigma_m^2 \in [1e-5, 1e-3]$

CMORPH $\longrightarrow m \in [1.67, 1.71]$

Error model 2.

$$P_e = P + m_e \bullet \varepsilon \longrightarrow \varepsilon = N(m, \sigma_m^2)$$

$$m_e = f(\frac{1}{L}, \frac{\Delta t}{T}, P) = a \cdot (\frac{1}{L})^b \cdot (\frac{\Delta t}{T})^c \cdot (P)^d$$

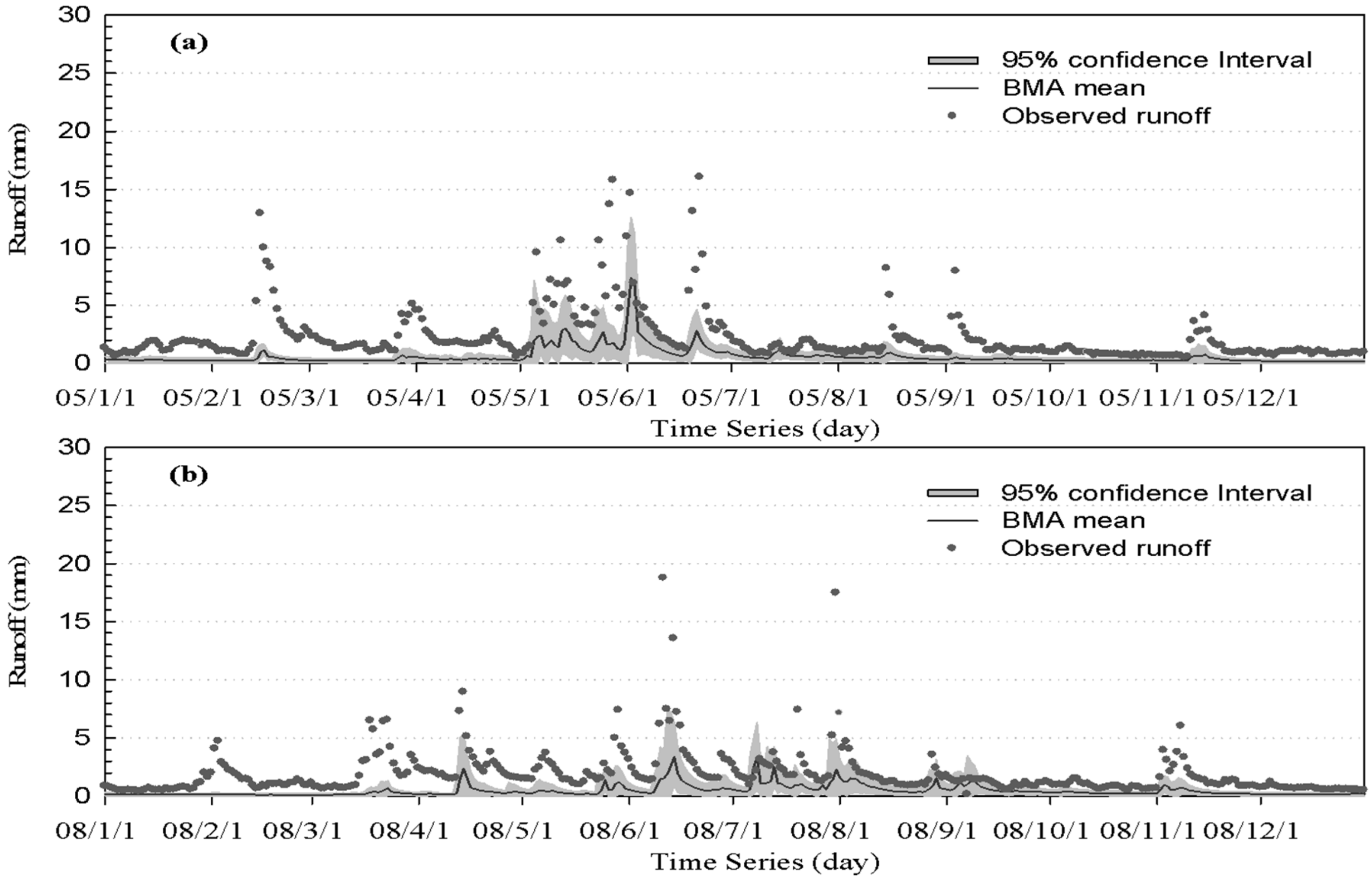
$$m \in [0.95, 1.05] \qquad \sigma_m^2 \in [1e-5, 1e-3]$$

Case 1:

Input:

Raw SP data

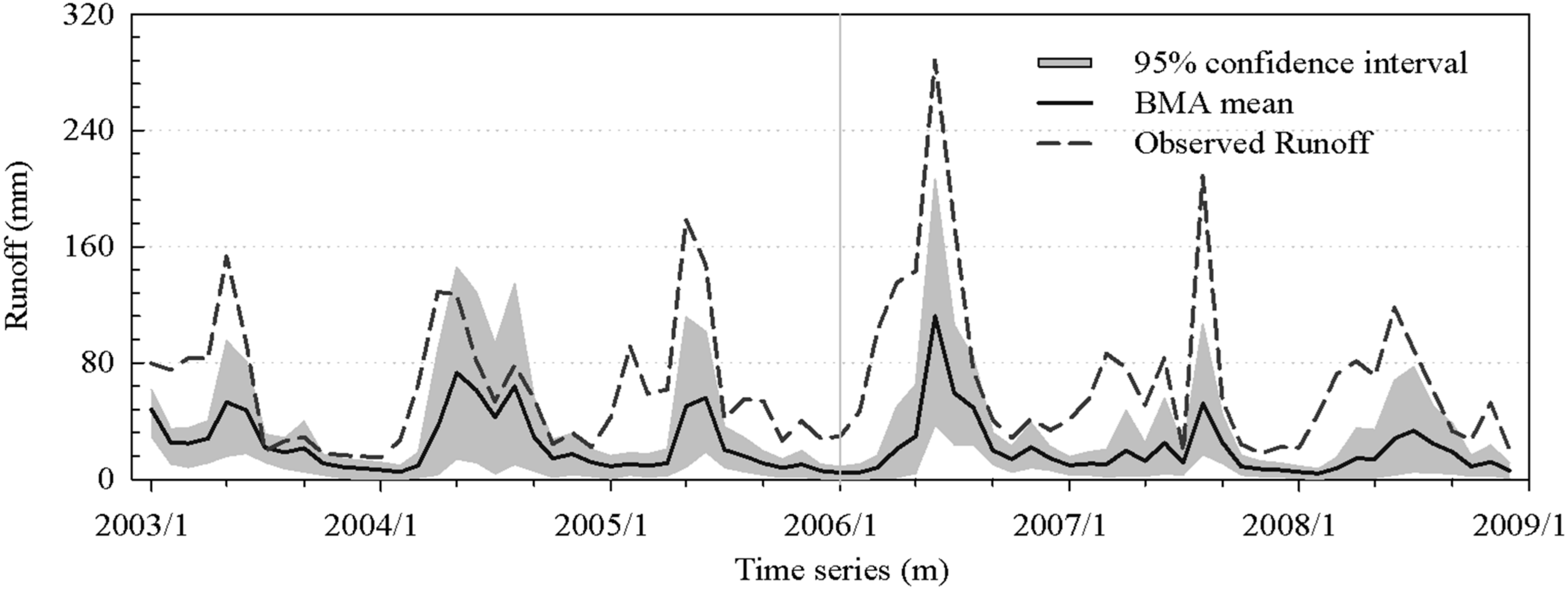
Parameters:
Gauge prec.
calibrated



The BMA combined simulation and the calculated 95% prediction interval are both with a severe underestimation for streamflow due to the large BIAS of the raw satellite precipitation over daily scale.

Case 1:

Input: R*aw SP* data



Calibration period:
NSCE=-0.29, CR=25.00%

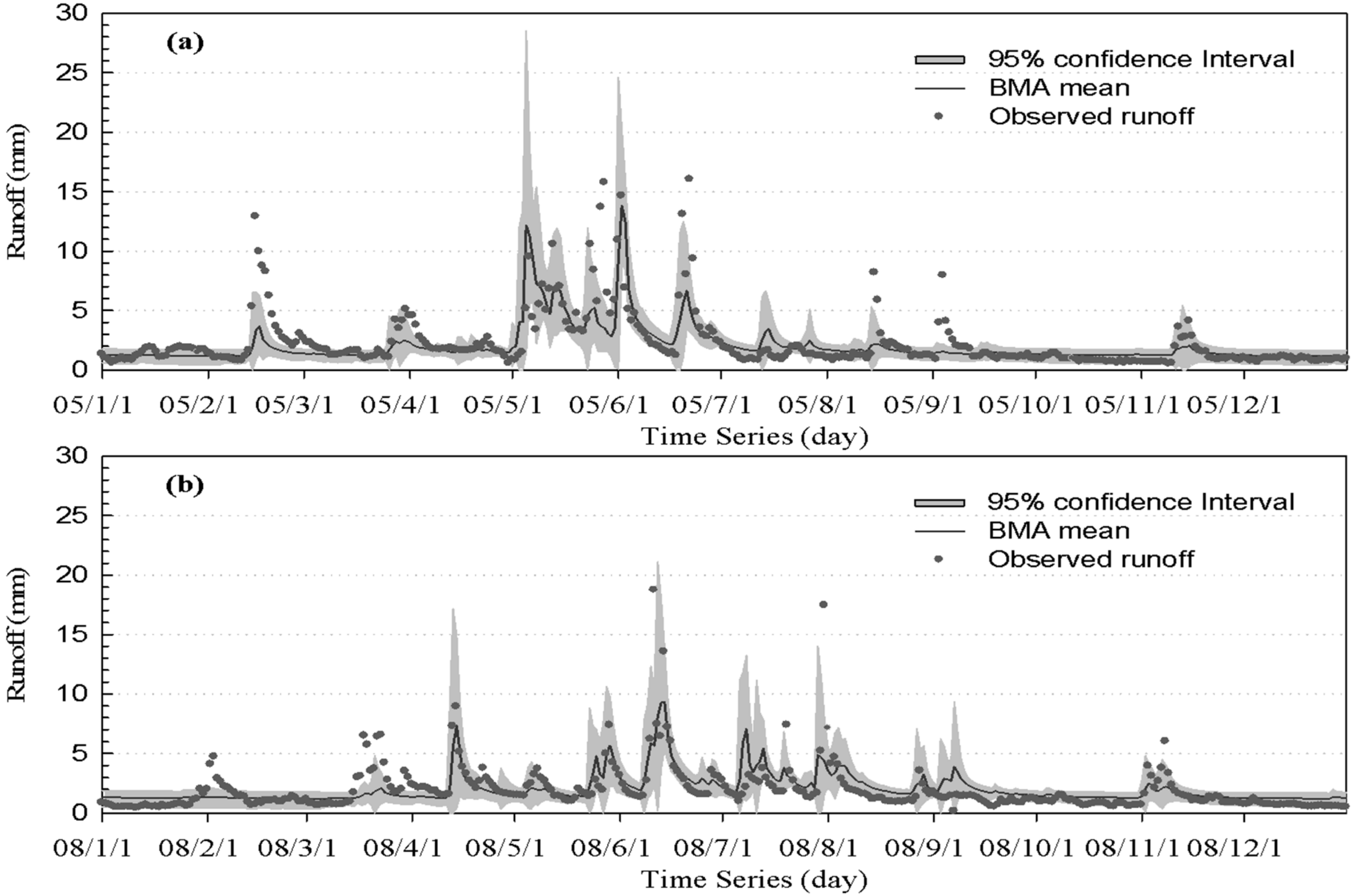
Validation period:
NSCE=-0.30, CR=8.33%

Monthly 95% uncertainty interval and BMA method also shows underestimation for streamflow, similar as daily situation.

Case 2:

Error model 1 for *Satell_Prec.*

Parameters: Recalibrated

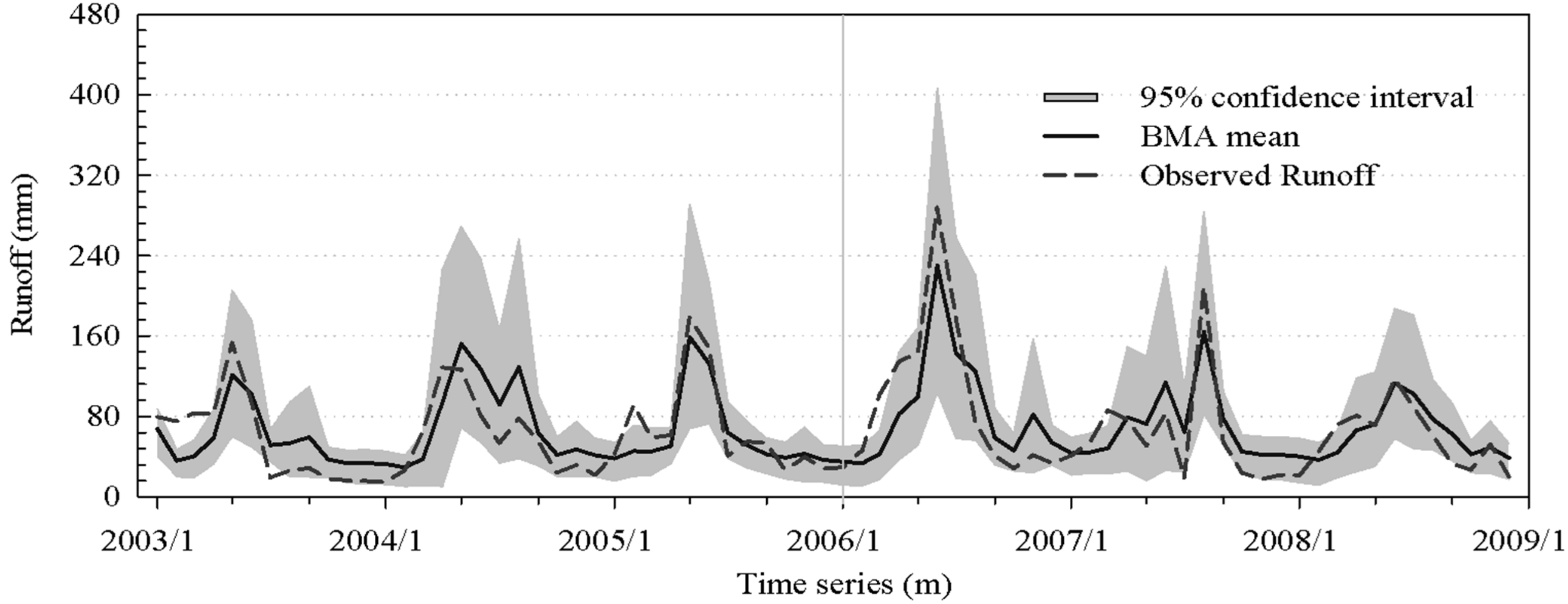


By introducing the precipitation error multiplier, the behavior of the simulated streamflow and calculated 95% prediction interval were significantly improved on daily scale.

Case 2:

Input:

Error model 1



Calibration period:
NSCE=0.64, CR=83.33%

Validation period:
NSCE=0.75, CR=83.33%

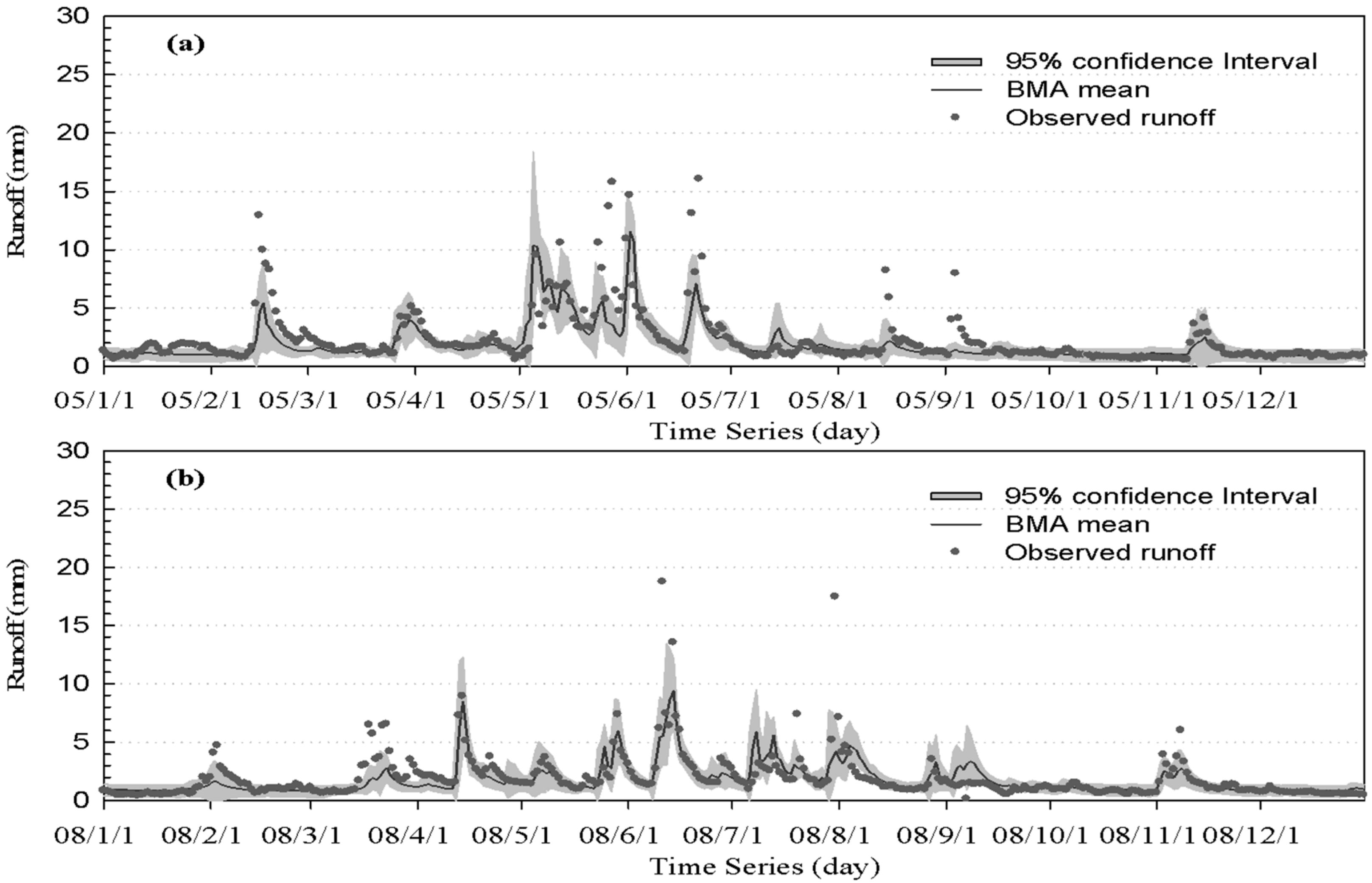
Monthly 95% uncertainty interval and BMA method perform better than that in Case1.

Case 3:

Input:

Error model 2

Parameters:
Recalibrated

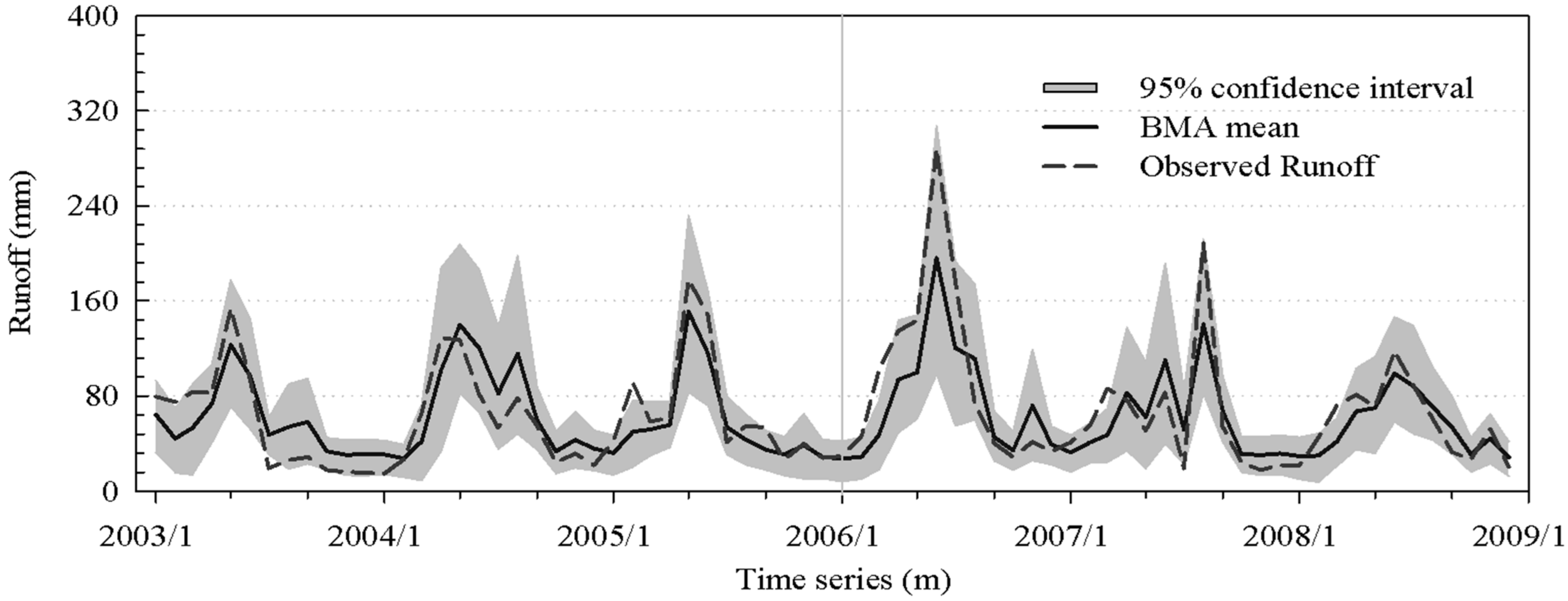


By introducing the precipitation error model 2, the behavior of the simulated streamflow and calculated 95% prediction interval were improved significantly.

Case 3:

Input:

Error model 2



Calibration period:
NSCE=0.74, CR=86.11%

Validation period:
NSCE=0.73, CR=86.11%

Monthly 95% uncertainty interval and BMA method show a significant improvement if compared with Case 1.

Validation statistical indices of simulated streamflow series

Data		Case 1			Case 2			Case 3		
		NSCE	BIAS(%)	RMSE	NSCE	BIAS(%)	RMSE	NSCE	BIAS(%)	RMSE
	3B42RT	0.11	-58.89	0.96	0.45	1.52	0.75	0.53	-3.90	0.70
	PERSIANN	-0.33	-80.21	1.17	0.39	-1.61	0.80	0.48	-0.58	0.74
CP	CMORPH	0.24	-48.66	0.89	0.40	14.13	0.79	0.54	5.26	0.69
	BMA (day)	**0.16**	**-56.42**	**0.93**	**0.50**	**4.78**	**0.72**	**0.58**	**0.29**	**0.66**
	BMA (month)	**-0.29**	**-56.42**	**47.83**	**0.64**	**4.78**	**25.20**	**0.74**	**0.29**	**21.32**
	3B42RT	0.20	-65.68	1.28	0.53	1.32	0.98	0.54	-12.19	0.98
	PERSIANN	-0.12	-83.01	1.52	0.35	10.64	1.16	0.37	-6.50	1.36
VP	CMORPH	0.17	-70.88	1.30	0.53	-6.42	0.99	0.52	-12.60	0.99
	BMA (day)	**0.17**	**-69.75**	**1.31**	**0.53**	**1.71**	**1.00**	**0.54**	**-10.48**	**1.00**
	BMA (month)	**-0.30**	**-69.75**	**65.78**	**0.75**	**1.71**	**28.99**	**0.73**	**-10.48**	**29.90**

In Case 2 and Case 3, by introducing a precipitation error multiplier and a precipitation error model respectively, the behavior of the simulated streamflow was significantly improved. The BMA combination method generates the optimal simulation. Case 3 is a little better than Case 2.

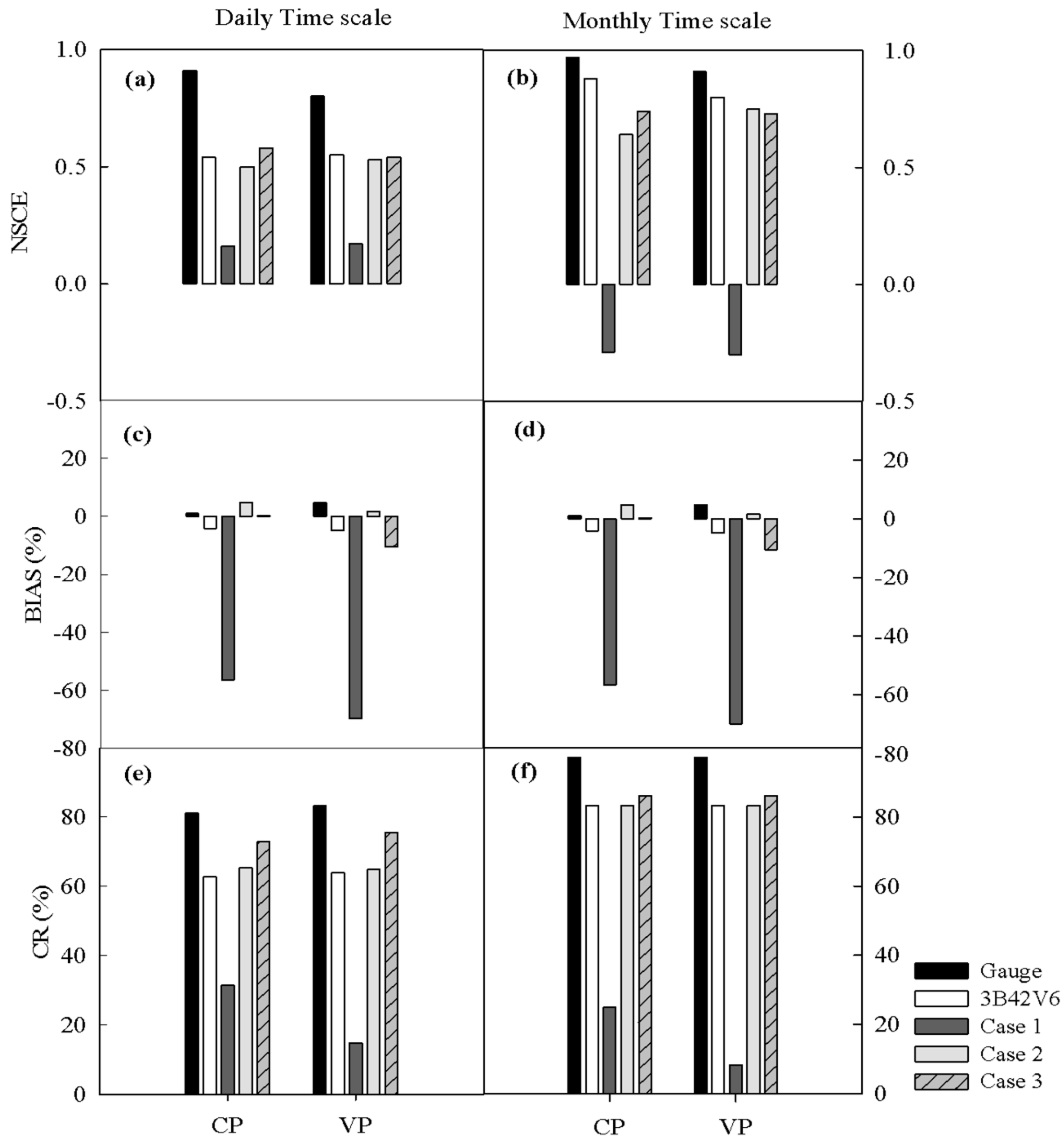
Notation. *CP* is Calibration Period, *VP* is Validation Period

Validation statistical indices of the prediction interval

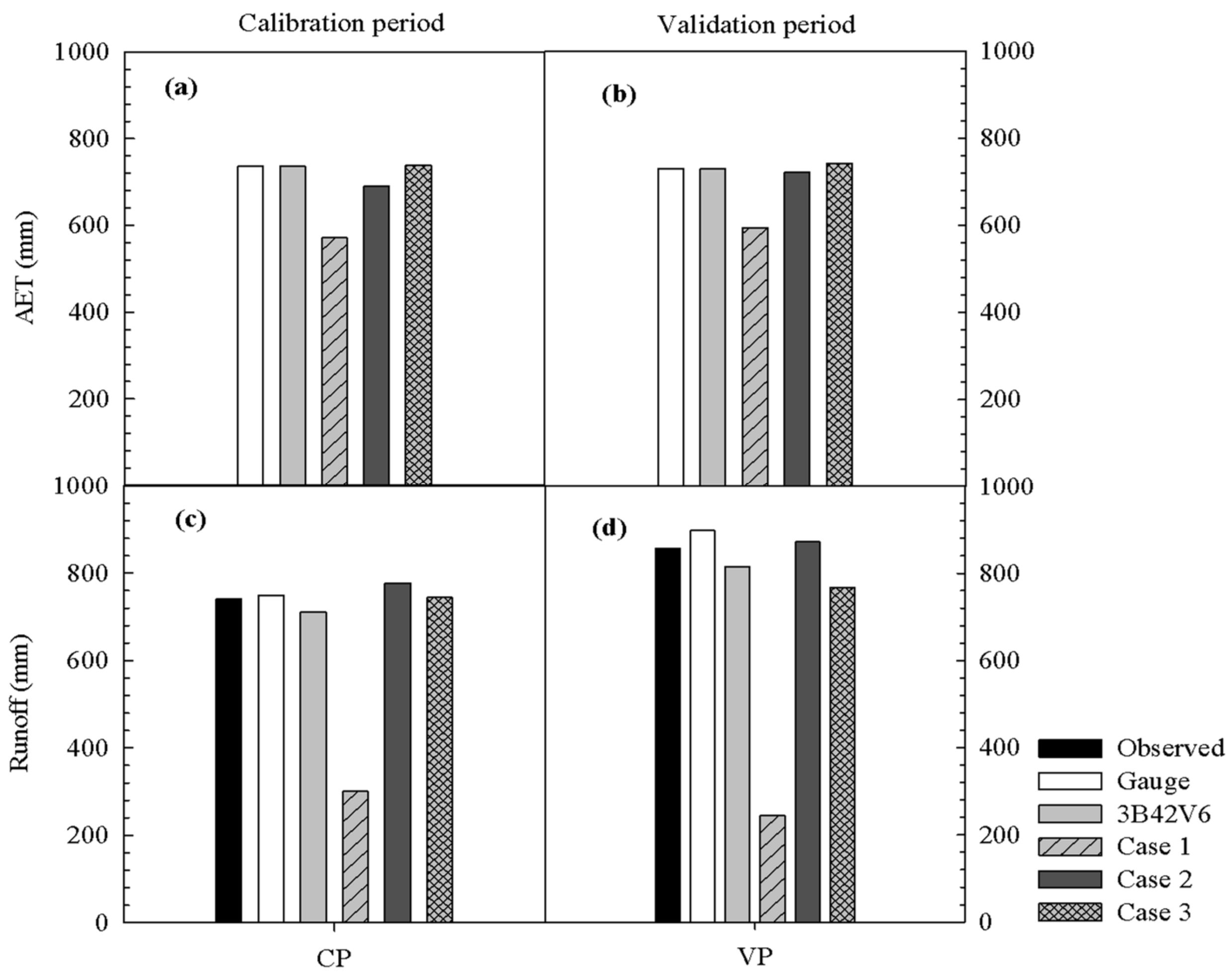
Data		Case 1			Case 2			Case 3		
		CR%	B(mm)	D(mm)	CR%	B(mm)	D(mm)	CR%	B(mm)	D(mm)
CP	3B42RT	21.99	0.83	1.24	55.02	1.90	1.02	54.74	1.36	0.88
	PERSIANN	7.30	0.54	1.63	51.28	1.65	1.03	54.20	1.18	0.89
	CMORPH	30.57	1.01	1.16	51.64	2.19	1.18	50.64	1.69	0.96
	BMA (day)	**31.48**	**1.31**	**1.24**	**65.33**	**2.55**	**1.05**	**72.90**	**2.12**	**0.86**
	BMA (month)	**25.00**	**39.83**	**35.49**	**83.33**	**77.64**	**21.76**	**86.11**	**64.54**	**17.99**
VP	3B42RT	16.51	0.92	1.51	57.39	2.20	1.25	65.05	1.53	1.00
	PERSIANN	8.30	0.62	1.91	43.34	2.20	1.60	54.74	1.36	1.27
	CMORPH	10.77	0.86	1.62	55.20	2.02	1.21	63.69	1.60	1.02
	BMA (day)	**14.87**	**1.13**	**1.62**	**64.87**	**2.87**	**1.33**	**75.55**	**2.21**	**1.06**
	BMA (month)	**8.33**	**34.48**	**48.58**	**83.33**	**87.31**	**23.48**	**86.11**	**67.29**	**21.67**

Also, by introducing a precipitation error multiplier and a precipitation error model, the behavior of the simulated prediction interval was significantly improved. The BMA method generates the optimal prediction interval. Case 3 is a little better than Case 2.

Notation: *CP* is Calibration Period, *VP* is Validation Period



The performance of Case 2 or Case 3 simulation in terms of NSCE, BIAS and CR is similar to the simulation by TRMM 3B42V6 with smallest errors of satellite precipitation data.



The simulated evapotranspiration and runoff in Case 2 and Case 3 are equivalent to the simulation by gauged precipitation and TRMM 3B42V6 data. It gives a good estimation on elements of water balance.

Conclusion 2

1. Three kinds of real-time satellite precipitation data sets have a large underestimation compared to gauged values. Streamflow simulation performed bad as the raw satellite precipitation data were taken as model input.

2. Using the precipitation error multiplier and the precipitation error model, the behavior of the simulated streamflow and calculated prediction interval were significantly improved.

3. The BMA combination of the multi-satellite precipitation simulations generate a much better prediction and a much more reliable prediction interval.

6. Suggestions

- **Uncertainty analysis method is feasible in hydrological practice.**
  - It is necessary to evaluate the uncertainty in application
  - Uncertainty analysis can help understanding hydrological character.

- **Combining inputs or models can improve the performance of hydrologic simulation.**
  - Application of multiple source data
  - Select suitable hydrological models
  - Select good combining method (BMA)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