HOHAI UNIVERSITY

XVIII World Water Congress
International Water Resources Association (IWRA)

Integrating deterministic forecast, real-time correction, and probabilistic forecast to improve hydrological model accuracy

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XVIII
WORLD WATER CONGRESS
Water for All
Harmony between Humans and Nature

第18届
世界水资源大会
水与万物：
人与自然和谐共生

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1. Background: Hydrological Uncertainty

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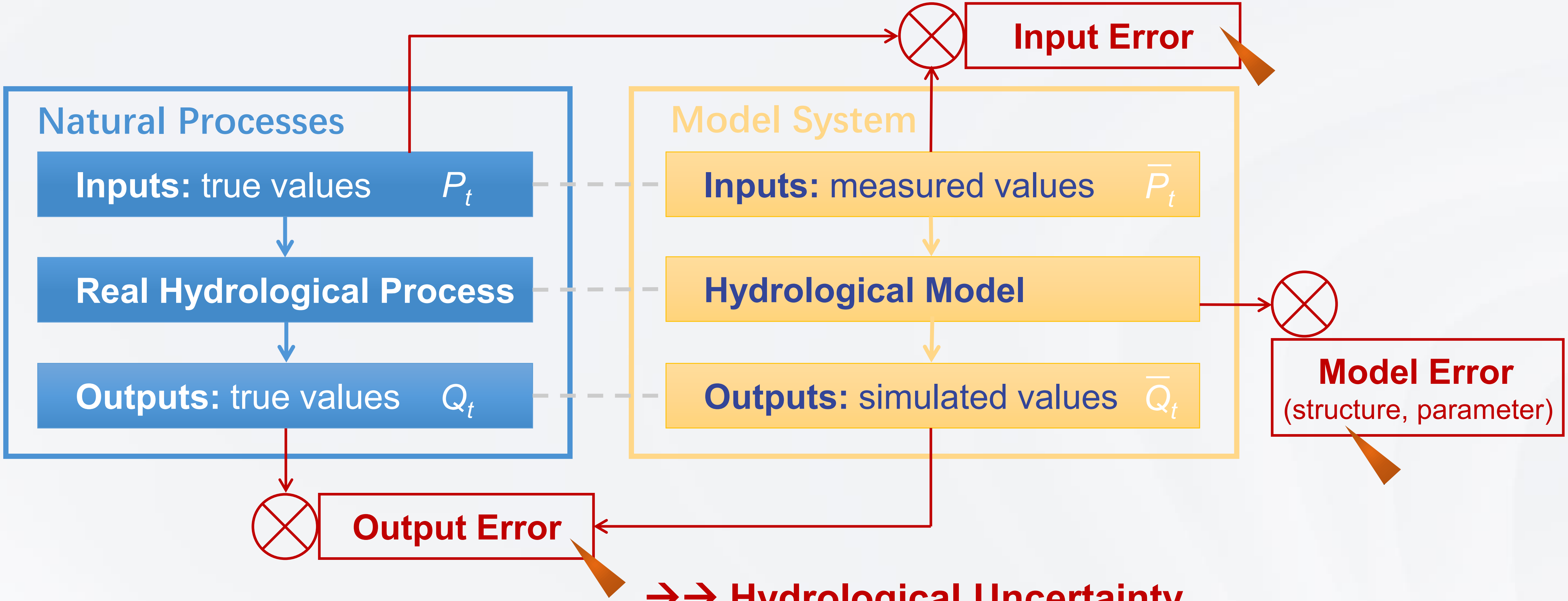
How to reduce forecast error and improve accuracy ?



→→ Hydrological Uncertainty

1. Background: Hydrological Uncertainty

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How to reduce forecast error and improve accuracy ?

In data-poor areas such as remote mountainous areas and alpine river basins, it is difficult to predict the process of flow generation and confluence, and the accuracy of the model is generally not high

Deterministic forecast accuracy is generally not high in data-poor regions

- Real-time correction: make the forecast result more consistent with the observations
- Probabilistic forecast: quantitatively evaluate the reliability and risk of decision-making schemes

Hydrological forecasting errors and the corresponding uncertainties

Can the comprehensive application of **real-time error correction and probabilistic forecasting methods** improve the accuracy of deterministic forecasting and provide uncertain results at the same time?

1. Background: Study Area →Houziyan Reservoir Basin

- **The Houziyan Reservoir** is the first cascade power station, located in the upper reaches of the Dadu River Basin, which is one of the important hydropower and clean energy bases in China.
- The inflow forecast of the Houziyan Reservoir has an important impact on the flood control and power generation dispatch of downstream cascade hydropower stations.
- The watershed has a variety of landforms such as ice and snow permafrost, meadows, alpine canyons, and a wide range of altitudes. **Complex hydrological conditions make hydrological prediction difficult and have large uncertainty.**

1. Background: Study Area →Houziyan Reservoir Basin

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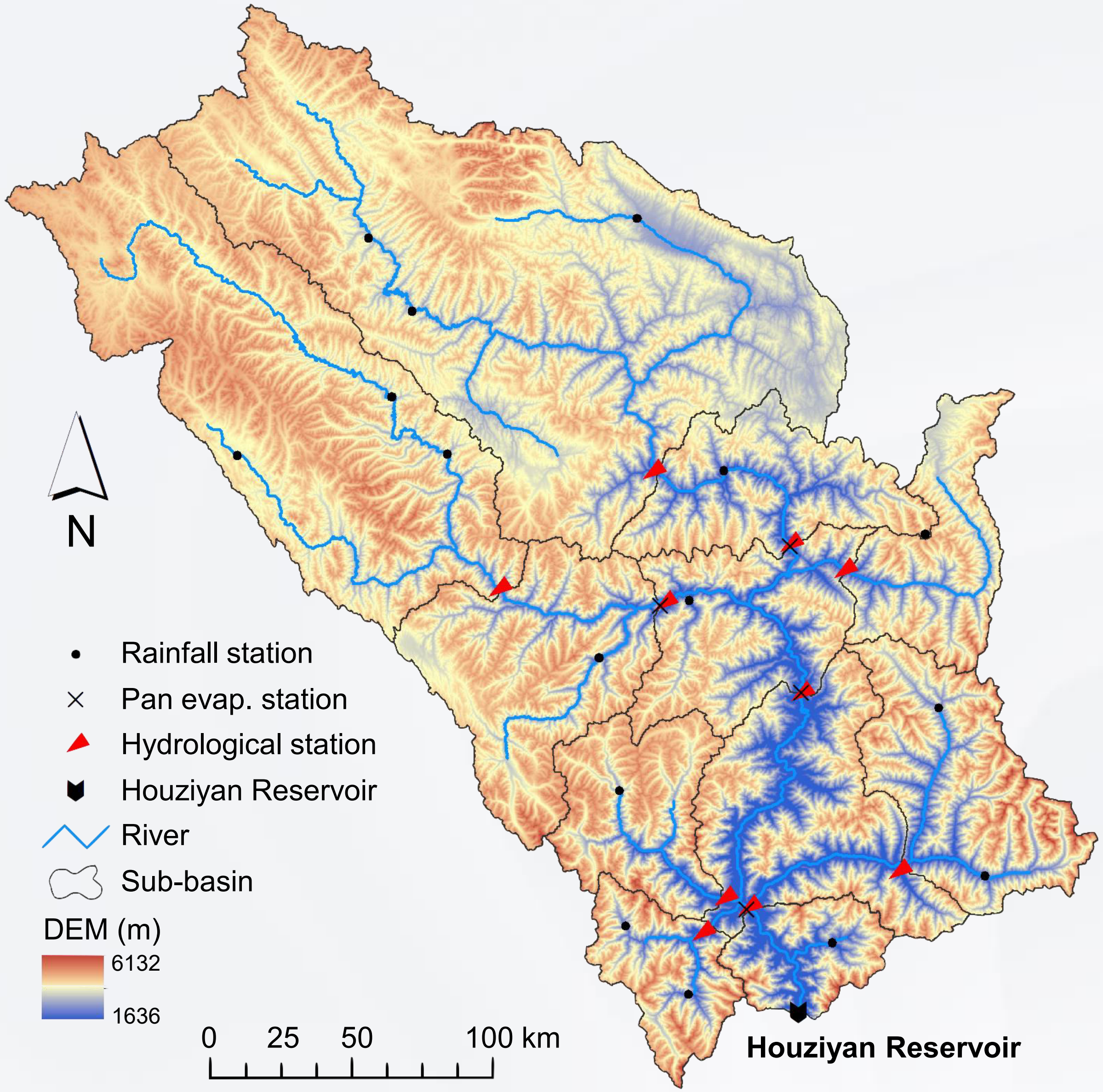
- **The controlled area:** 54000 km^2, accounting for ~70% of the total area of the Dadu River Basin.
- The snow accumulation period can be as long as 4 months, and the precipitation is concentrated in Jun-Oct → **Rivers are fed by both rainfall and snowmelt.**

- Daily and hourly **measured precipitation and streamflow data** from 2009 to 2020 (16 rainfall stations, 10 hydrological stations)
- **Forecasted rainfall data:** daily data of the rolling forecast for the next 7 days from Jun to Oct 2020, and the hourly data of the next 48 hours from Jun to Oct 2020
- **Pan evap data:** daily data from 2009 to 2014
- **Air temperature data:** daily data from 2009 to 2016



2. Deterministic Streamflow Forecasts

How to choice the applicable hydrological model ?

- A semi-humid area, with an annual average rainfall of 700 mm and an annual average runoff coefficient of 0.68. The underlying surface conditions and the *P~R* relationship are in line with the characteristics of Dunne runoff in flood season.
- **The Xin'anjiang (XAJ) model**, which has been widely and successfully applied in humid and semi-humid regions in China, is selected for deterministic forecasting.

Daily XAJ model for consecutive forecasts
- Nov. – Feb. — Receding period — Recession Curve method
- Mar. – May — Transition period — XAJ + Degree-day method
- Jun. – Aug. — Summer flood period — The original XAJ model
- Sep. – Oct. — Autumn flood period — The original XAJ model

Hourly XAJ model for flood events — The original XAJ model

Calibration and validation of daily models

- In the 7-yr calibration period, the average runoff error is 9.87%, and the average Nash-Sutcliffe efficiency (NSE) coefficient is 0.83
- In the 4-yr validation period, the average runoff error is 7.32%, and the average NSE coefficient is 0.83
- On the whole, the daily model has acceptable accuracy and good applicability

Calibration:

- **Runoff volume error:** within 10% (except for 2013), and the |avg.| of 9.87%
- **NSE:** avg.of 0.83

Validation:

- **Runoff volume error:** within 10%, and the |avg.| of 7.32%
- **NSE:** avg.of 0.83

Period	Year	Precip /mm	Obs. runoff /mm	Cal. runoff /mm	Relative error /mm	NSE
Calibration	2009	741	484	517	-6.82	0.91
	2010	663	457	488	6.78	0.79
	2011	651	431	480	11.17	0.78
	2012	781	594	639	-7.50	0.89
	2013	657	388	478	23.05	0.65
	2014	749	501	531	-5.85	0.90
	2015	750	450	485	7.89	0.86
Validation	2016	642	408	434	6.38	0.74
	2017	723	546	493	-9.80	0.84
	2018	743	552	504	-8.73	0.89
	2019	750	527	504	-4.38	0.86

Calibration and validation of hourly model

- **Calibration period →** For most events, the relative error of flood volumes (REV) and flood peaks (REP) is within 10% : avg. |REV| = 6.65%, avg. |REP| = 4.92%, avg. NSE = 0.69
- **Validation period →** Both REV and REP are within 10% : avg. |REV| = 7.52%, avg. |REP| = 3.64%, avg. NSE = 0.72
- On the whole, the hourly XAJ model has acceptable accuracy and good applicability

Period	Flood No.	REV /%	REP /%	Peak lag /h	NSE	Period	Flood No.	REV /%	REP /%	Peak lag /h	NSE
	20110601	-6.58	3.14	-1	0.55		20170610	-9.40	-1.89	0	0.85
	20110614	-7.23	-4.07	3	0.47		20170828	-11.73	-4.86	-1	0.83
	20110701	9.77	8.22	-2	0.73		20180703	-8.46	0.50	-1	0.77
	20110729	-4.81	-4.49	0	0.85		20180911	2.54	8.01	2	0.55
Calibration	20120601	8.50	-0.47	-1	0.78	**Validation**	20190626	-8.48	-6.71	1	0.50
(18 floods)	20120625	-6.87	-1.35	1	0.80	(7 floods)	20190716	-5.33	-2.93	1	0.74
	20120715	-7.18	-5.92	-1	0.67		20190912	-6.73	0.61	1	0.79
	20130704	-4.66	1.21	0	0.86						
	20140609	-1.67	0.26	0	0.92						
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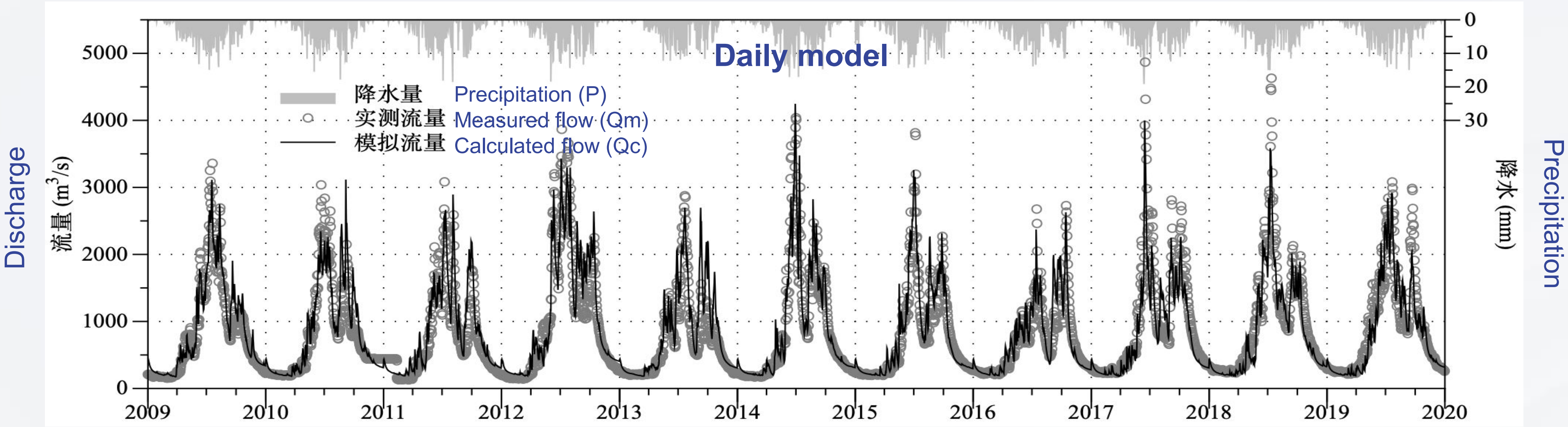
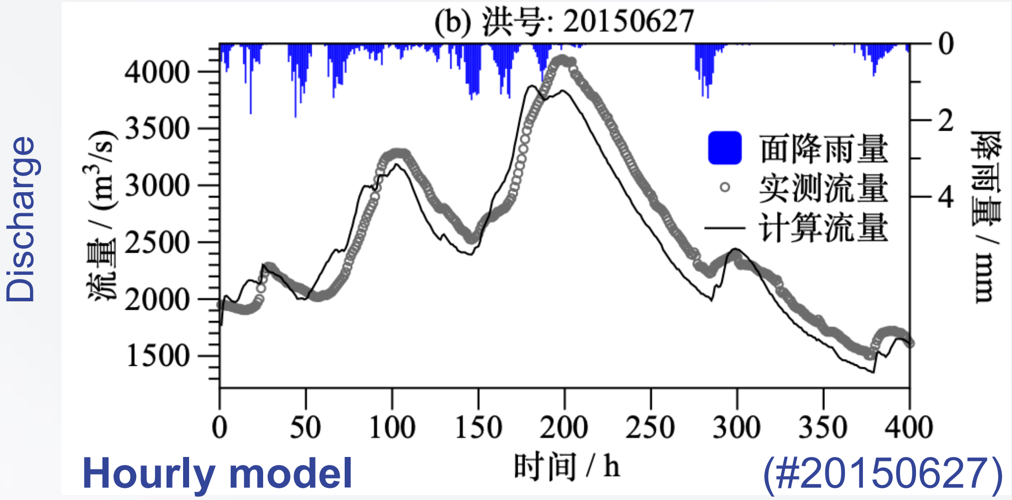
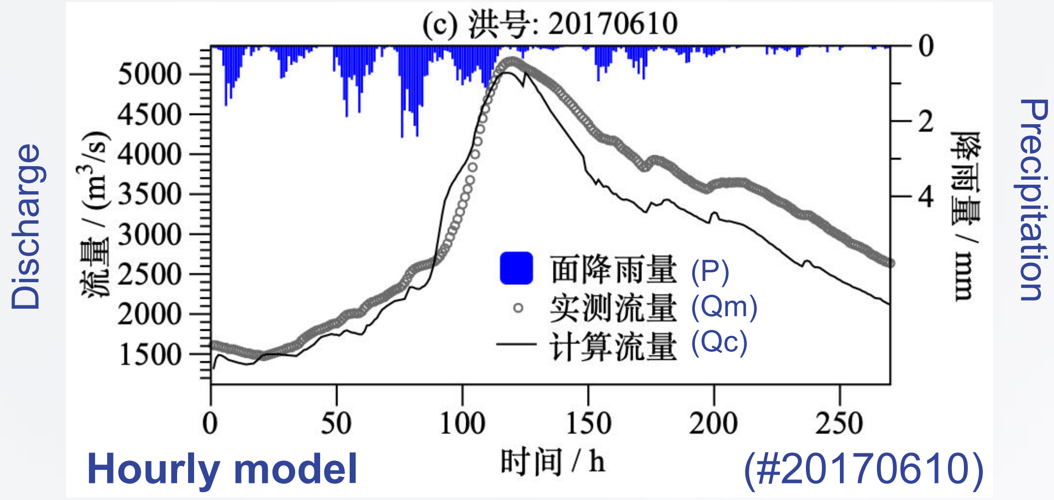
2. Deterministic Streamflow Forecasts

Hydrographs







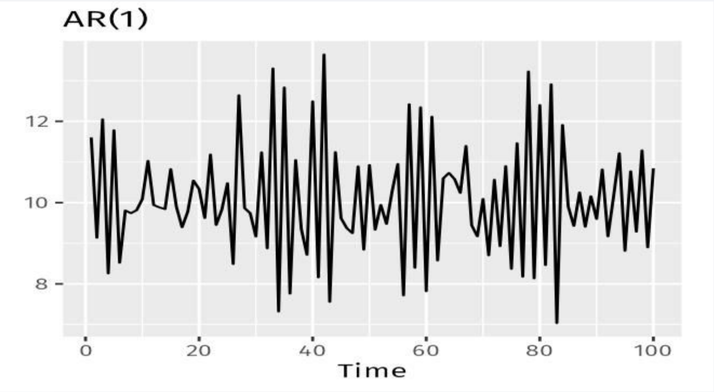
Different real-time correction methods for daily and hourly forecasts

Daily forecasts with lead time of 7 days — **Terminal** Bias Correction → Auto-Regressive (AR) model

Hourly forecasts with lead time of 48 hours — **Process** Bias Correction → Dynamic System Response Curve (DSRC) method

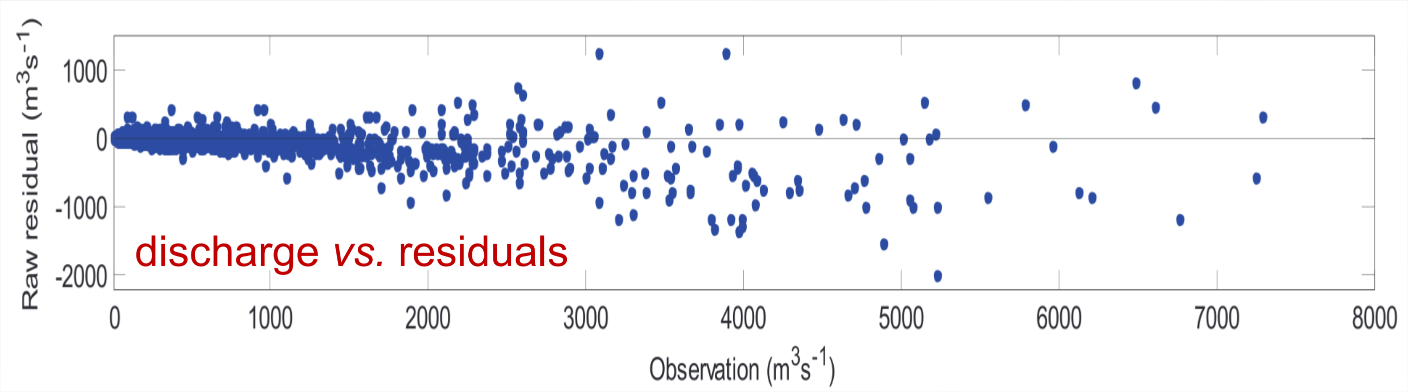
Why different ? The applicability of AR/DSRC in daily/hourly scales

Daily Time Scale



Strong linear correlation between the ***target value*** to be predicted and its ***past values***

Hourly Time Scale



The **conditionally heteroscedastic nature of the model residual**, while also suggesting some degree of conditional bias

3. Real-time Forecasting Correction

Real-time daily forecasting correction using AR model

- AR model is a typical Terminal Bias Correction (TBC) method. In an autoregression model, we forecast the variable of interest using a linear combination of *past values of the variable*. The term *auto*regression indicates that it is a regression of the variable against itself.
- **The AR model for the next 7 days** was established using the model residual series from 2009 to 2019 in the study basin (*with the forecasted rainfall data as input*).

- **avg. |REV|:** 13.90% → 6.63%
- **avg. NSE:** 0.45 → 0.66

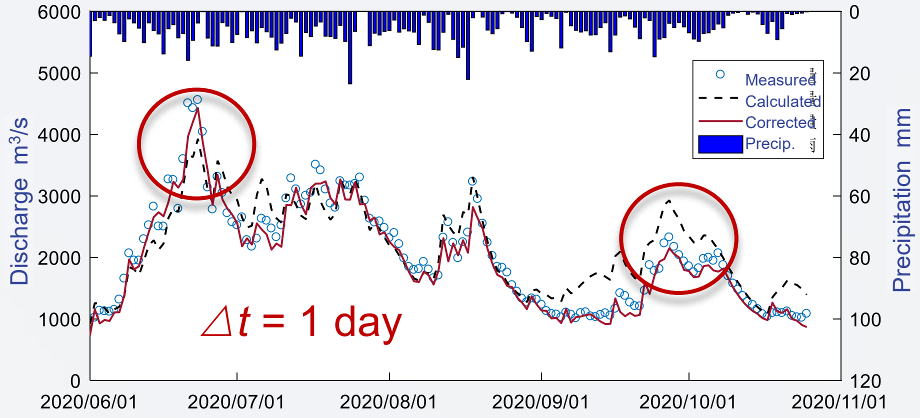
After correction, the model accuracy improves for all forecast lead time.

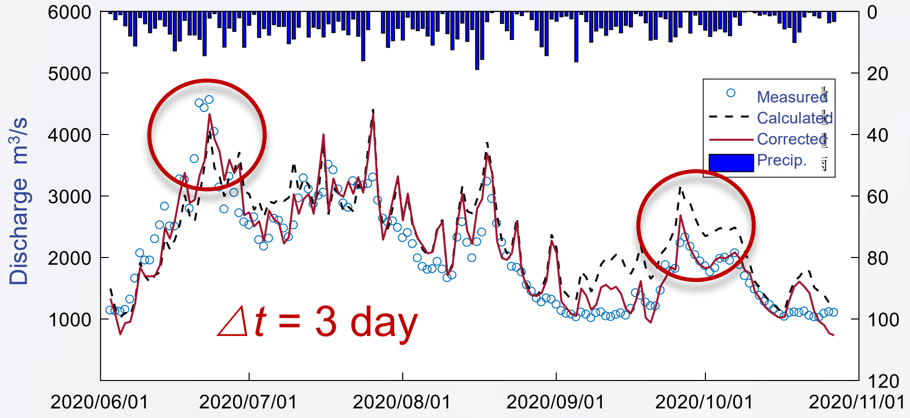
Forecast lead time /day	Before Correction			After Correction		
	REV /%	REP /%	NSE	REV /%	REP /%	NSE
$\Delta t = 1$	5.54	-13.87	0.81	-4.73	-2.87	0.95
$\Delta t = 2$	9.71	-8.07	0.71	0.38	-1.68	0.90
$\Delta t = 3$	14.04	13.49	0.54	5.21	5.00	0.77
$\Delta t = 4$	16.58	5.58	0.41	5.09	0.04	0.64
$\Delta t = 5$	17.25	30.69	0.27	9.13	27.6	0.51
$\Delta t = 6$	17.03	14.87	0.25	9.24	5.53	0.48
$\Delta t = 7$	17.17	14.99	0.19	9.63	12.63	0.38

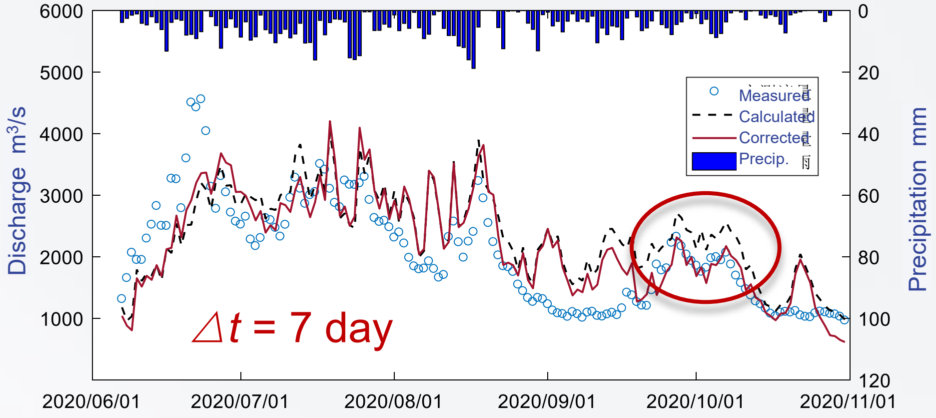
3. Real-time Forecasting Correction

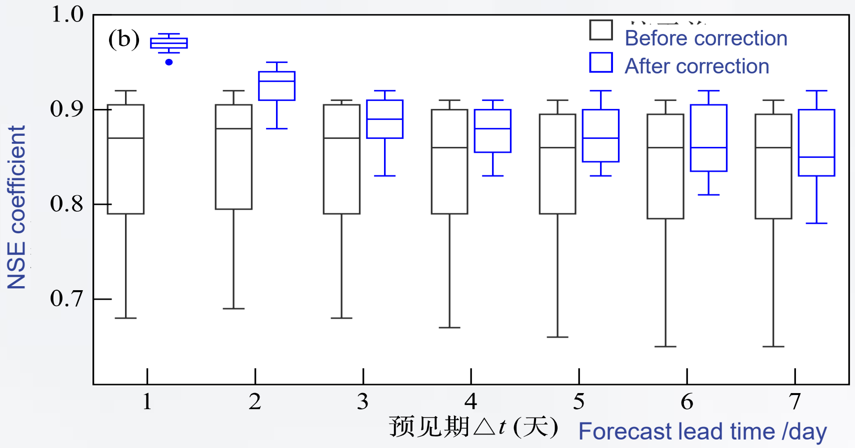
Real-time daily forecasting correction using AR model

- With the extension of the forecast lead time, the forecast accuracy decreases
- The correction effect is most significant in the peak flows









3. Real-time Forecasting Correction

Real-time hourly forecasting correction using DSRC method

- DSRC belongs to the Process Bias Correction (PBC) approach, proposed by Prof. BAO Wei-min of Hohai University in 2014.
- The DSRC takes the forecast model as the response system, and corrects the input variables by calculating the system response matrix corresponding to the input variables. The corrected input variables are "re-calculated" for flood forecasting, and finally the corrected flow results are obtained.

Hourly XAJ Model
with lead time of 48 hours

⇩

Process Bias Correction

⇩

Dynamic System Response Curve (DSRC) method

P-DSRC : Areal precip.

R-DSRC : Runoff volume

S-DSRC : Free water storage

W-DSRC : Soil water storage

……

Input *X* → Hydrological Model → Output *Q*

Areal precip, *P*

⇩

DSRC requires that the outlet flow needs to correspond to the areal rainfall of the sub-basin, so only the sub-basin with no upper section inflow is corrected.

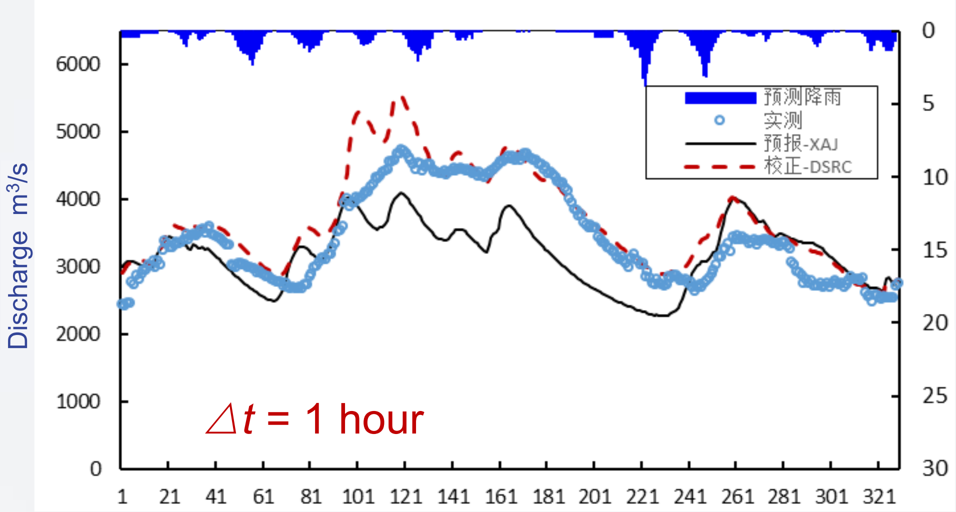
3. Real-time Forecasting Correction

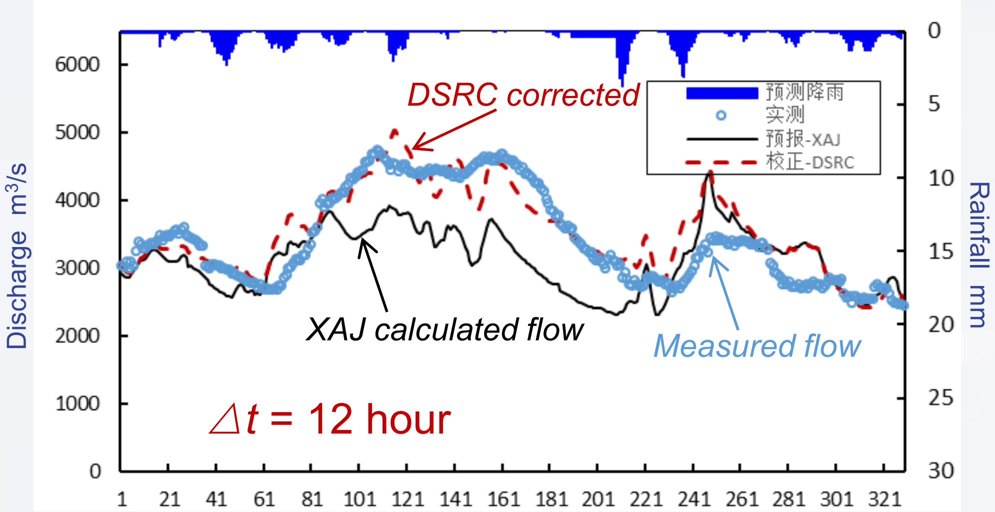
Real-time hourly forecasting correction using DSRC method

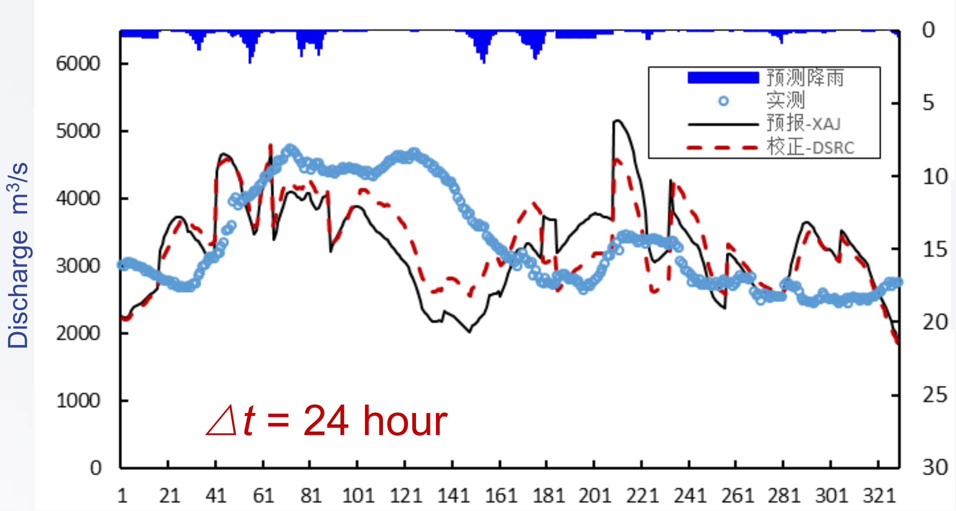
- On the whole, the accuracy of the XAJ flood model with forecasted rainfall as input is low
- After correction, the avg. |REV| has decreased, and the correction effect of REP and NSE indices is better when the forecast lead time is less than 24h
- ***Why:*** On the one hand, with the extension of the forecast lead time, the accuracy of rainfall forecast decreases; on the other hand, the real-time correction method is only a correction basin on historical forecasts, so the correction effect will decrease with the extension of the forecast lead time.

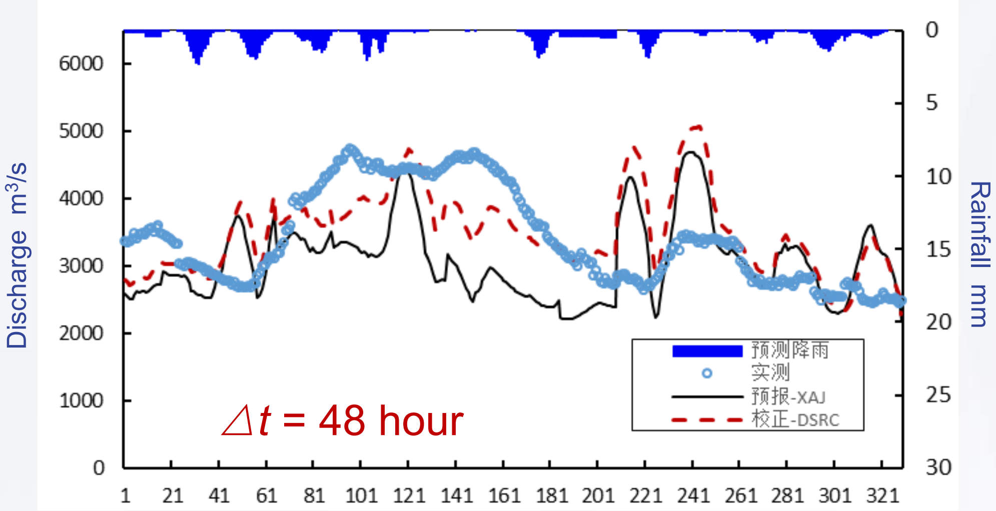
Flood No.	Lead time /h	Before Correction			After Correction		
		REV	REP	NSE	REV	REP	NSE
20200616	Δt = 1	-7.76	-13.53	0.24	7.30	17.20	0.74
	Δt = 12	-5.22	-7.26	0.12	2.86	6.29	0.70
	Δt = 24	-10.27	-1.08	-0.63	2.90	7.01	0.05
	Δt = 48	-9.32	8.97	-0.36	2.07	-1.19	-0.15
20200710	Δt = 1	-21.41	-13.38	0.23	-4.45	2.67	0.32
	Δt = 12	-14.92	6.03	0.05	-8.89	11.55	0.21
	Δt = 24	-19.49	22.59	-3.88	2.11	38.36	-2.23
	Δt = 48	-15.38	-1.21	-4.05	-7.12	11.35	-1.78

Real-time hourly forecasting correction using DSRC method (#20200616)









4. Probabilistic Streamflow Forecasts

Hydrologic Uncertainty Processor (HUP)

- HUP is a component of the Bayesian forecasting system (BFS) which produces a short-term probabilistic river stage forecast (PRSF) based on a probabilistic quantitative precipitation forecast (PQPF). The hydrologic uncertainty is the aggregate of all uncertainties arising from sources other than those quantified by the PQPF. *(Krzysztofowicz & Maranzano, JH, 2004)*
- **One hypothesis:** there is no precipitation uncertainty.
- **Two premises:** *a.* The measured flow series obeys the first-order Markov process and is strictly stable; *b.* The sample series after the normal quantile transformation of the measured value and the predicted value obey the linear relationship.

Measured value (h_i) + **Predicted value** (s_i) → **Marginal Probability Density Function (PDF) Estimation** (Log-Weibull) → **Normal Quantile Transformation (NQT)** transform (h_i, s_i) from a skewed distribution to a normal distribution → **Estimation of Prior PDF and Likelihood Function** → **Posterior PDF of Predictand → Probabilistic Forecasts**

4. Probabilistic Streamflow Forecasts

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Daily HUP results (example: Δt = 1 day)

- Probabilistic Results: The *coverage rate* (*CR*) and *dispersion index* (*DI*) of the 90% confidence interval were about 90% and below 0.40, respectively, indicating that it can cover most of the measured discharge values in a relatively narrow interval and has high reliability.
- Deterministic Results: The forecast accuracy of the median of the HUP's posterior PDF (*Q50*) was better than the original deterministic forecast to a certain extent.

Period	Year	HUP's Probabilistic Results, 90% Confidence Interval			HUP's Deterministic Results, Median (*Q50*)	
		Interval (m^3/s)	Coverage Rate /%	Dispersion Index /%	REV /%	NSE
Calibration	2009	[2920, 3730]	93.7	0.24	-0.27	0.98
	2010	[2630, 3360]	92.9	0.24	-0.38	0.98
	2011	[2690, 3430]	86.8	0.24	0.12	0.97
	2012	[3370, 4290]	91.0	0.24	-0.32	0.98
	2013	[2520, 3220]	912	0.24	0.25	0.97
	2014	[3540, 4500]	89.8	0.24	0.33	0.97
	2015	[3320, 4230]	90.4	0.24	-0.25	0.97
Validation	2016	[2380, 3050]	91.0	0.25	-0.31	0.96
	2017	[4240, 5380]	90.4	0.25	0.93	0.97
	2018	[4020, 5110]	94.2	0.24	0.82	0.98
	2019	[2700, 3440]	92.9	0.25	-0.67	0.98

4. Probabilistic Streamflow Forecasts

Daily HUP results (example: Δt = 1~7 days)

- With the extension of the forecast lead time, the HUP median (*Q50*) accuracy is better than the original deterministic forecast results (*XAJ+AR_corrected*) to a certain extent, and the 90% confidence interval provided has a low dispersion (*DI*) when ensuring a high coverage rate (*CR*), indicating that the results have relatively high high reliability.

Probabilistic forecasts:

CR = 83%~84%

DI = 0.25~0.43

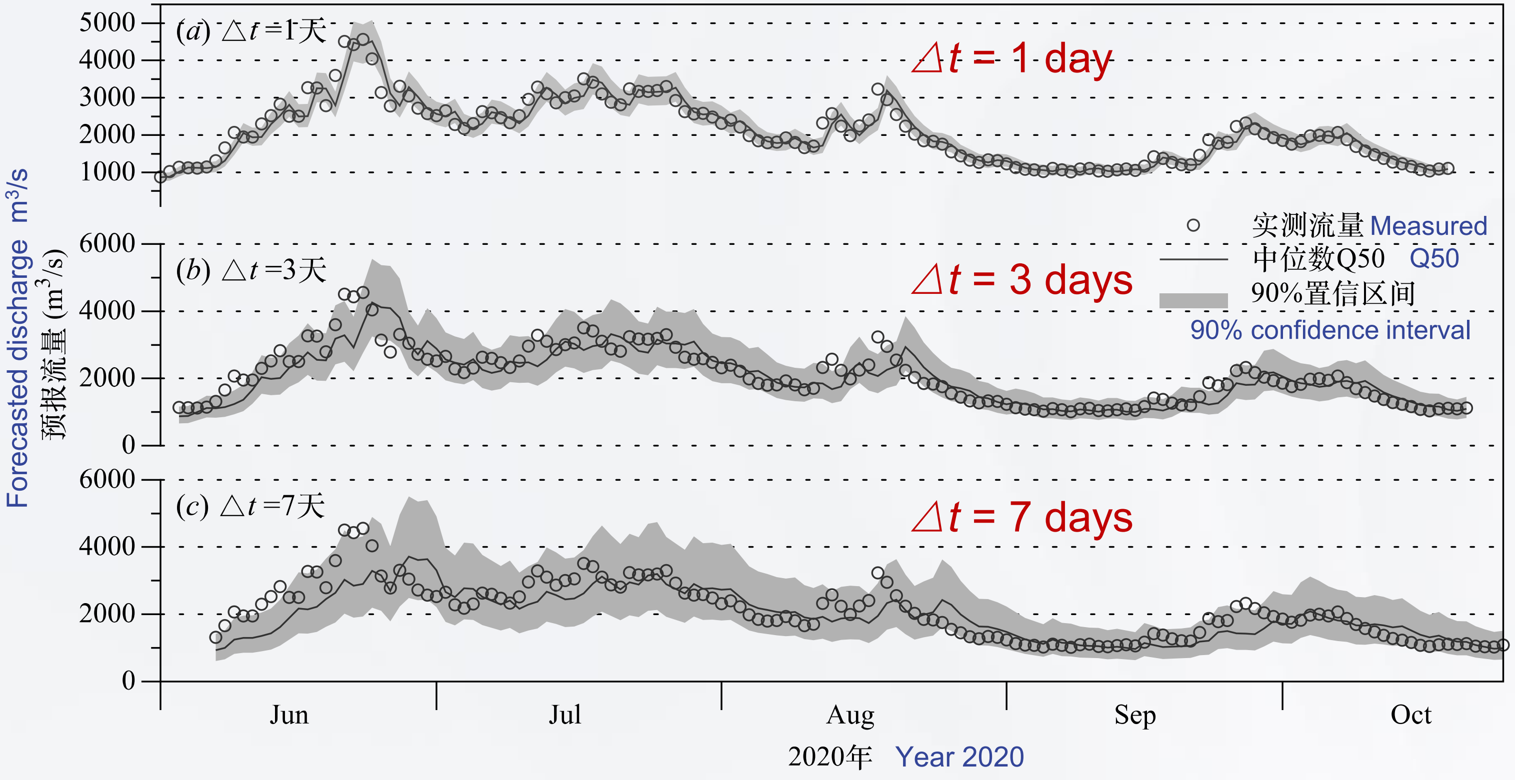
Deterministic forecasts:

XAJ+AR_corrected:

NSE = 0.38~0.95

HUP_Q50:

NSE = 0.62~0.91



4. Probabilistic Streamflow Forecasts

Hourly HUP results (example: Δt = 1 hour)

- **Probabilistic Results:** The coverage rate (*CR*) of the 90% confidence interval is mostly above 90%, and the dispersion (*DI*) is mostly 0.19, which can cover most of the measured flow in a narrow interval, so the forecast reliability is high.
- **Deterministic Results:** The forecast accuracy of the median of the HUP's posterior PDF (*Q50*) was better than the original deterministic forecast to a certain extent.

Calibration:

- **Probabilistic forecasts:**
  CR = 90%~97%
  DI = 0.19~0.20
- **Deterministic forecasts:**
  avg |REV|, |REP| < 5%
  avg. NSE = 0.85~0.99

Validation:

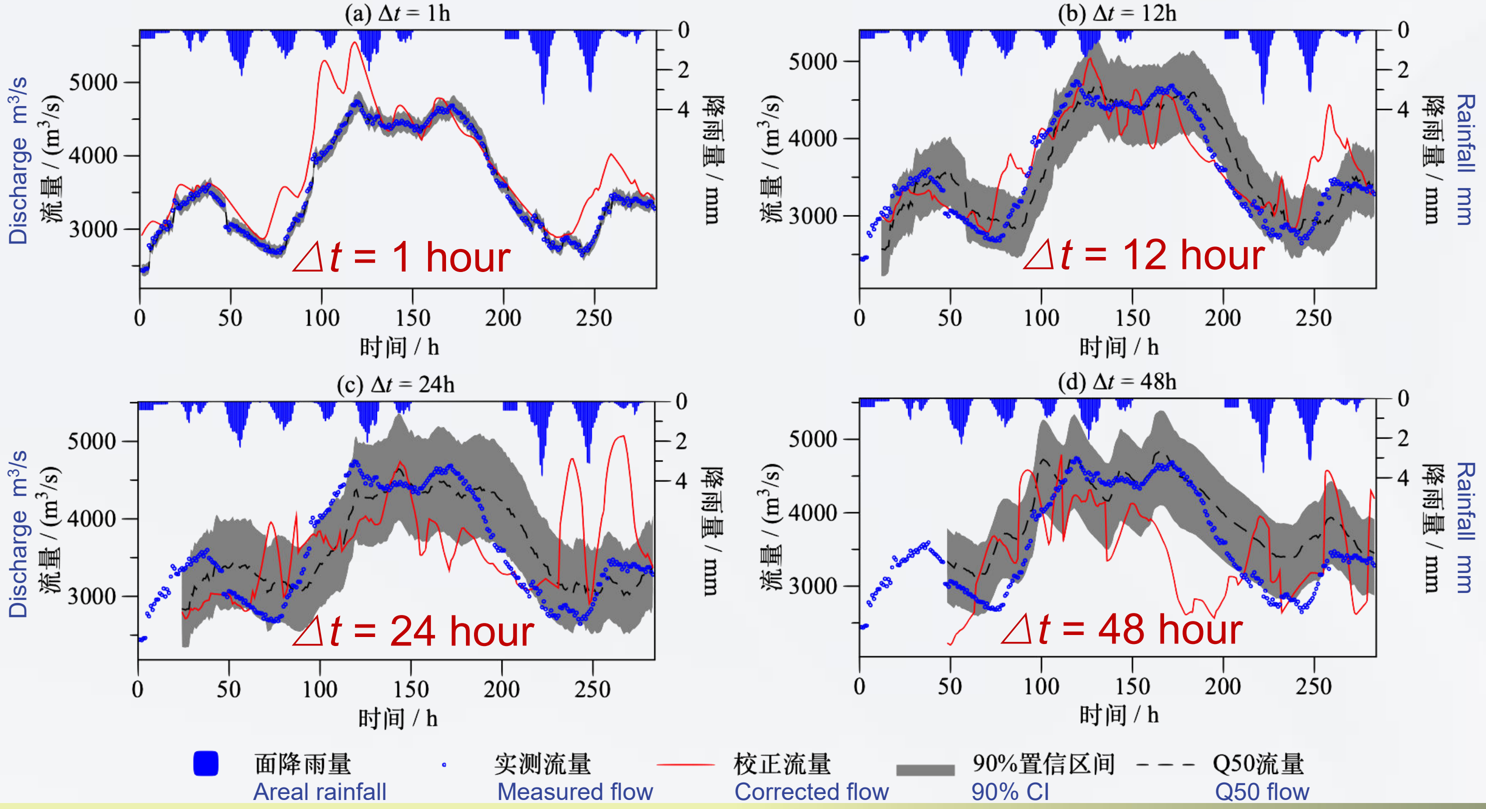
- **Probabilistic forecasts:**
  CR = 88%~95%
  DI = 0.18~0.19
- **Deterministic forecasts:**
  avg |REV|, |REP| < 5%
  avg. NSE = 0.93~0.98

Period	Flood No.	90% CI_CR /%	90% CI_DI	Q50_REV /%	Q50_REP /%	Q50_NSE
Calibration (18 floods)	20110601	95.65	0.20	-2.30	2.23	0.93
	20110614	97.09	0.19	1.77	-0.12	0.94
	20110701	94.08	0.19	0.89	-0.91	0.94
	20110729	94.24	0.19	0.05	0.05	0.98
	20120601	94.78	0.19	0.27	0.64	0.97
	20120625	94.82	0.18	-0.04	-1.73	0.96
	……	……	……	……	……	……
Validation (7 floods)	20170610	87.87	0.19	0.81	-1.73	0.96
	20170828	90.77	0.19	-1.45	0.54	0.95
	20180703	88.96	0.19	-0.23	0.53	0.98
	……	……	……	……	……	……

4. Probabilistic Streamflow Forecasts

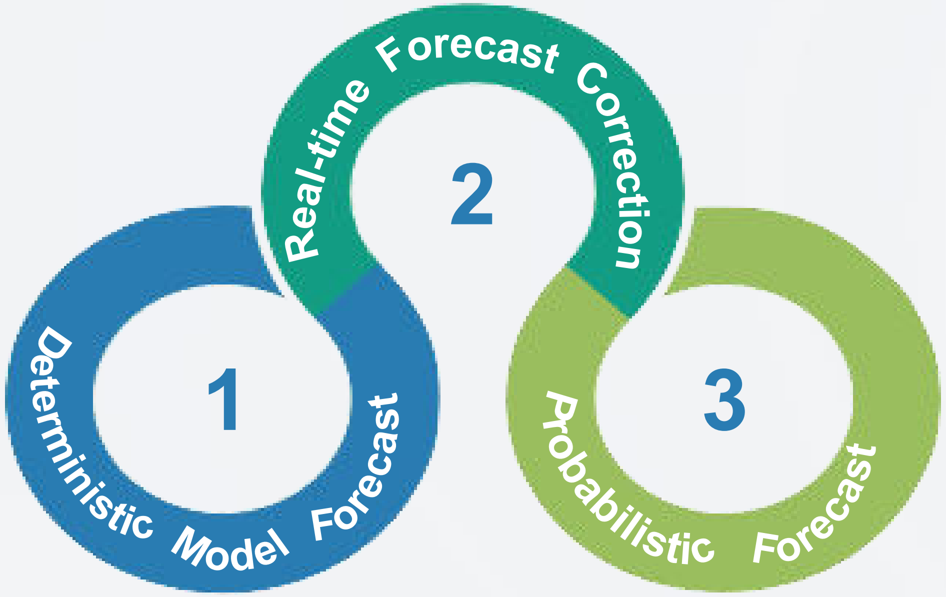
Hourly HUP results (example: #20200616, △t = 1~48 hours)

- Probabilistic Results: For all forecast lead time, *CR* > 80% and *DI* ~ 0.30. It provides reliable forecast results with 90% confidence intervals.
- Deterministic Results: *avg* |REV|, |REP| within 10%, NSE > 0.5. With the extension of the forecast lead time, the *Q50* forecast accuracy is declining.



Conclusion

On the scale of daily flow forecast and hourly flood forecast, the technical framework integrating deterministic forecast, real-time correction and probabilistic forecast can improve the accuracy of deterministic forecast step by step, and can also provide reliable uncertainty forecast information.



How to reduce model forecast error and improve accuracy ?

Thanks for your attention!

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