Thesis Defense

Runoff simulation in the source region of the Yellow River based on satellite precipitation products

Author : Shengli Zhu

Supervisor : Zhaofei Liu

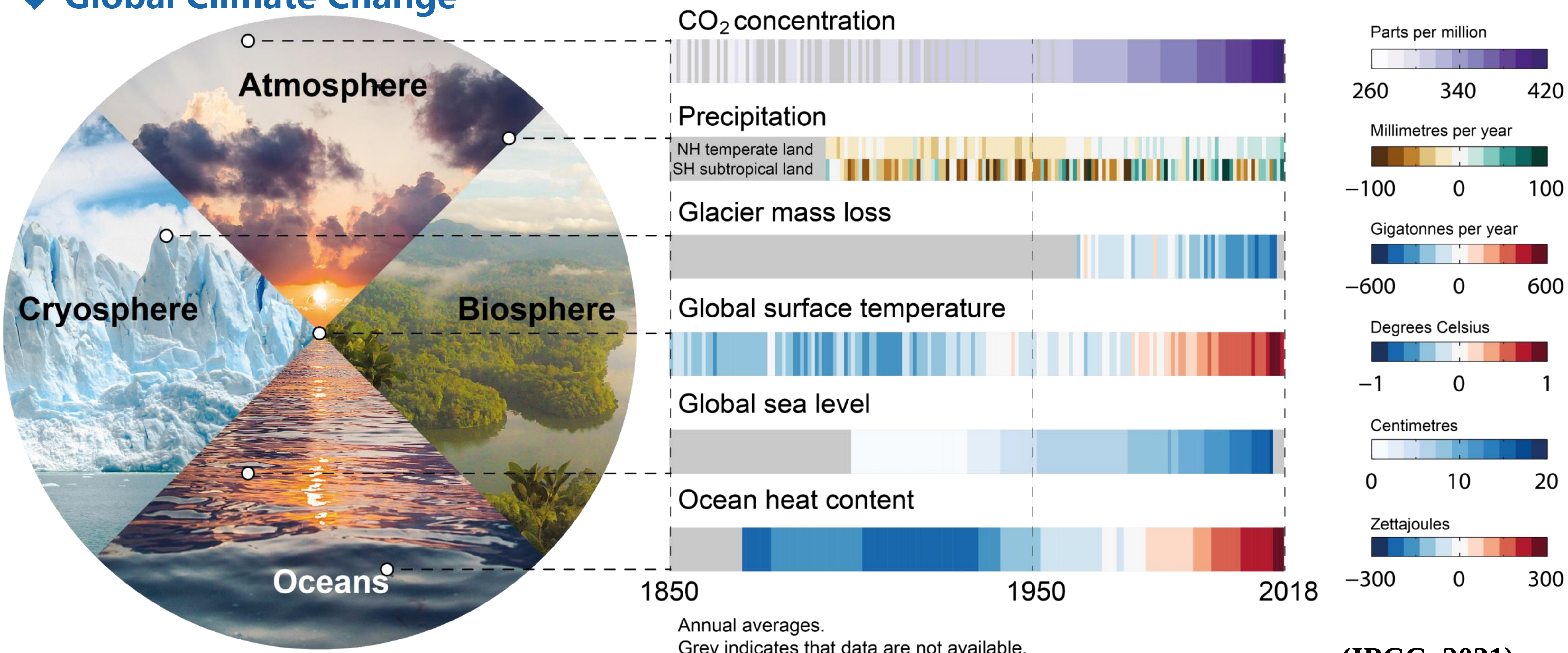
May 16, 2025

Outline

1 Introduction

1.1 Background and Significance

◆ Global Climate Change



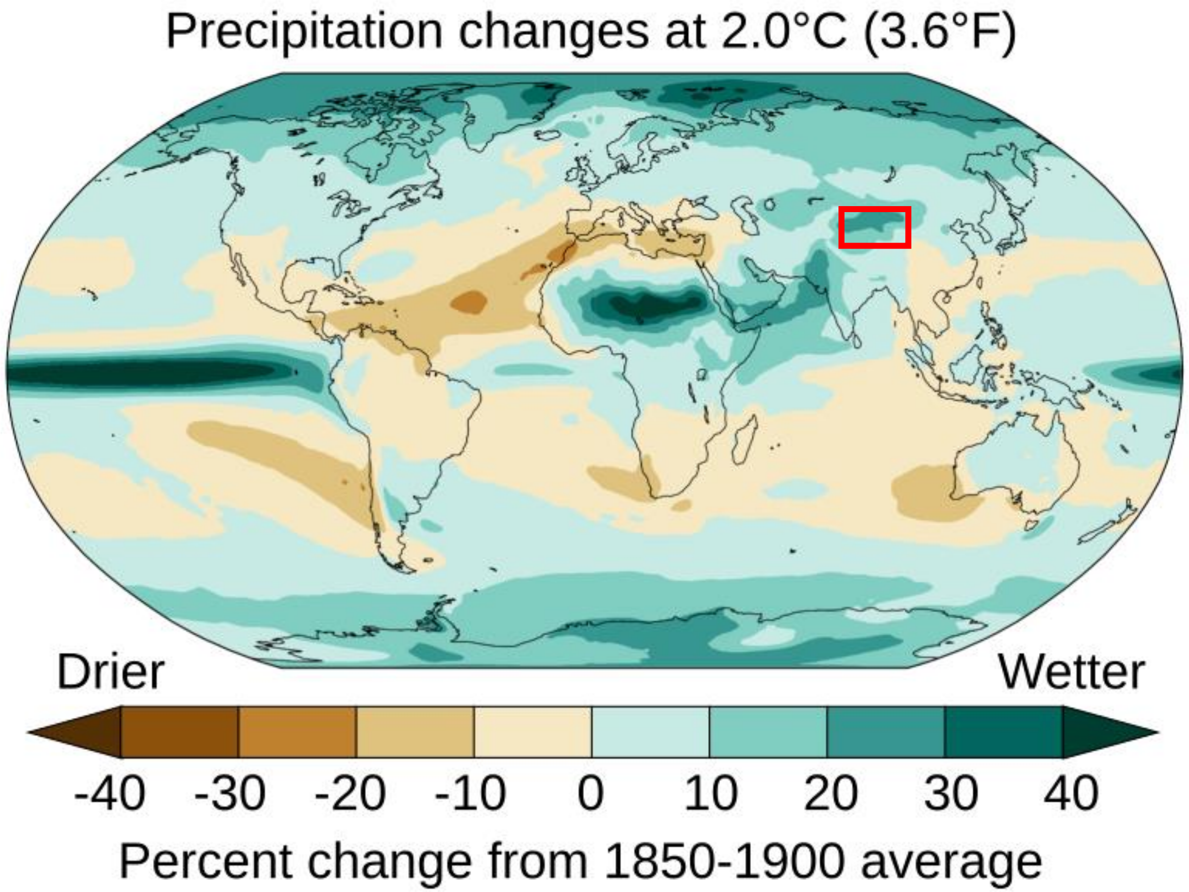
Annual averages.
Grey indicates that data are not available.

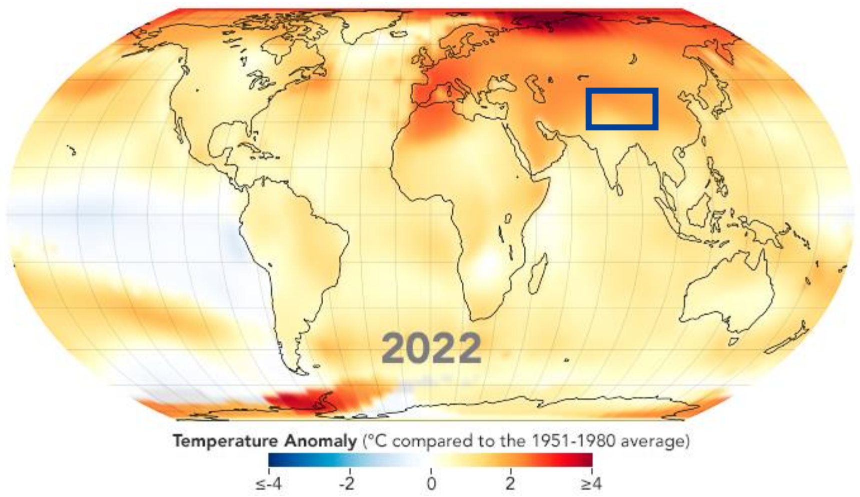
(IPCC, 2021)

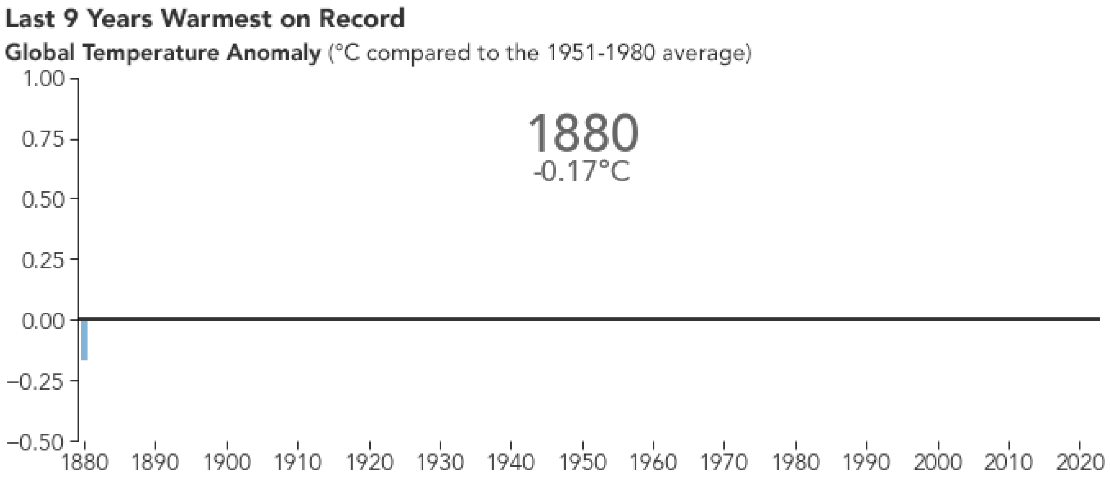
1 Introduction

1.1 Background and Significance

◆ Global Climate Change







(IPCC, 2021; NASA, 2023)

1 Introduction

1.1 Background and Significance

◆ **"Asian Water Tower" and "Yellow River Water Tower"**

● **"Asian Water Tower"**

● The highest independent land unit, most sensitive and fragile region to climate change

◆ Global "**engine**" and "**radiator**" for climate regulation

● **"Yellow River Water Tower"**

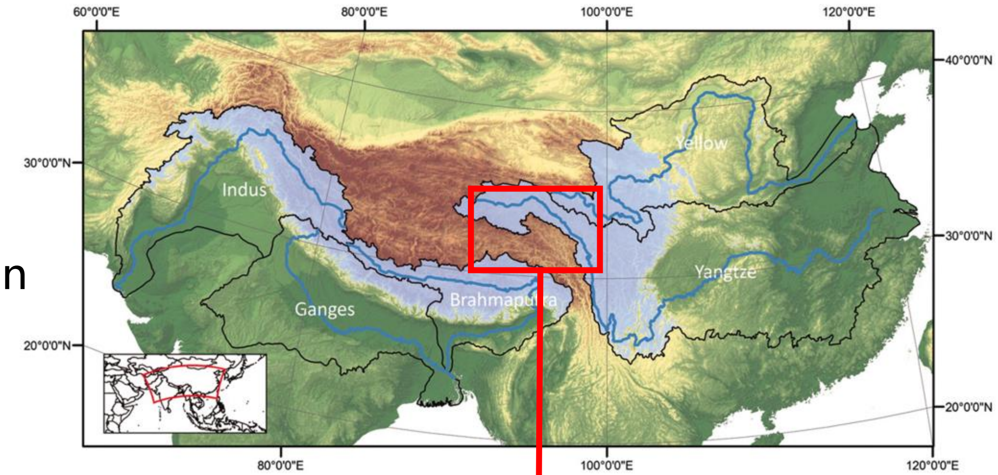
◆ **Climate**, **ecology**, and **hydrology** are undergoing significant changes

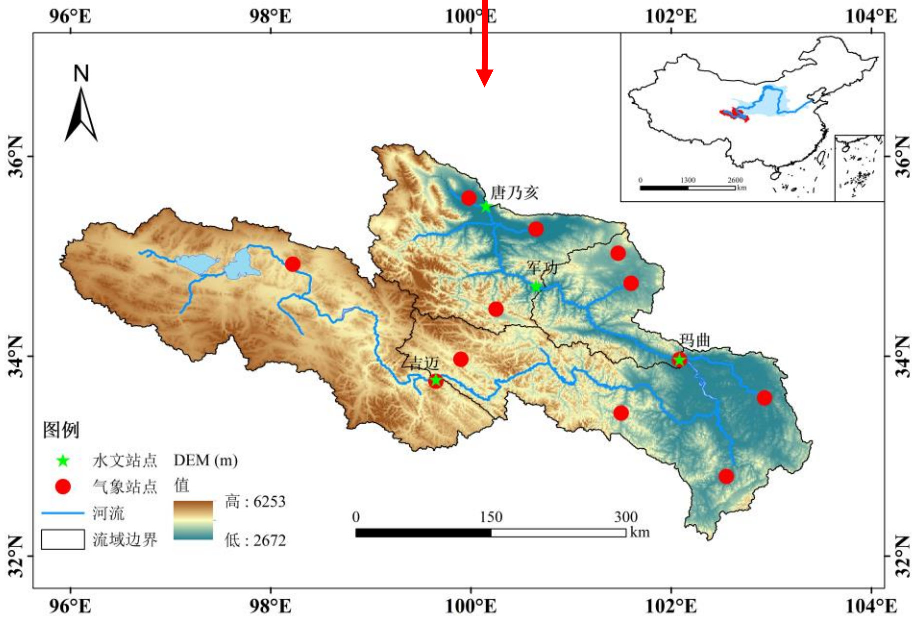
◆ The **warming** trend continues globally, with a larger-than-average increase in temperature in the region

◆ Yearly **precipitation** shows a clear increase, especially during the spring, summer, and winter seasons

◆ potential and actual **evapotranspiration** have shown an increasing trend

◆ **Runoff** exhibits an interdecadal cyclical variation of alternating wet and dry periods, with an overall decreasing trend





(Immerzeel et al., 2010)

1 Introduction

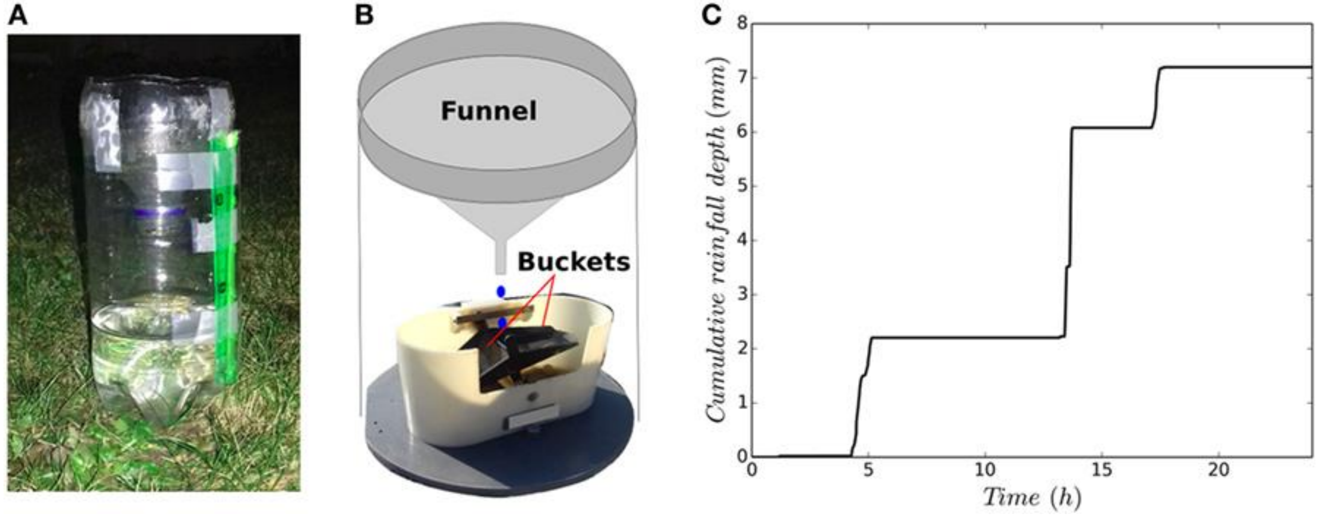
1.1 Background and Significance

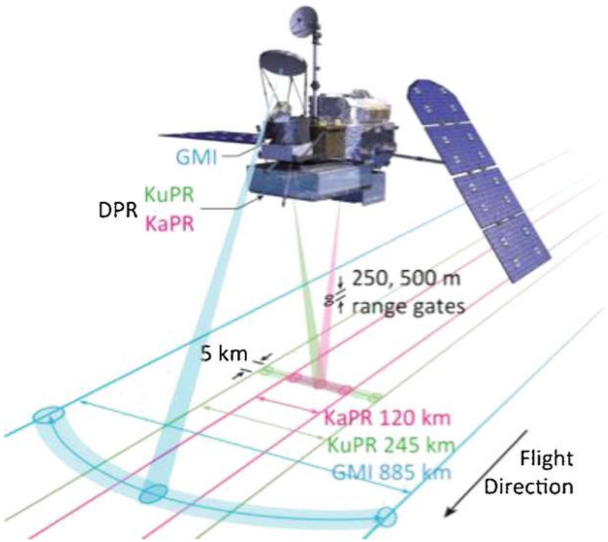
◆ Precipitation

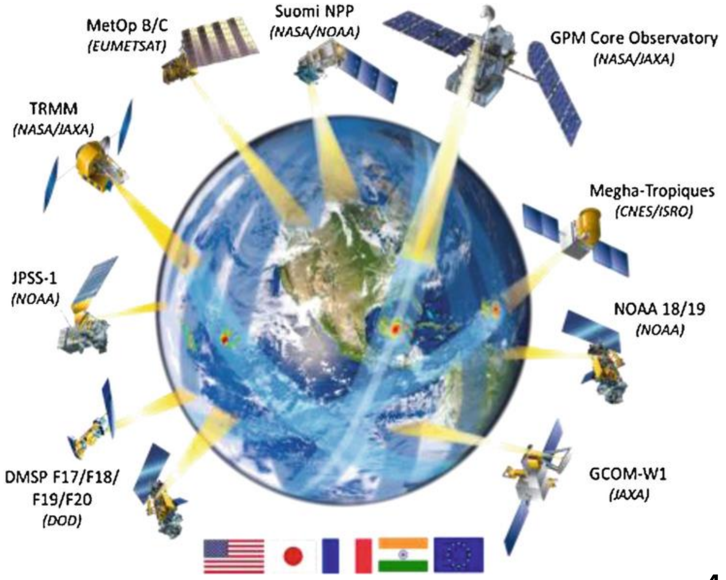
- ◆ An important **component** of the water cycle
- ◆ Accurate precipitation records and research on trends and variations are crucial for water resource management, weather forecasting, and **hydrological modeling**

● Precipitation Observation

- ◆ **Rain gauges** can provide relatively accurate and reliable point measurements of precipitation
- ◆ **Satellites** can provide global spatial coverage and more consistent time intervals for observation
- ◆ Many satellite-based observational methods have been implemented, using different methods to improve data acquisition by optimizing the global observation network



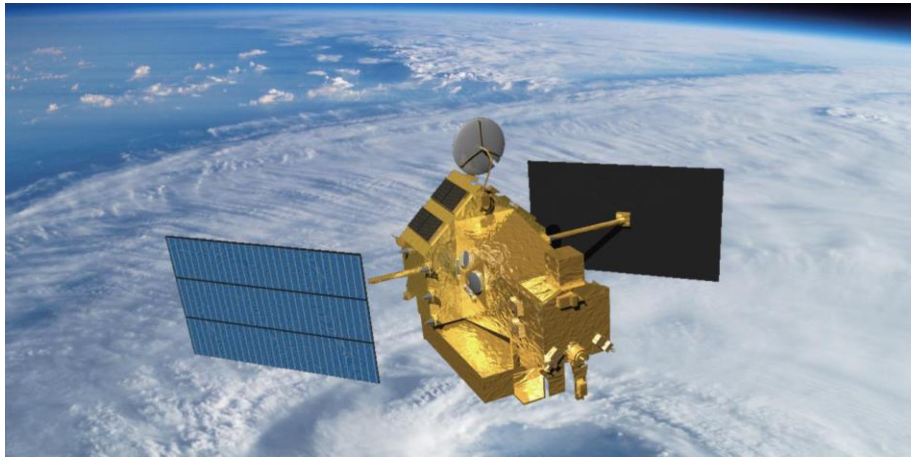




1 Introduction

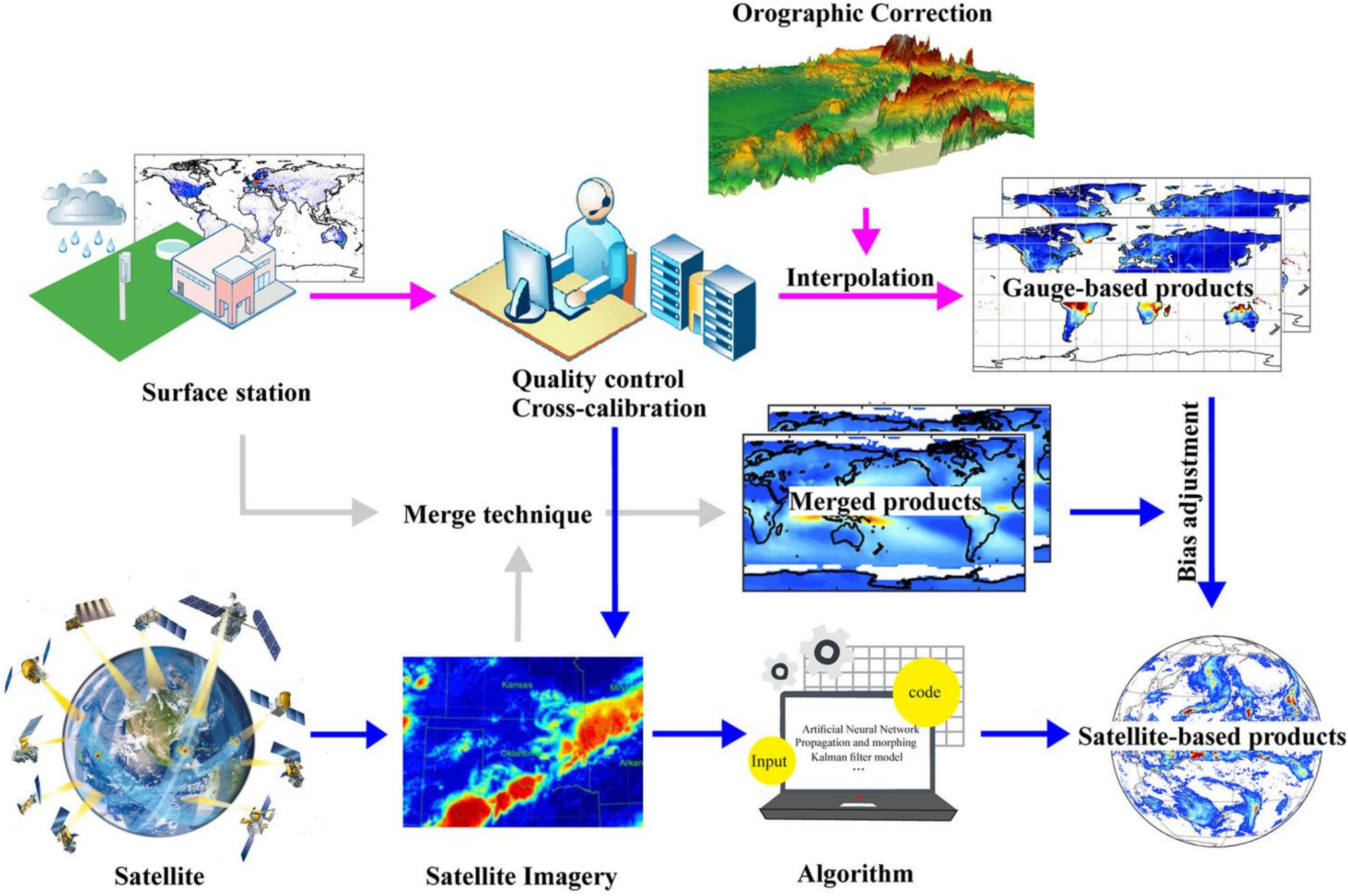
1.2.1 Development of Satellite Precipitation Products

◆ TRMM → GPM



Tropical Rainfall Measuring Mission (1997~2015)

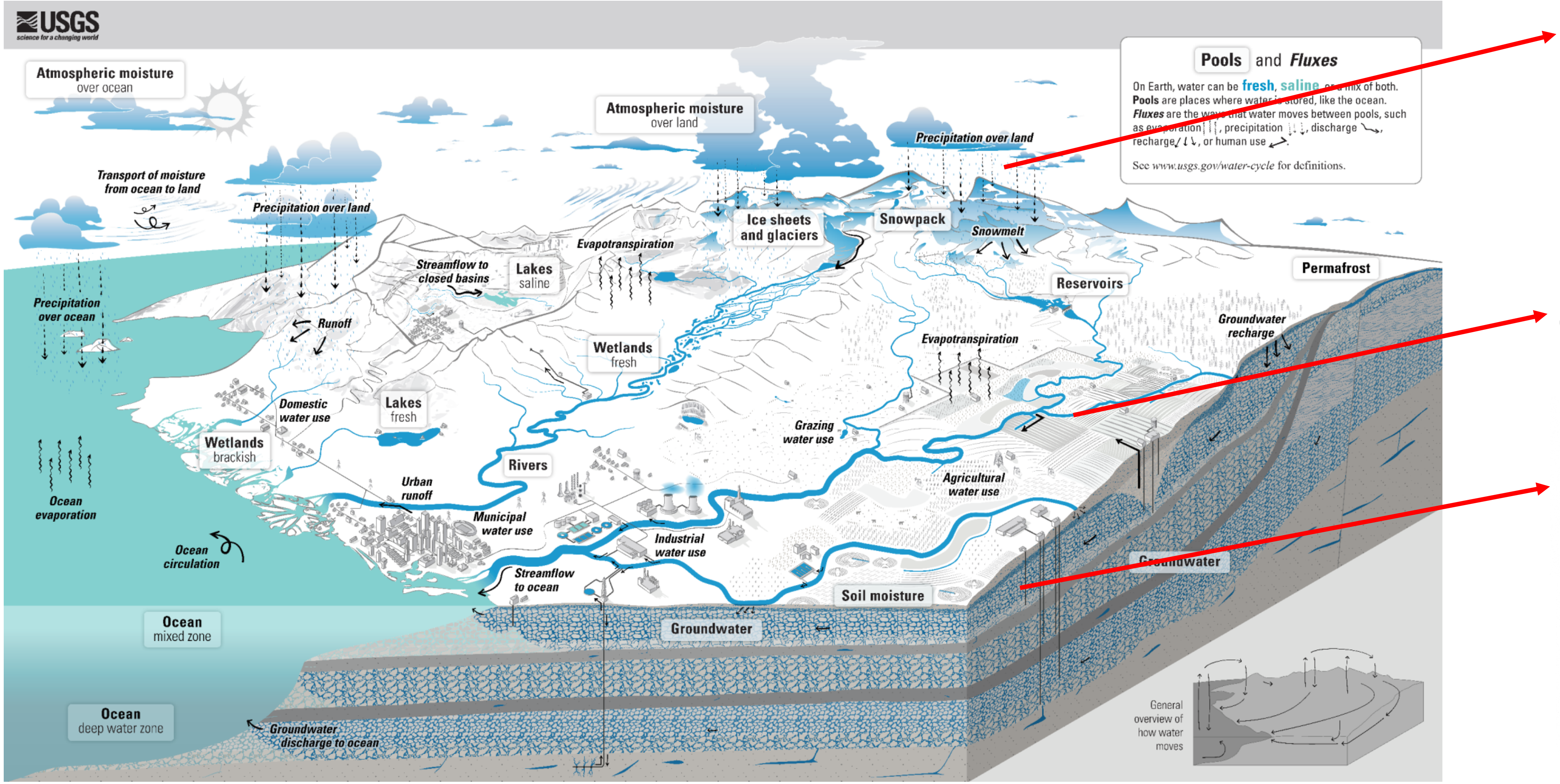
Global Precipitation Measurement (2014~present)

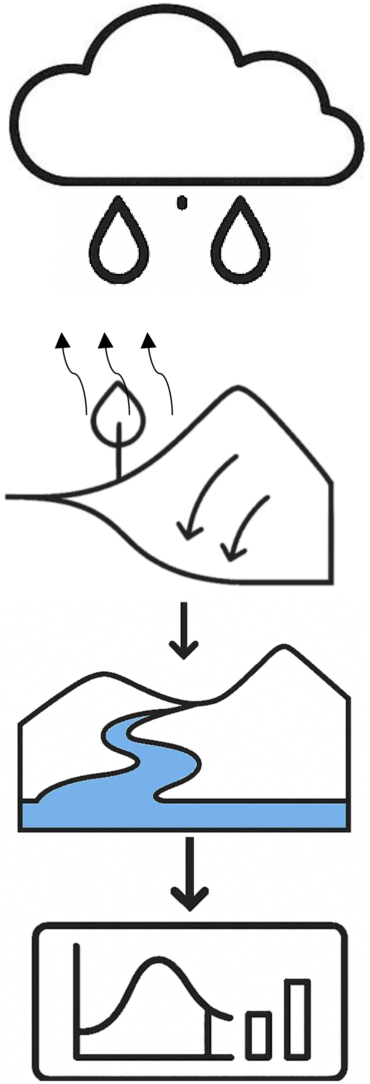


(Sun et al., 2017)

1 Introduction

1.2.2 Development of Hydrological Modeling

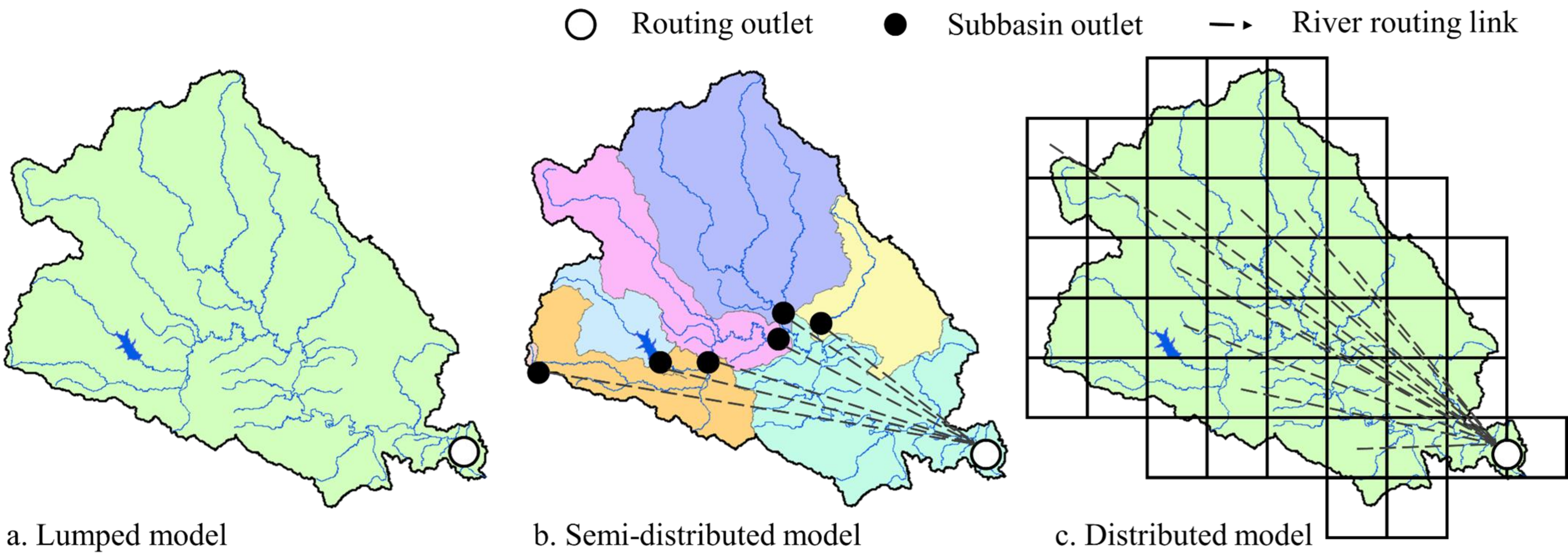




(USGS, 2022)

1 Introduction

1.2.2 Development of Hydrological Modeling

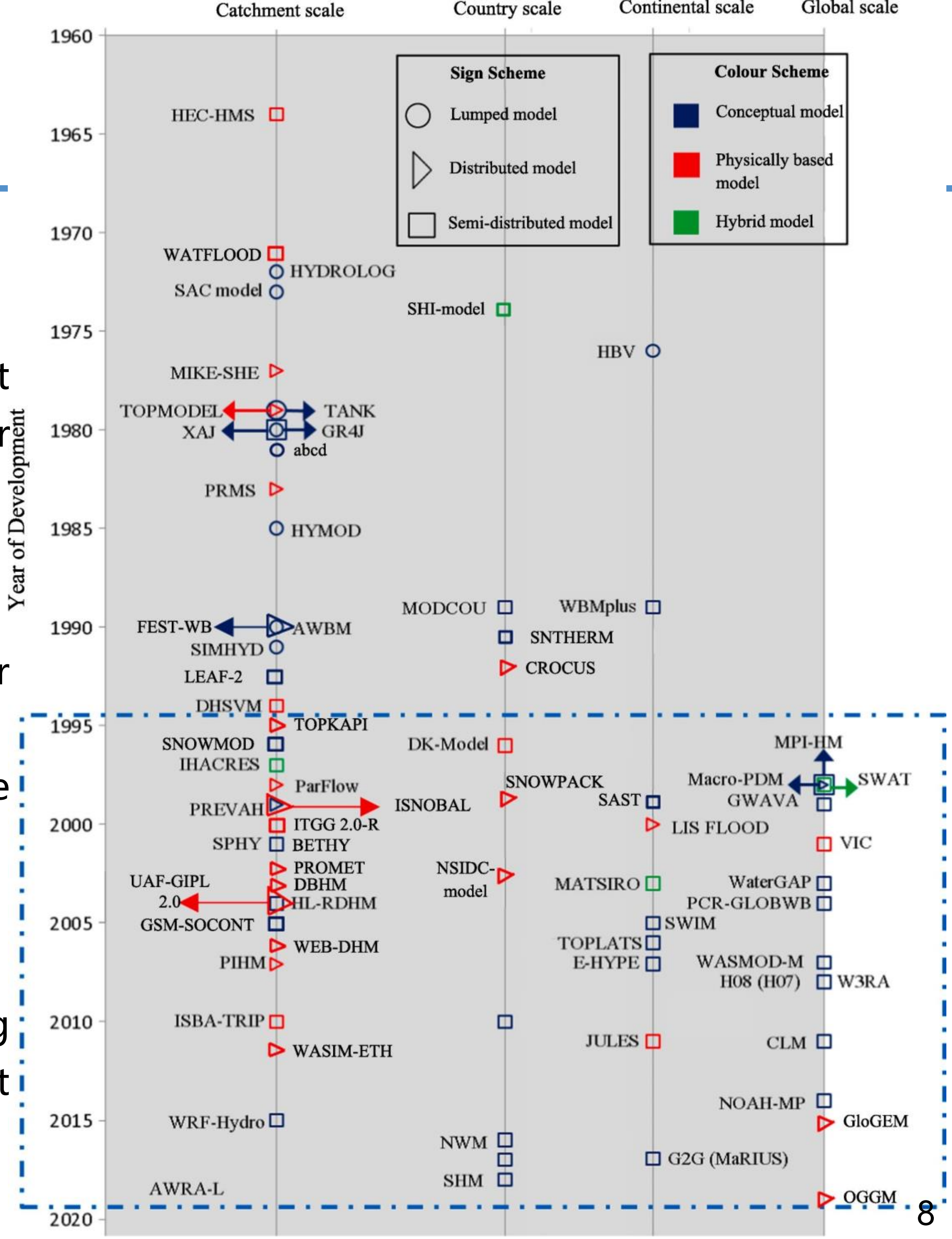


(Lin et al., 2022)

1 Introduction

1.2.2 Development of Hydrological Modeling

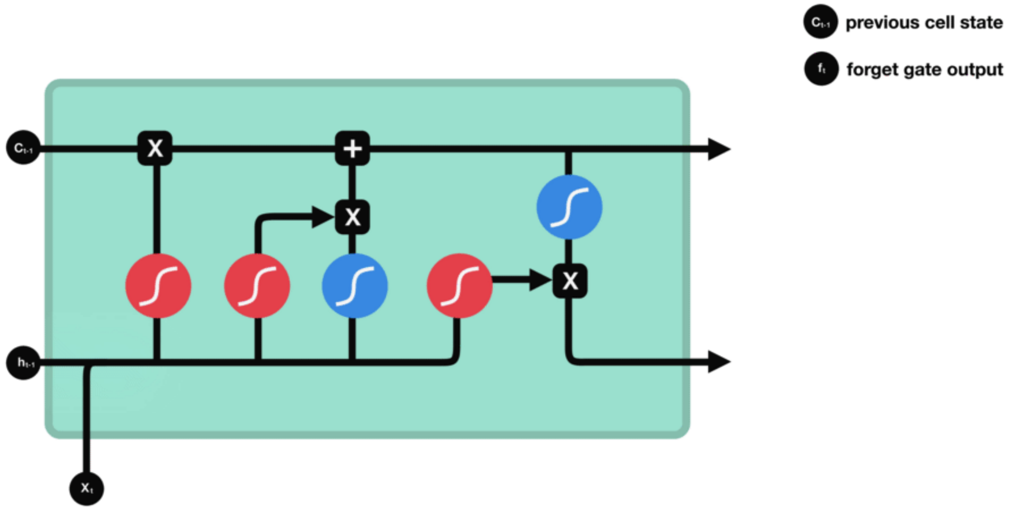
- **Lumped model**
- Simple in structure and **highly efficient in computation**, without considering the spatial distribution of input variables or parameters
- e.g. HBV、Tank、 SAC-SAM、GR4J etc.
- **Semi-distributed model**
- Divides the catchment area into **sub-basins** with similar characteristics
- Considers spatial variations in hydrological factors within the catchment area
- e.g. TOPMODEL、SWAT、TOPKAPI etc.
- **Distributed model**
- Considers spatial heterogeneity and performs detailed modeling of the hydrological process in each grid unit, with each unit having an independent response
- e.g. VIC、DHSVM、MIKE-SHE etc.

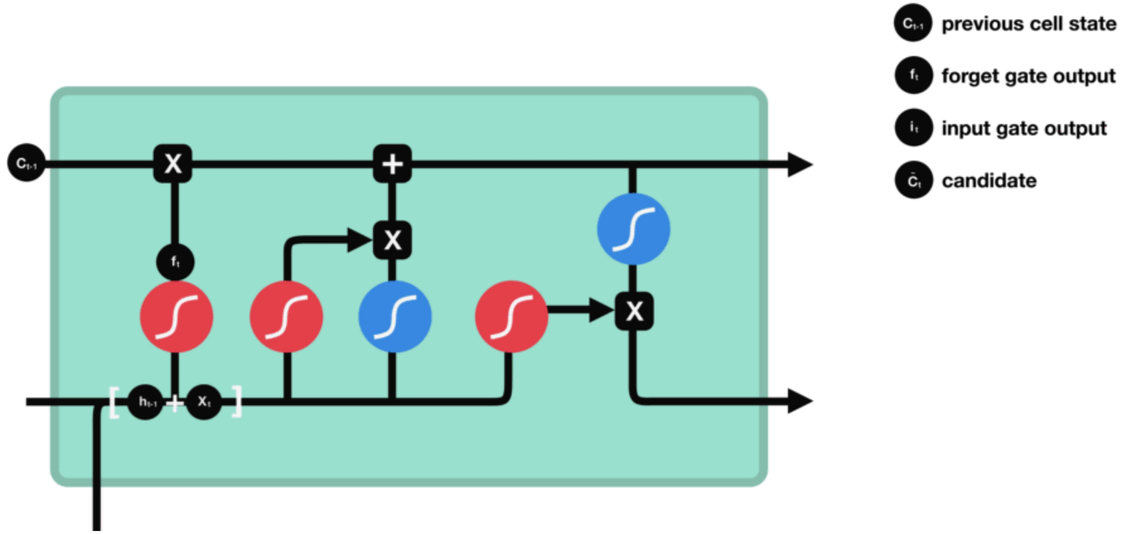


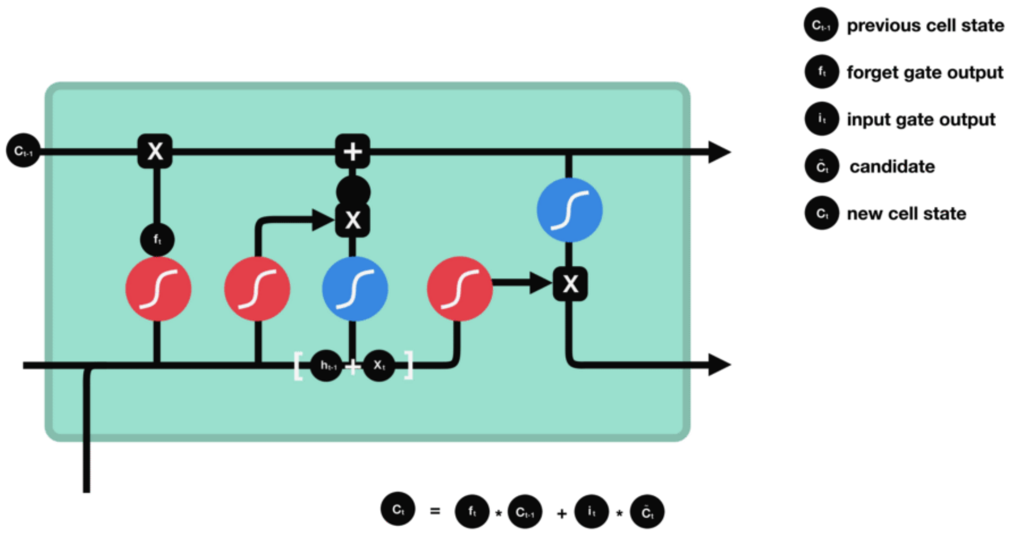
(Paul et al., 2021)

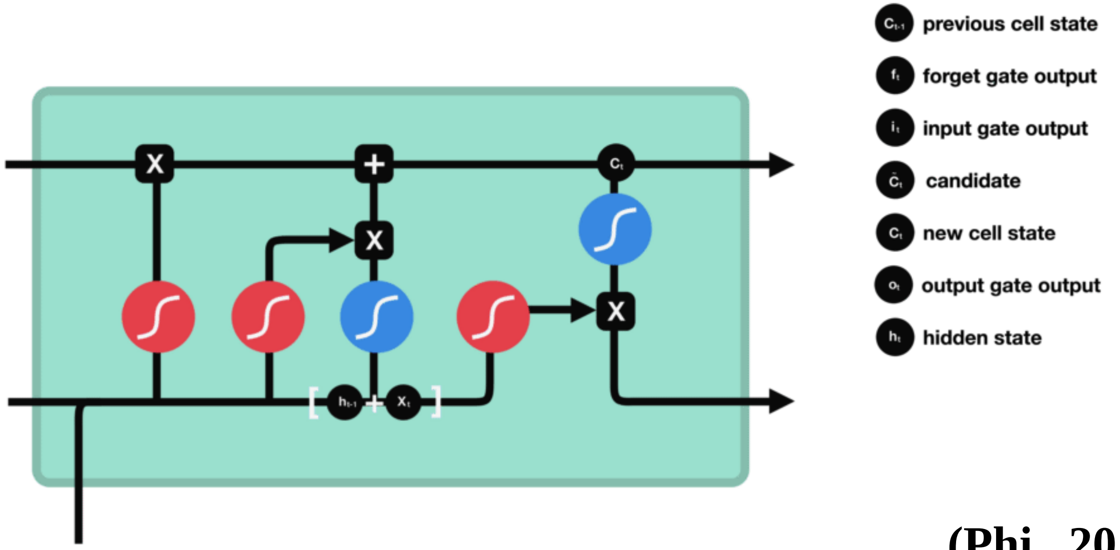
1 Introduction

1.2.3 LSTM hydrological simulation





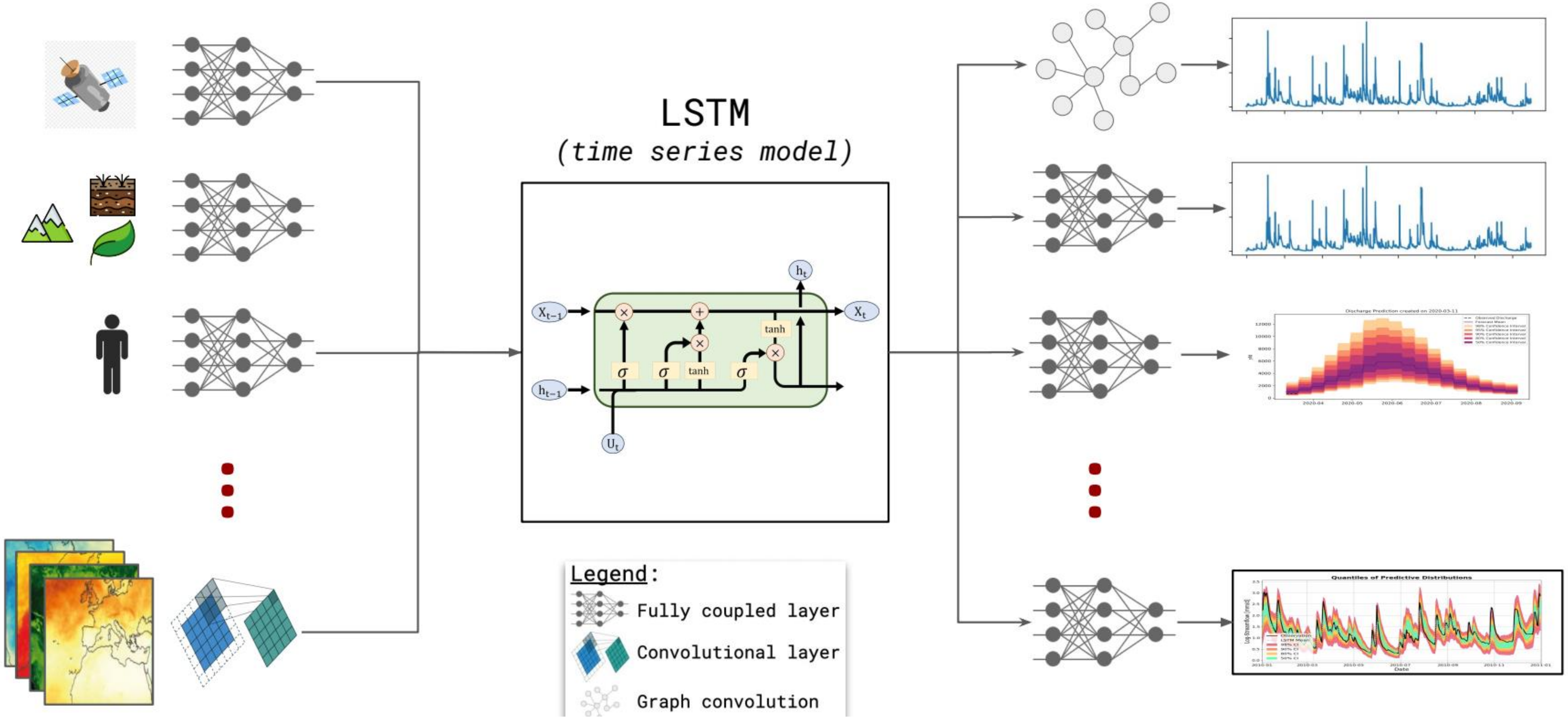




(Phi , 2018)

1 Introduction

1.2.3 LSTM hydrological simulation



(Kratzert et al., 2019)

1 Introduction

1.2.3 Development of Hydrological Modeling in the SRYR

S
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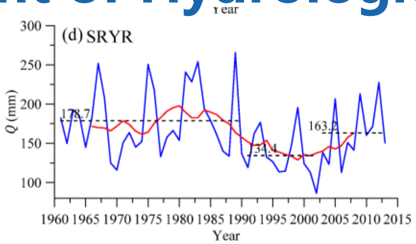
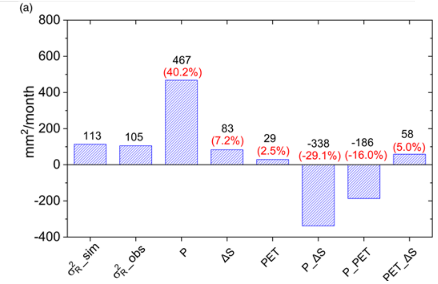
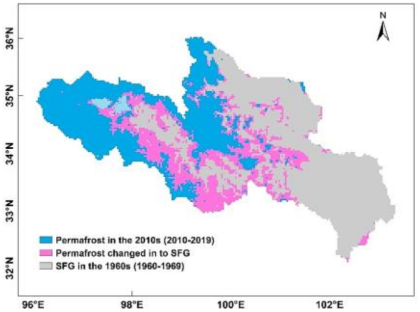
Runoff



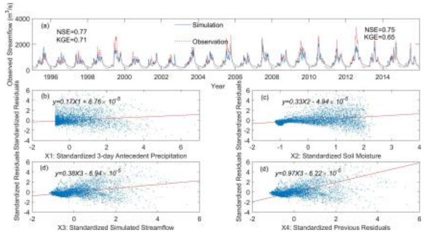
Precipitation



Frozen soil



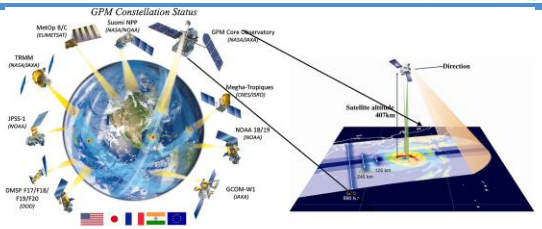
Hydrological modeling

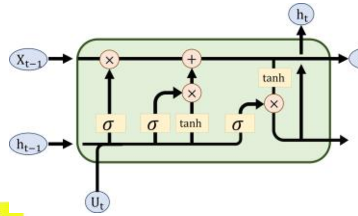


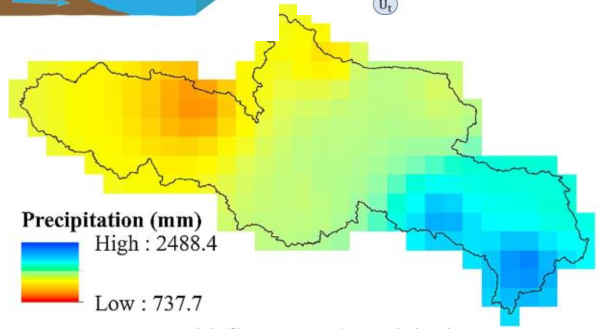
Lack of analysis on the impact of precipitation distribution on runoff simulation

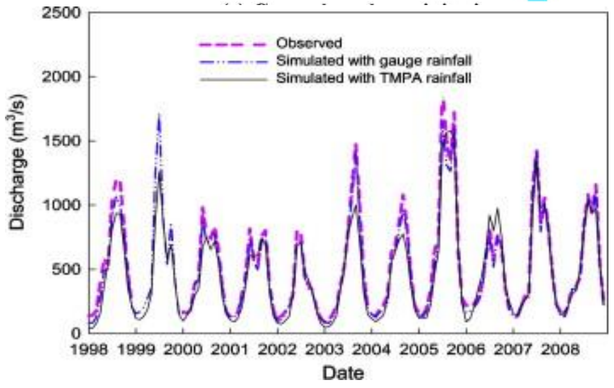
Lack of use of the latest SPPs

Lack of comparison between traditional hydrological models and data-driving models for hydrological simulation





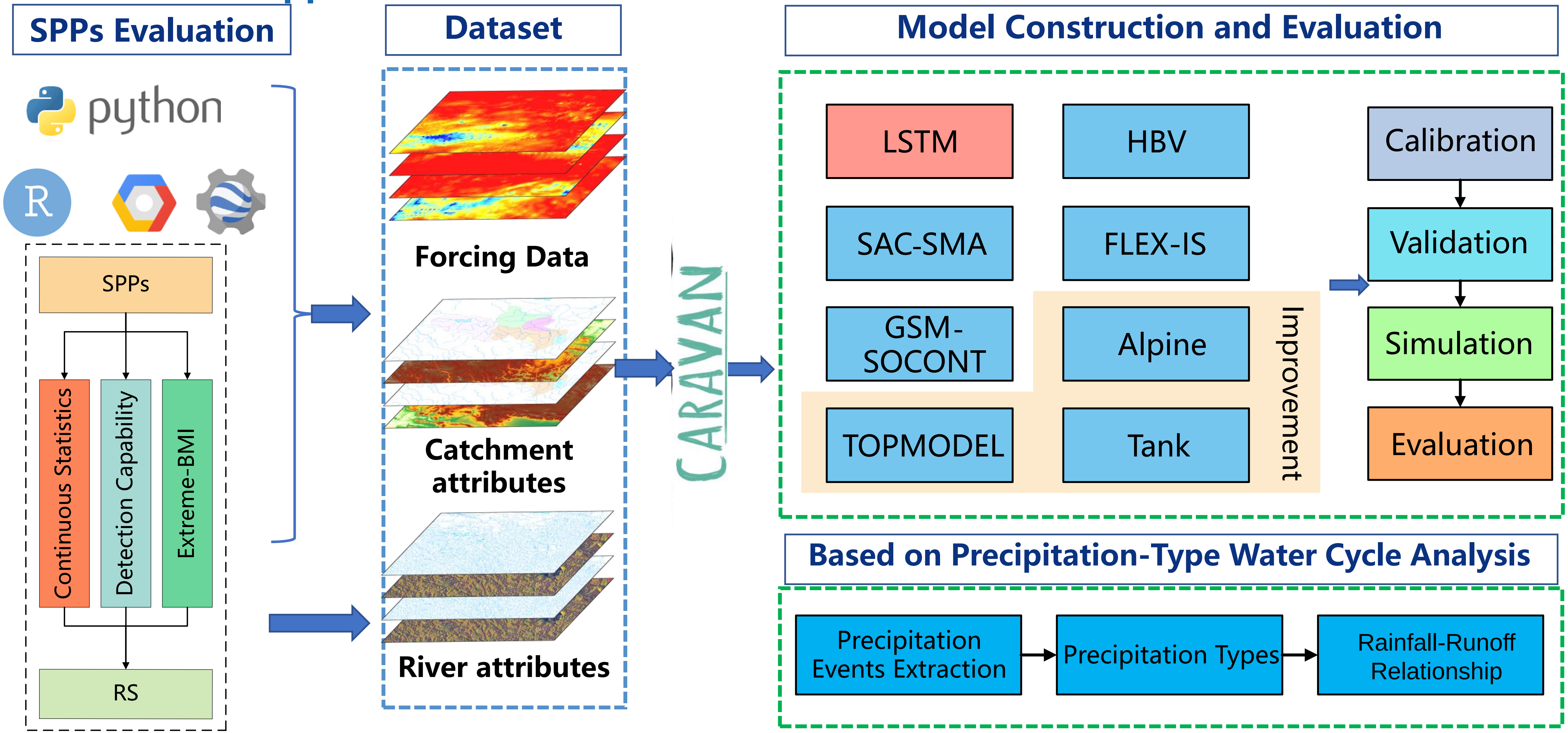




(Li et al., 2021; Xie et al., 2021; Yang et al., 2023)

1 Introduction

1.3 Research Approach



Outline

2 Study Area and Data

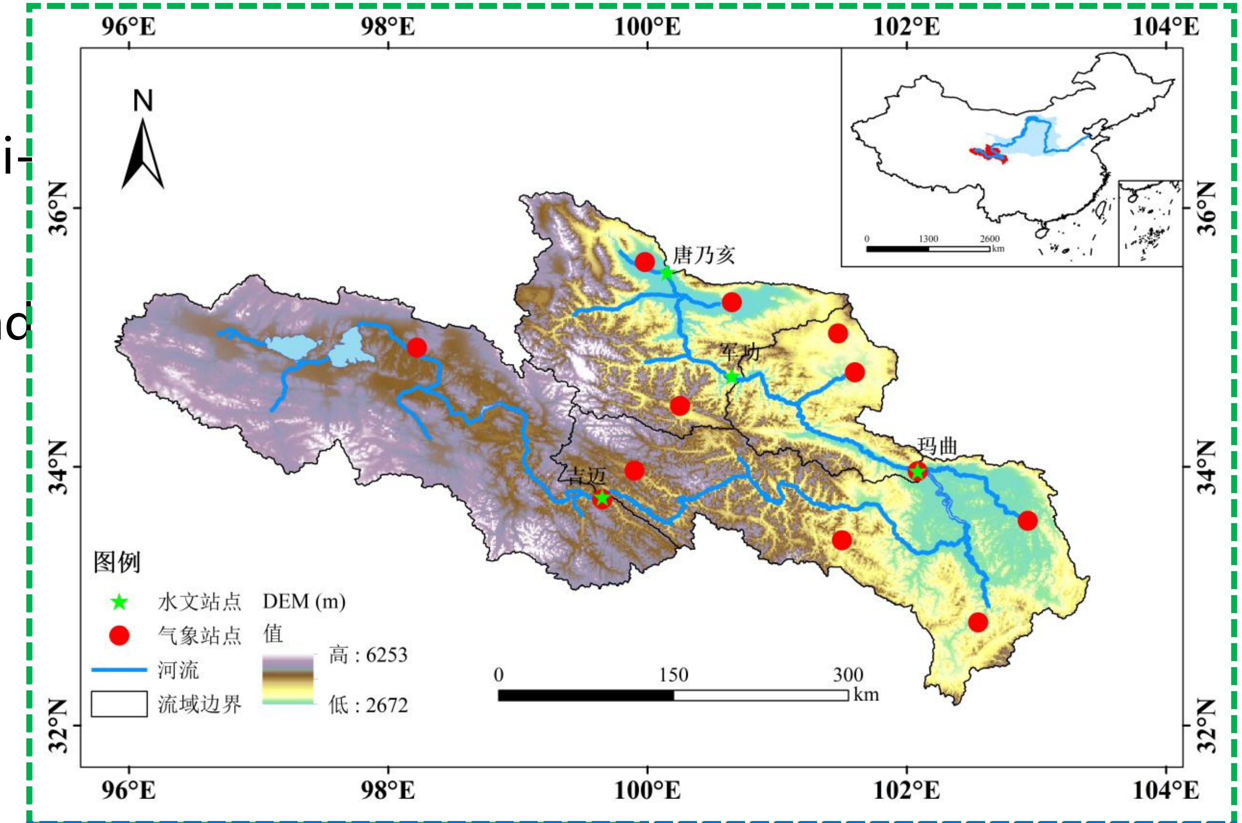
2.1 Study area

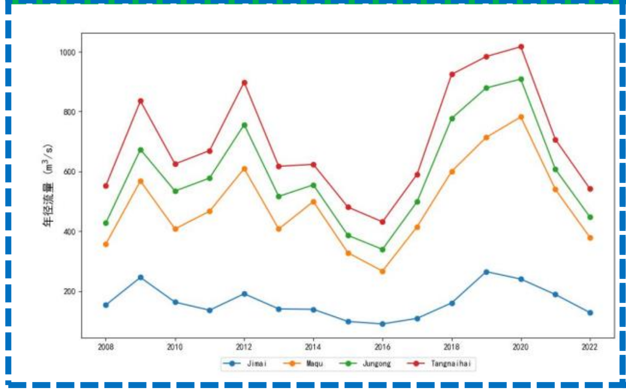
- ◆ Located in the northeastern part of the Qinghai-Tibet Plateau
- ◆ The terrain is generally lower in the west and higher in the east
- ◆ The average altitude is around 4000 meters
- ◆ Area : $1.22\times10^{5}km^{2}$

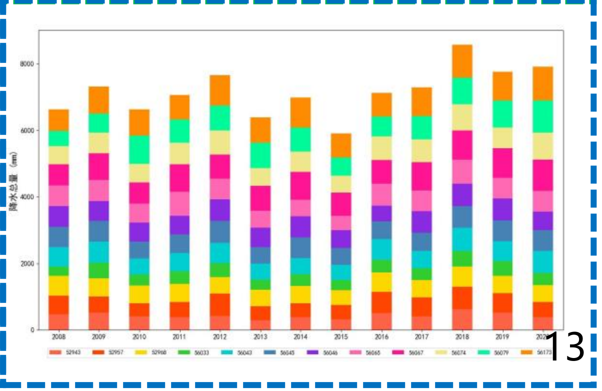
2.2 Data

◆ Ground Station Observation Data

- ● Meteorological data: From 2000 to 2020, covering 12 meteorological stations
- ● Streamflow data: From 2008 to 2022, covering the four hydrological stations







2 Study Area and Data

2.2 Data

◆ SPPs

The use of various SPPs such as CHIRPS, CMORPH, GSMaP, IMERG, MSWEP, PERSIANN, and TMPA for daily precipitation data from **2000 to 2020**

◆ Other Data

HydroATLAS and **ERA5-Land**, from 2008 to 2022, for constructing the Caravan dataset

Table 2-1 Description of 15 SPPs

SPPs	Abbreviation	Resolution	Period
CHIRPS	CHI	0.05° /1 d	1981.01~present
CMORPH-BLD	CMD	0.25° /1 d	1998.01~present
CMORPH-CRT	CMT	0.25° /1 d	1998.01~present
GSMaP-Gauge	GaG	0.1° /1 d	2000.03~present
GSMaP-MVK	GaM	0.1° /1 d	2014.03~present
GSMaP-NRT	GaN	0.1° /1 d	2000.03~present
IMERG-Early	IME	0.1° /1 d	2000.06~present
IMERG-Final	IMF	0.1° /1 d	2000.06~present
IMERG-Late	IML	0.1° /1 d	2000.06~present
MSWEP	MSP	0.1° /1 d	1979.01~present
PERSIANN-CCS	PCS	0.04° /1 d	2003.01~present
PERSIANN-CDR	PDR	0.25° /1 h	1983.01~present
PDIR-Now	PDI	0.04° /1 d	2000.03~present
TMPA-3B42	TM	0.25° /1 d	1998.01-2019.12
TMPA-3B42RT	TMT	0.25° /1 d	2000.03-2019.12

Outline

3 SPPs Comprehensive and Quantitative Evaluation

3.1 Methodology

Step1

Continuous Statistics

$$CC = \frac{\sum_{i=1}^{n}(G_i - \overline{G})(S_i - \overline{S})}{\sqrt{\sum_{i=1}^{n}(G_i - \overline{G})^2 \sum_{i=1}^{n}(S_i - \overline{S})^2}}$$

$$RE = \frac{1}{n}\sum_{i=1}^{n}\frac{S_i - G_i}{G_i}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_i - G_i)^2}$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(G_i - S_i)^2}{\sum_{i=1}^{n}(G_i - \overline{G})^2}$$

$$KGE = 1 - \sqrt{(1 - CC)^2 + \mathrm{RE}^2 + (1 - \frac{SD_S}{SD_G})^2}$$

Detection Capability

$$POD = \frac{H}{H + M}$$

$$FAR = \frac{F}{H + F}$$

$$CSI = \frac{H}{H + M + F}$$

Extreme-BMI

- PRCPTOT
- SDII
- RX5
- R95
- R99

$$I = \frac{N\sum_{i=1}^{N}\sum_{j\neq i}^{N}\omega_{ij}Z_i^G Z_i^S}{(N-1)\sum_{i=1}^{N}\sum_{j\neq i}^{N}\omega_{ij}}$$

Step2

$$RS_i = \begin{cases} \dfrac{m_i - m_{min}}{m_{max} - m_{min}}, & \text{positive} \\ 1 - \dfrac{m_i - m_{min}}{m_{max} - m_{min}}, & \text{negative} \end{cases}$$

→ CC, POD , CSI , NSE , KGE , Bivariate Moran's I

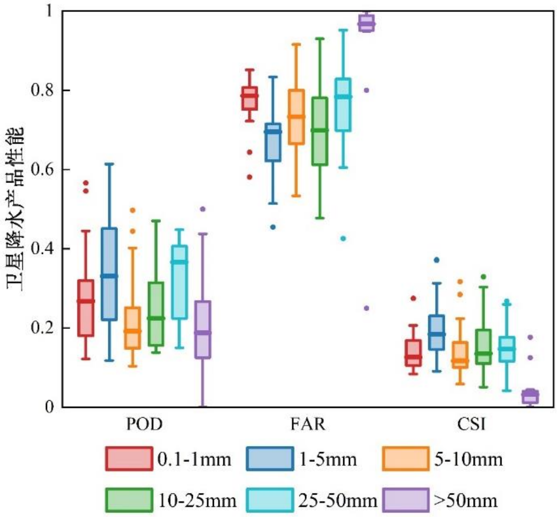
→ RMSE、FAR、RE

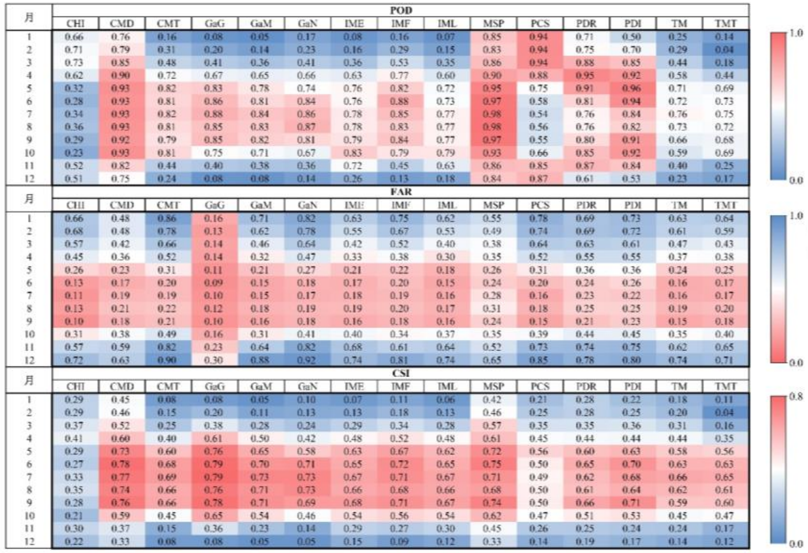
3 SPPs Comprehensive and Quantitative Evaluation

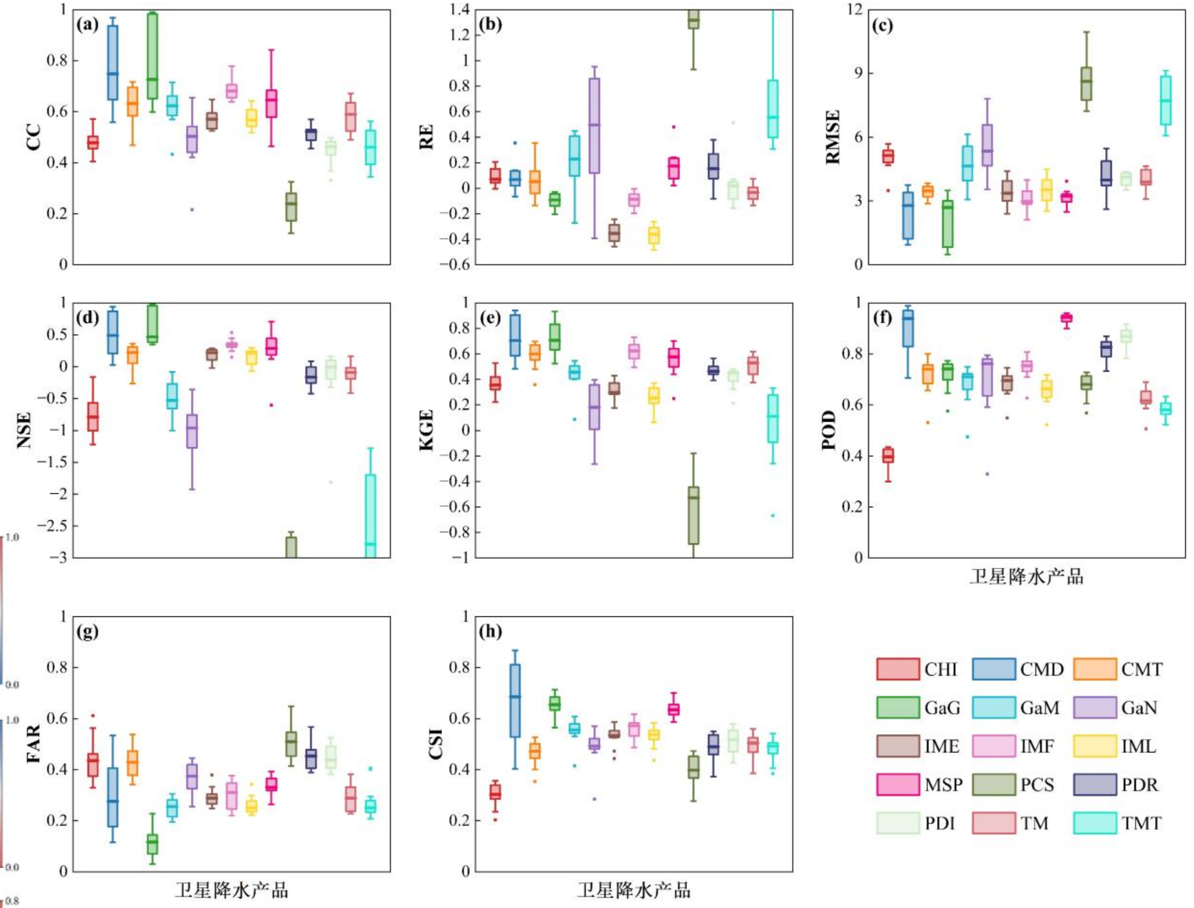
3.2 Comprehensive Quantitative Evaluation of SPPs

◆ Statistics Metrics

- **CMD**, **GaG** and **IMF** show superior performance on all continuous statistical indicators compared to other SPPs
- **CMD** , **GaG** and **MSP** exhibit better precipitation detection capability
- SPPsare stronger in detecting precipitation during the **rainy** season and weaker during the **dry** season
- SPPs generally perform similarly under different precipitation intensities





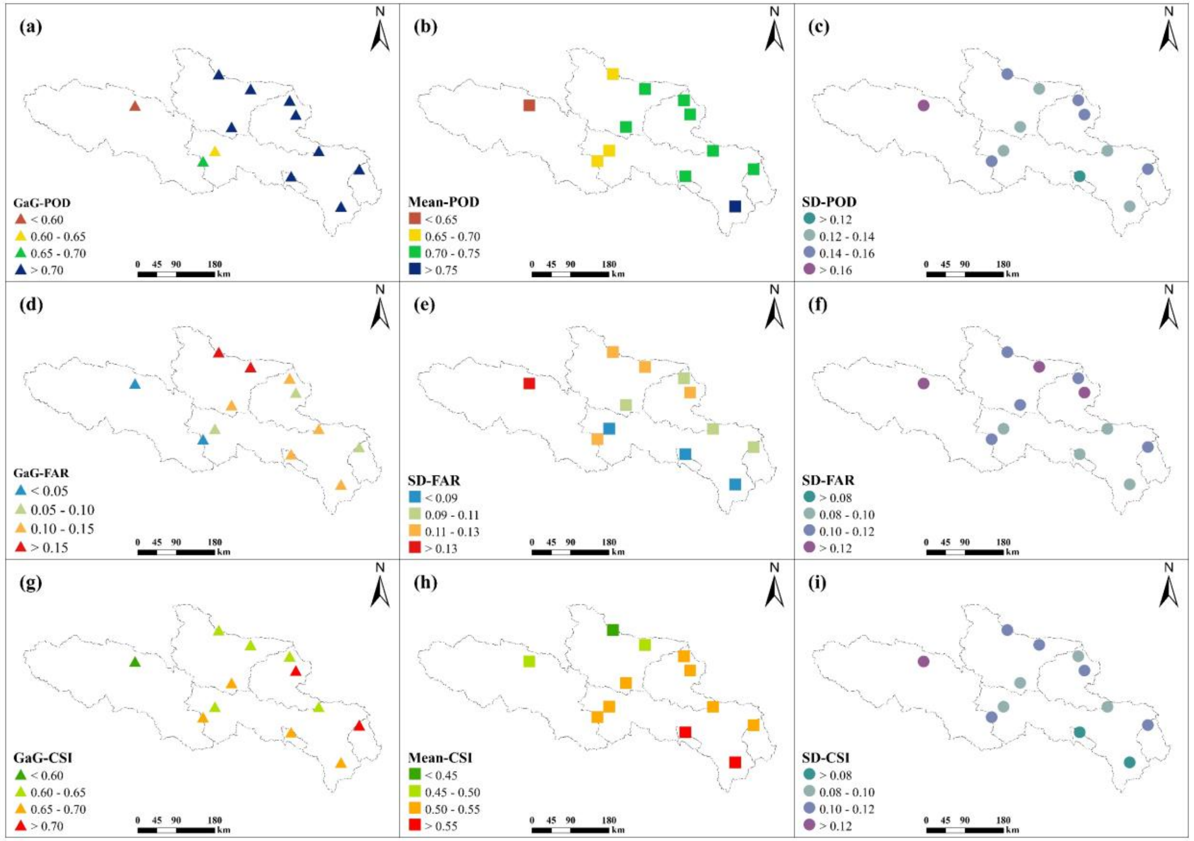


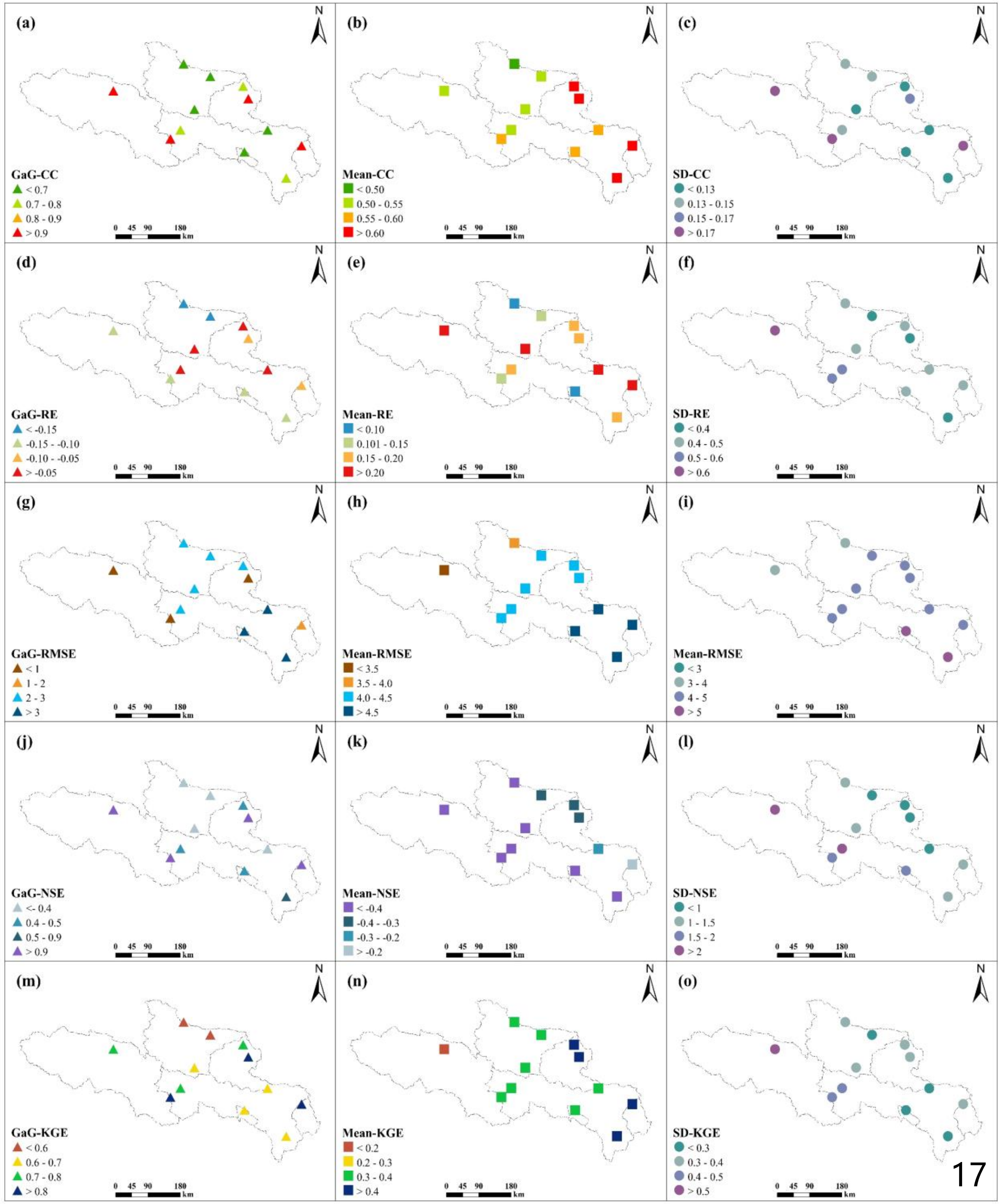
3 SPPs Comprehensive and Quant

3.2 Comprehensive Quantitative Evaluation of SPPs

◆ Spatial Distribution of Statistical Metrics

In the SRYR, many SPPs show weak performance in the **western** area, with **stronger** performance at the eastern stations, which are more densely located





3 SPPs Comprehensive and Quantitative Evaluation

3.2 Comprehensive Quantitative Evaluation of SPPs

◆ **Extreme Precipitation Index BMI and Comprehensive and Quantitative Evaluation**

- SPPs showed patterns of extreme precipitation distribution across the surface
- **IMF** showed the strongest spatial correlation with ground observations of extreme precipitation
- Based on continuous statistics, precipitation detective and the BMI of extreme precipitation indices, **IMF** demonstrates superior performance, with an RSA value greater than 0.85

Table3-1 Extreme precipitation index BMI

SPPs	PRCPTOT	SDII	RX5	R95	R99
GaN	**0.45**	0.37	0.42	0.47	0.53
IME	0.44	0.52	**0.51**	0.55	0.57
IMF	0.43	0.41	0.40	**0.66**	**0.63**
IML	0.44	**0.52**	0.50	0.53	0.55

Table 3-2 Comprehensive and Quantitative Evaluation

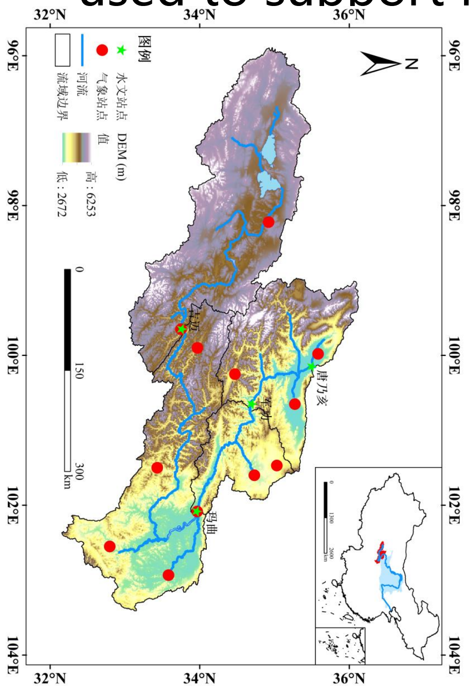
SPPs	RSC	RSD	RSE	RSA
CHI	0.69	0.07	0.75	0.57
CMD	0.98	0.81	0.71	0.83
CMT	0.87	0.42	0.74	0.72
GaG	**0.99**	**0.86**	0.49	0.77
GaM	0.75	0.64	0.84	0.76
GaN	0.58	0.49	0.86	0.67
IME	0.76	0.58	0.96	0.80
IMF	0.90	0.64	**0.93**	**0.85**
IML	0.75	0.59	0.95	0.79
MSP	0.86	0.80	0.16	0.58
PCS	0.00	0.26	0.35	0.19
PDR	0.76	0.48	0.75	0.69
PDI	0.75	0.54	0.21	0.49
TM	0.81	0.51	0.64	0.68
TMT	0.37	0.49	0.61	0.49

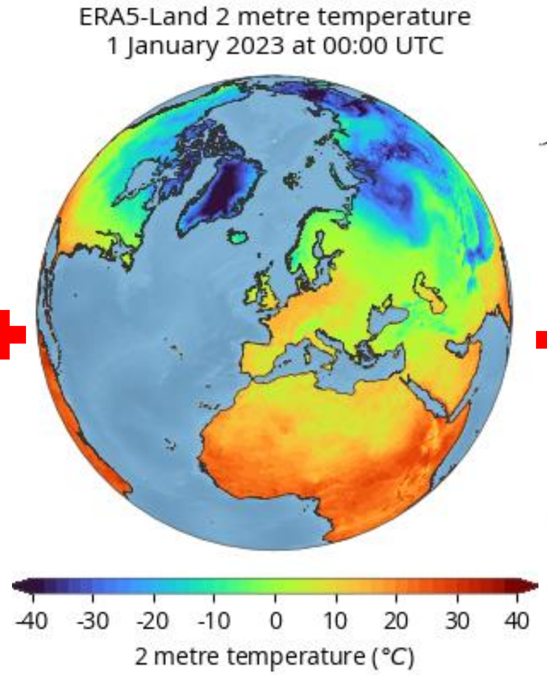
3 SPPs Comprehensive and Quantitative Evaluation

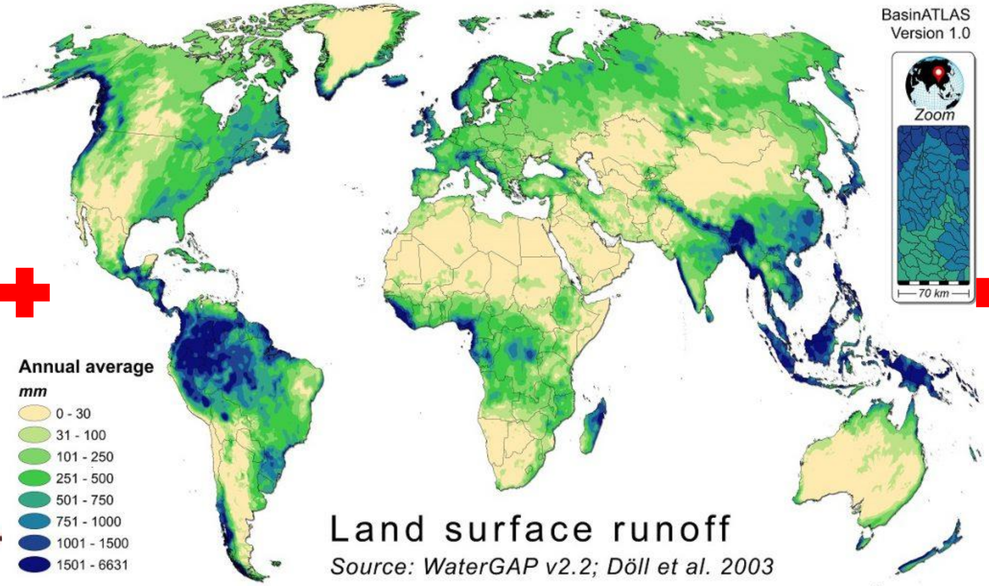
3.3 Caravan-SRYR Hydrological Dataset

Caravan is a global hydrological community dataset that uses publicly available global data such as ERA5-Land and HydroATLAS, which provide climate forcing data and hydrological characteristic data support

This research extends the Caravan dataset to the SRYR. The data from 2008 to 2022 will be used to build the Caravan-SRYR dataset, which will be used to support hydrological modeling







Google Earth Engine

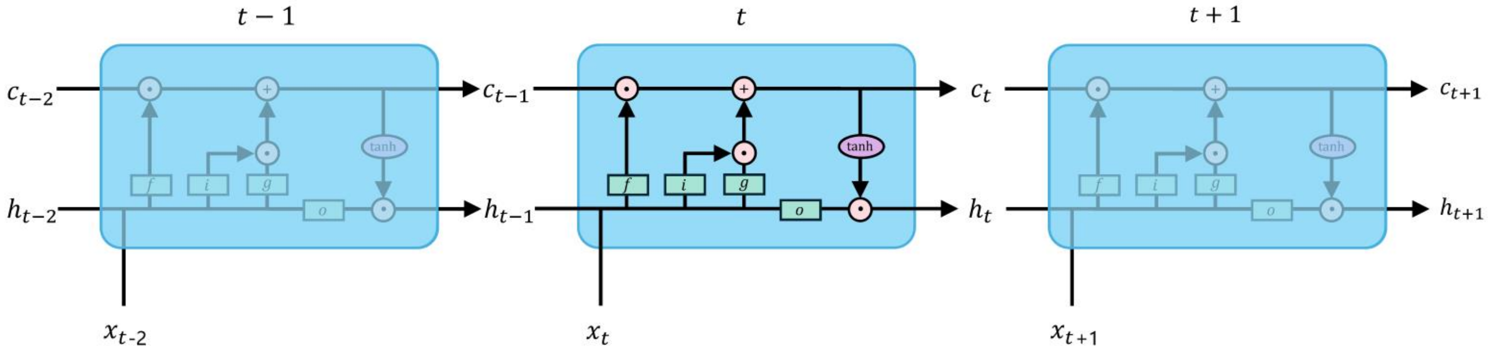
Outline

4 Rainfall-Runoff Modeling Based on Deep Learning

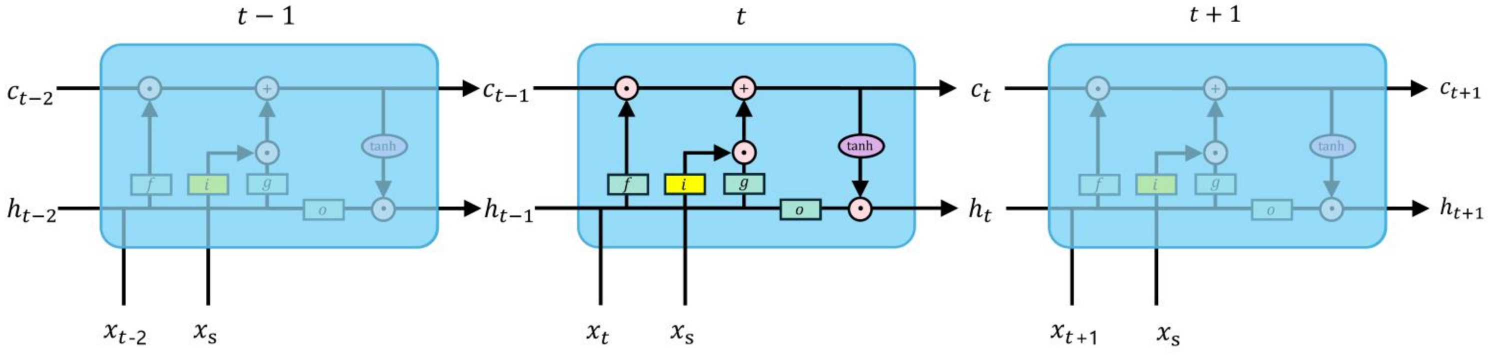
4.1 Methodology

◆ CudaLSTM and EA-LSTM

CudaLSTM



EA-LSTM



$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i)$$

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f)$$

$$g_t = \tanh\left(W_g x_t + U_g h_{t-1} + b_g\right)$$

$$o_t = \sigma(W_o x_t + U_o + b_o)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t$$

$$h_t = o_t \odot \tanh\left(c_t\right)$$

$$i_t = \sigma(W_i x_s + b_i)$$

4 Rainfall-Runoff Modeling Based on Deep Learning

4.1 Methodology

◆ Hyperparameters and Training Data

Based on the data from four hydrological stations in the Caravan-SRYR, the **CudaLSTM** and **EA-LSTM** models were trained. The models were then optimized by adjusting the hyperparameters through grid search methods

Table 4-1 Hyperparameters of the LSTM Model in the SRYR

No	LSTM Hyperparameter		Range	Value
1	Initial input gate value		-3, -1, 0, 1, 3	3
2	dropout		0.1, 0.2, 0.3, 0.4, 0.5, 0.6	0.4
		Lr0	1e-3, 1e-2, 5e-2	0.01
3	Learning rate	Lr30	5e-4, 1e-3, 5e-3	0.005
		Lr40	1e-4, 1e-3	0.001
4	Batch size		32, 64, 128, 256	256
5	Hidden size		20, 30, 40, 50	20
6	epochs		20, 30, 40, 50	50
7	Sequence length		146, 182, 365, 730, 1095	365

Table 4-2 Data Used for LSTM Training

Data type	Variable	Description
Meteorological forcing data	precipitation_IMF	Daily precipitation (mm)
	potential_evaporation	Daily potential evaporation (mm)
	temperature_2m_mean	Daily mean temperature (°C)
	temperature_2m_max	Daily max temperature (°C)
	temperature_2m_min	Daily min temperature (°C)
Static catchment attributes	area	Area (km^2)
	elev_mean	Average elevation (m)
	p_mean	Mean daily precipitation (mm)
	pet_mean	Mean daily potential evaporation (mm)
	aridity	Aridity index, ratio of mean PET and mean precipitation
	frac_snow	Fraction of precipitation falling as snow
	moisture_index	Mean annual moisture index
	seasonality	Moisture index seasonality
	high_prec_freq	Frequency of high precipitation days, where precipitation ≥5 times mean daily precipitation
	low_prec_freq	Frequency of low precipitation days, where precipitation <1 mm/d
	high_prec_dur	Average duration of high precipitation events (d)
	low_prec_dur	Average duration of low precipitation events (d)

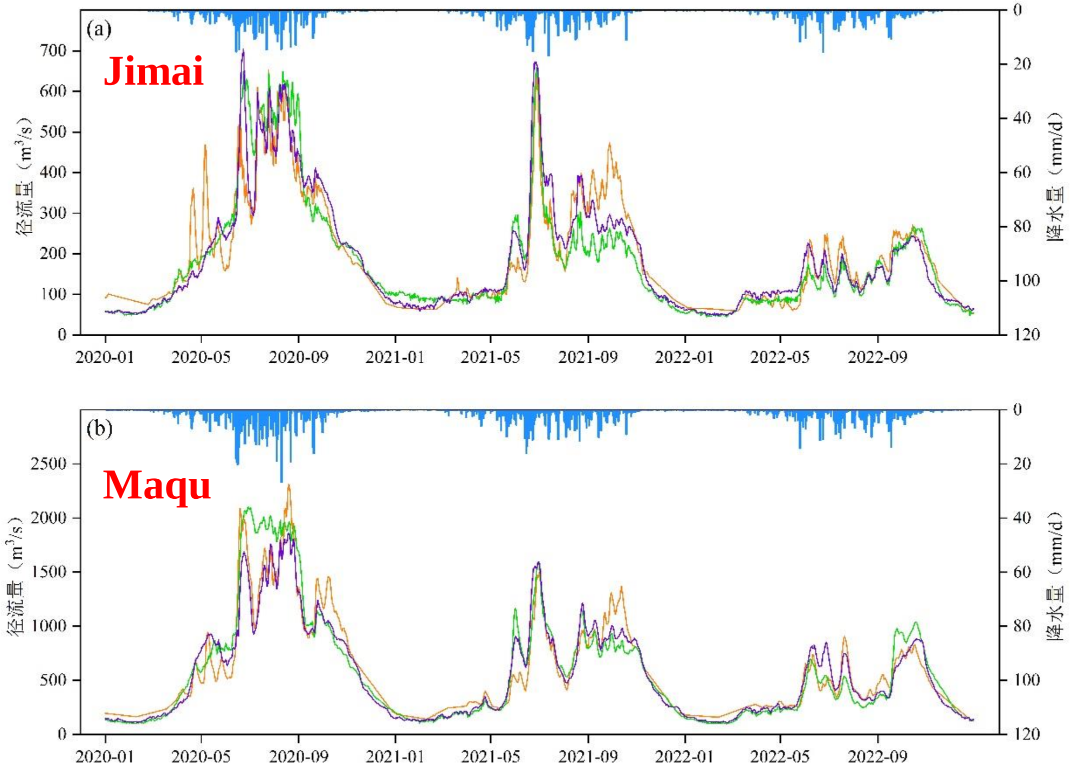
4 Rainfall-Runoff Modeling Based on Deep Learning

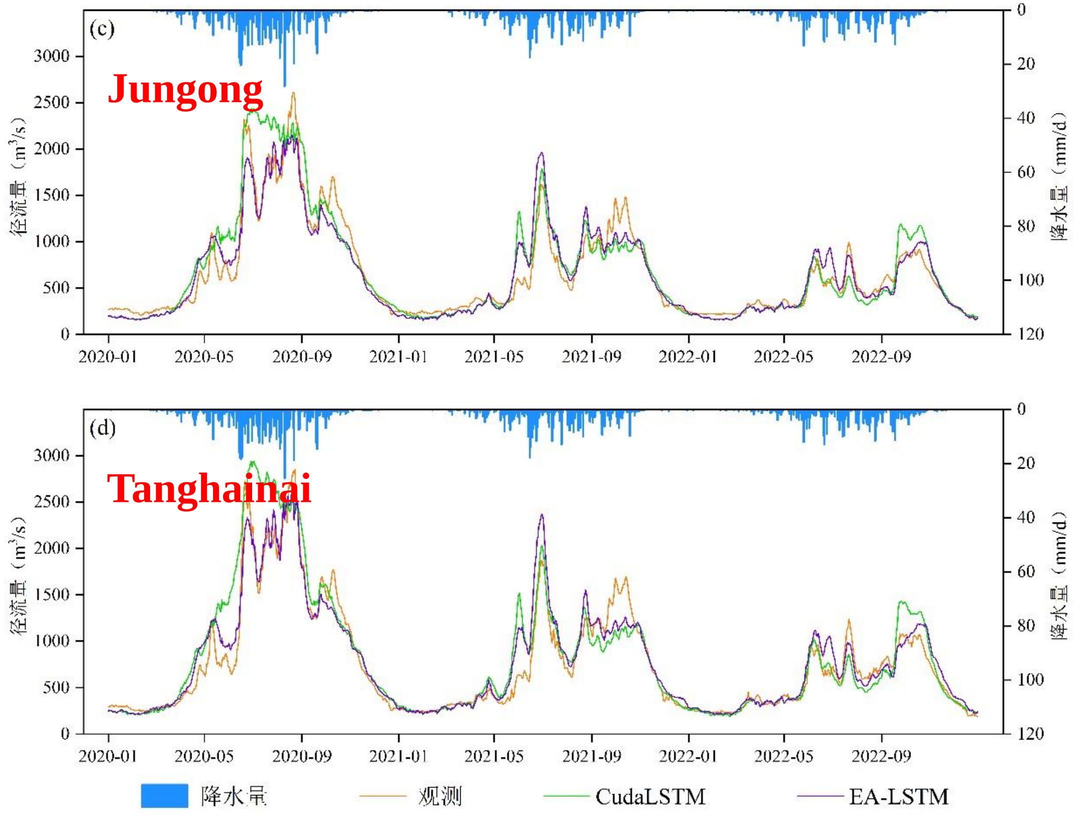
4.2 LSTM Model for Rainfall-Runoff Simulation

The EA-LSTM performed better by leveraging the spatial features of the catchment region and more accurately identifying the relationship between precipitation and runoff. At the Tangnaihai station, EA-LSTM achieves an NSE value of 0.92, while CudaLSTM only reaches 0.79

Table 4-3 Performance of LSTM Models in the SRYR

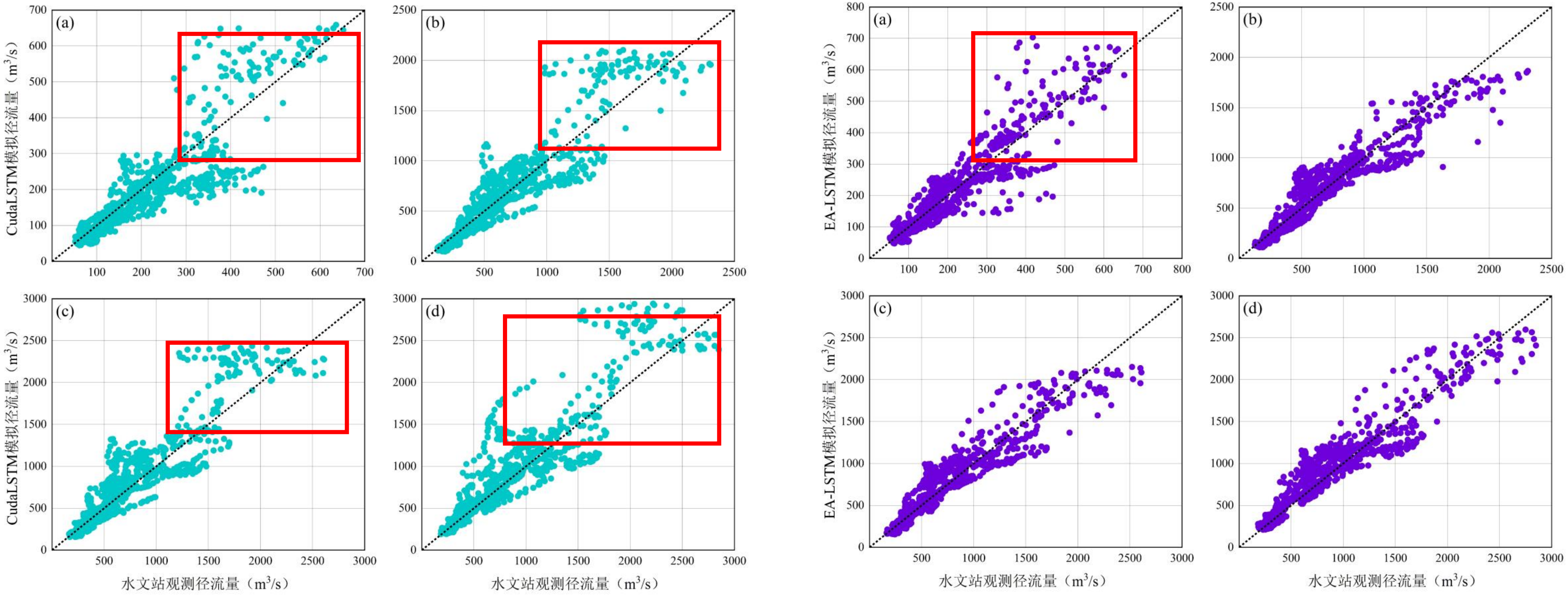
Station	CudaLSTM	EA-LSTM
Jimai	0.77	0.85
Maqu	**0.84**	0.91
Jungong	0.82	0.91
Tangnaihai	0.79	**0.92**





4 Rainfall-Runoff Modeling Based on Deep Learning

4.2 LSTM Model for Rainfall-Runoff Simulation



◆ Both models show high precision in simulating **medium and low** flow ranges, effectively capturing the relationship between precipitation and runoff in the SRYR

◆ The ability of both LSTM models to simulate **extreme runoff** values still needs improvement

Outline

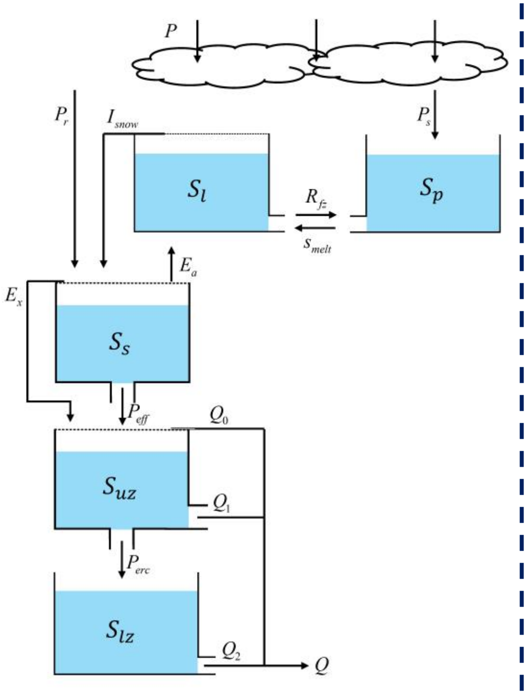
5 Rainfall-Runoff Modeling Based on Hydrological Models

5.1 Hydrological models

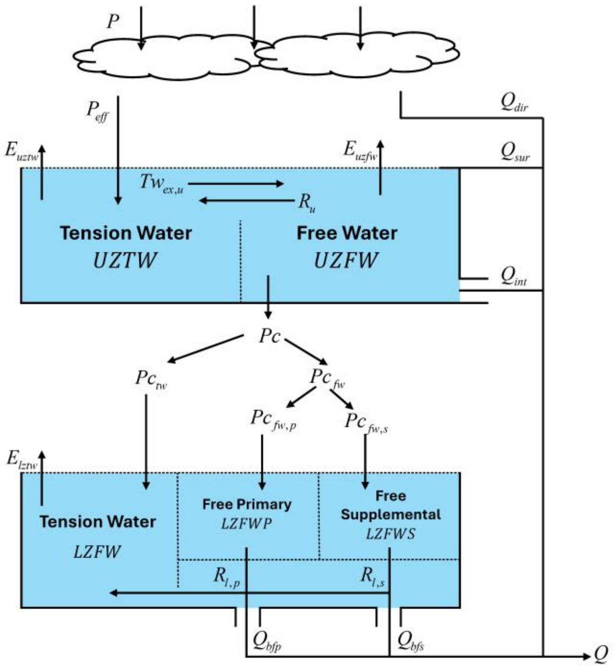
◆ Model Structure

Caravan-SRYR → 7 Hydrological models → Calibration → Validation → AET improvement

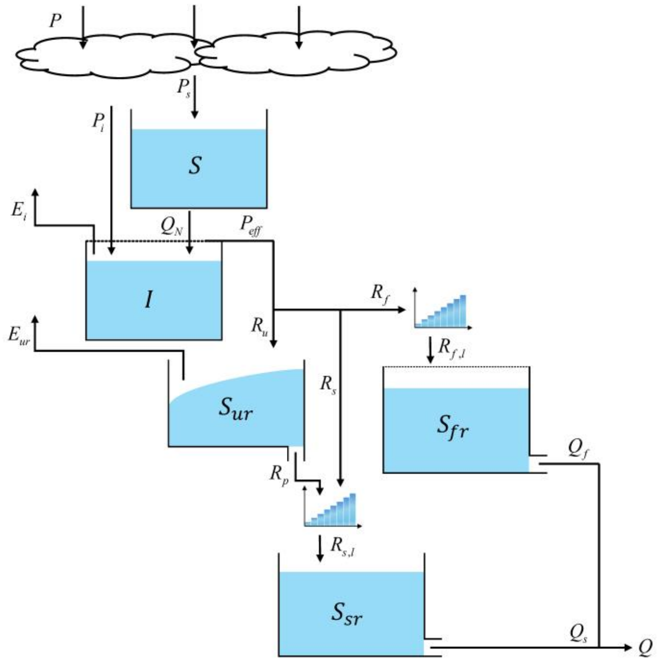
HBV



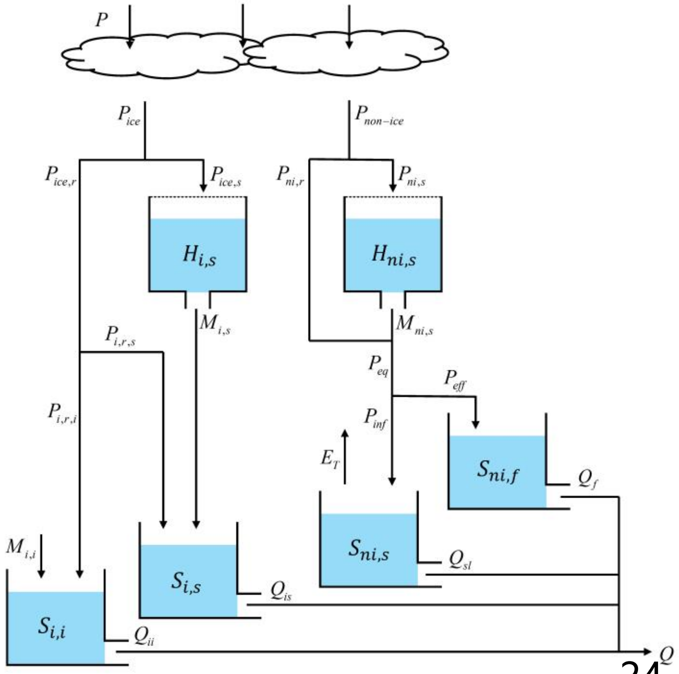
SAC-SMA



FLEX-IS



GSM-SOCONT

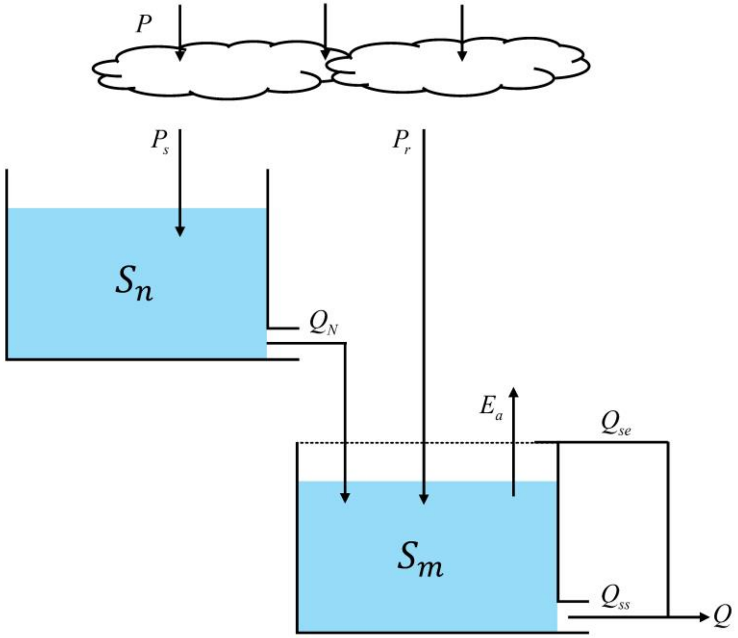


5 Rainfall-Runoff Modeling Based on Hydrological Models

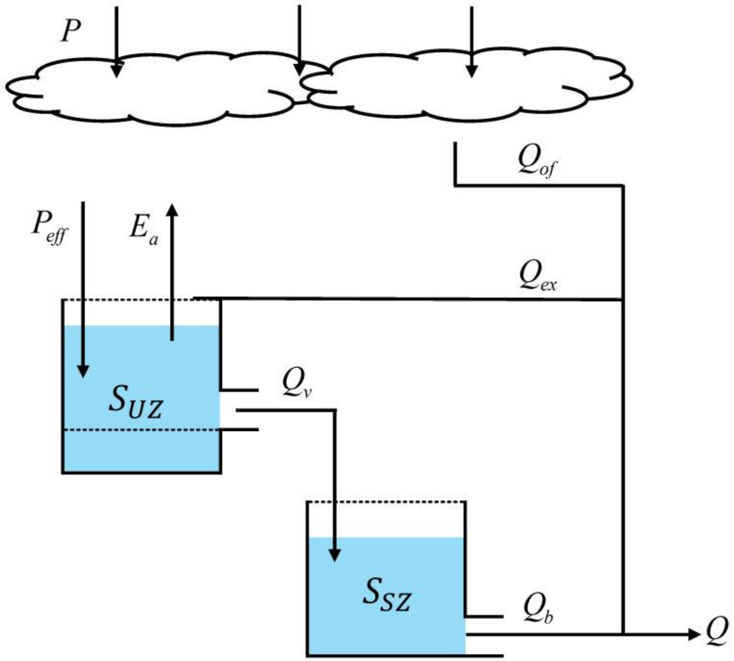
5.1 Hydrological models

◆ Model Structure

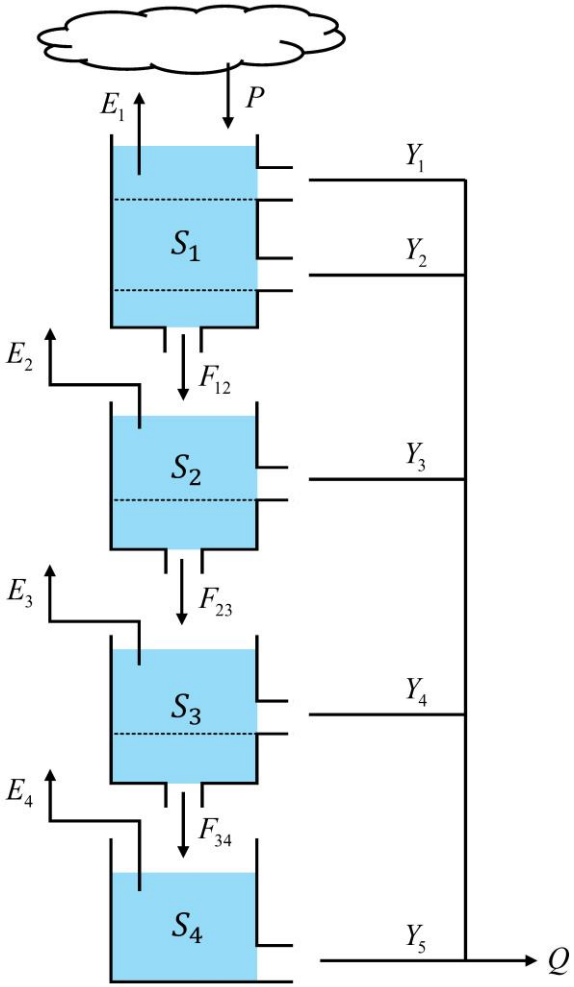
Alpine



TOPMODEL



Tank



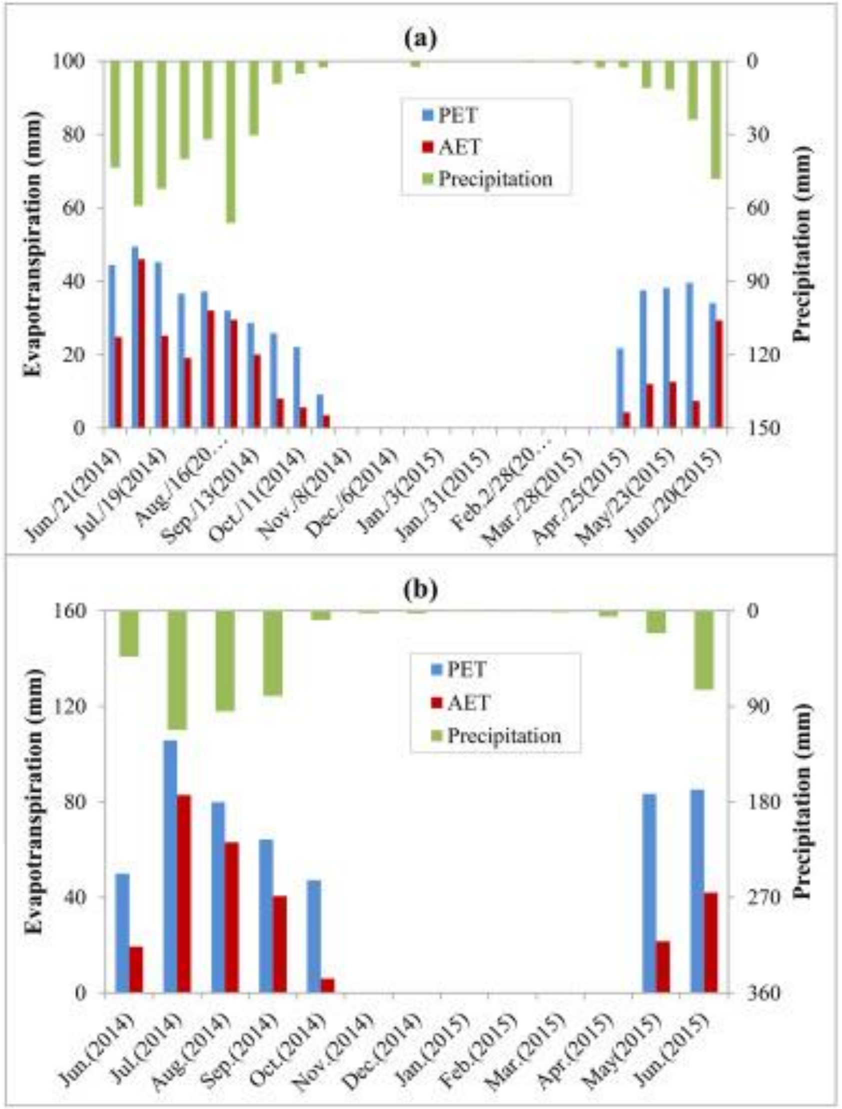
5 Rainfall-Runoff Modeling Based on Hydrological Models

5.1 Hydrological Model

◆ Model Improvement

- In arid and semi-arid regions, the proportion of ET to precipitation is much higher than that of runoff
- Hydrological models often simulate AET using **PET** for calculations. In the process of simulating rainfall-runoff, AET is typically assumed to be a function of PET
- The original Alpine, TOPMODEL, and Tank models equate PET to AET, ignoring the constraints imposed by soil moisture. To improve this, a **nonlinear soil moisture constraint factor** is introduced to modify the calculation of AET in Alpine, TOPMODEL, and Tank models:

$$E_a = \begin{cases} E_p, \text{ if } S_m > 0 \\ 0 \text{ , otherwise} \end{cases} \rightarrow \quad E_a = \alpha_e^{(SWI-1)} E_p,\ \alpha_e \in [1,10]$$

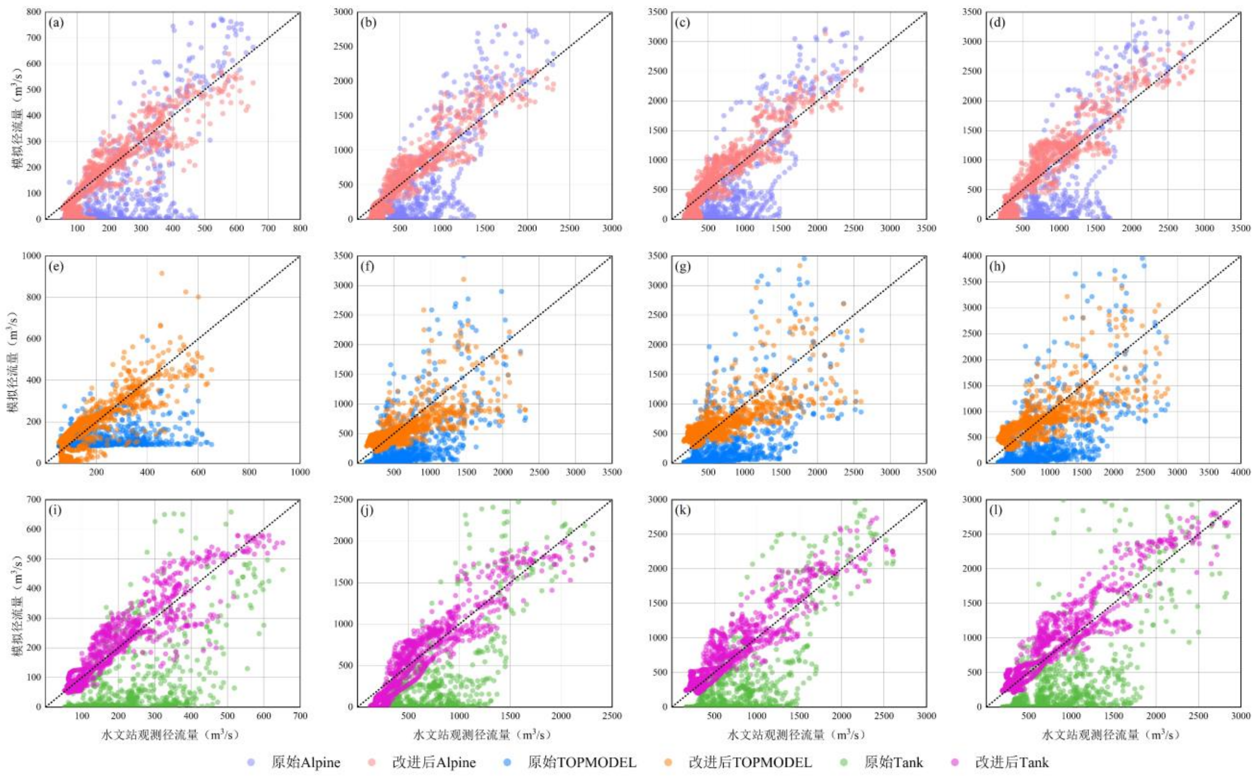


(Liu et al., 2019)

5 Rainfall-Runoff Modeling Bas

5.2 Results of Model Improvement

- After improvement, the Alpine model achieved an NSE value greater than **0.75** for the Jimai, Maqu, and Tangnaihai stations
- **TOPMODEL** improvement showed significant enhancement in the low-flow simulations at Jimai, Maqu, and Tangnaihai stations, but a clear discrepancy still existed between the model results and the observed data for **high-flow** values
- **Tank** model showed a significant improvement, with NSE value of **0.83** for the Tangnaihai station. It performed well across all stations, especially for high-flow values

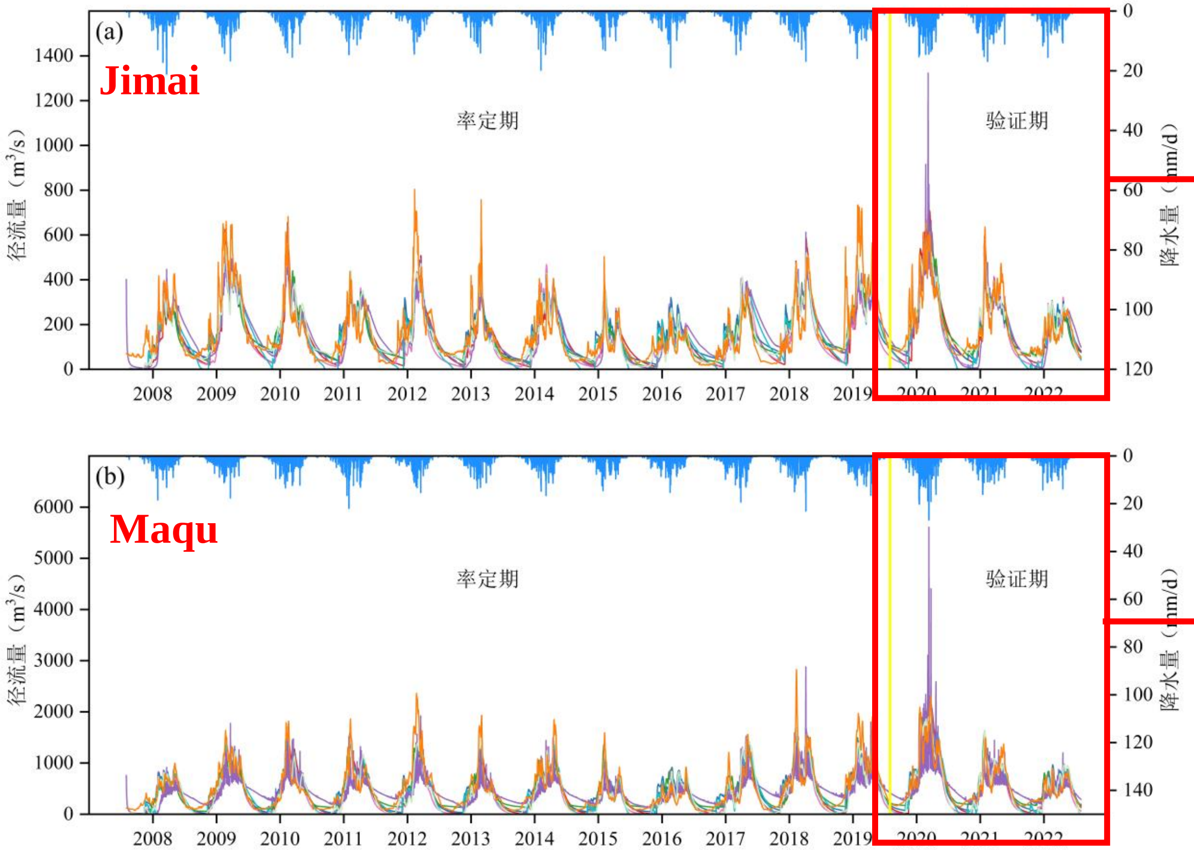


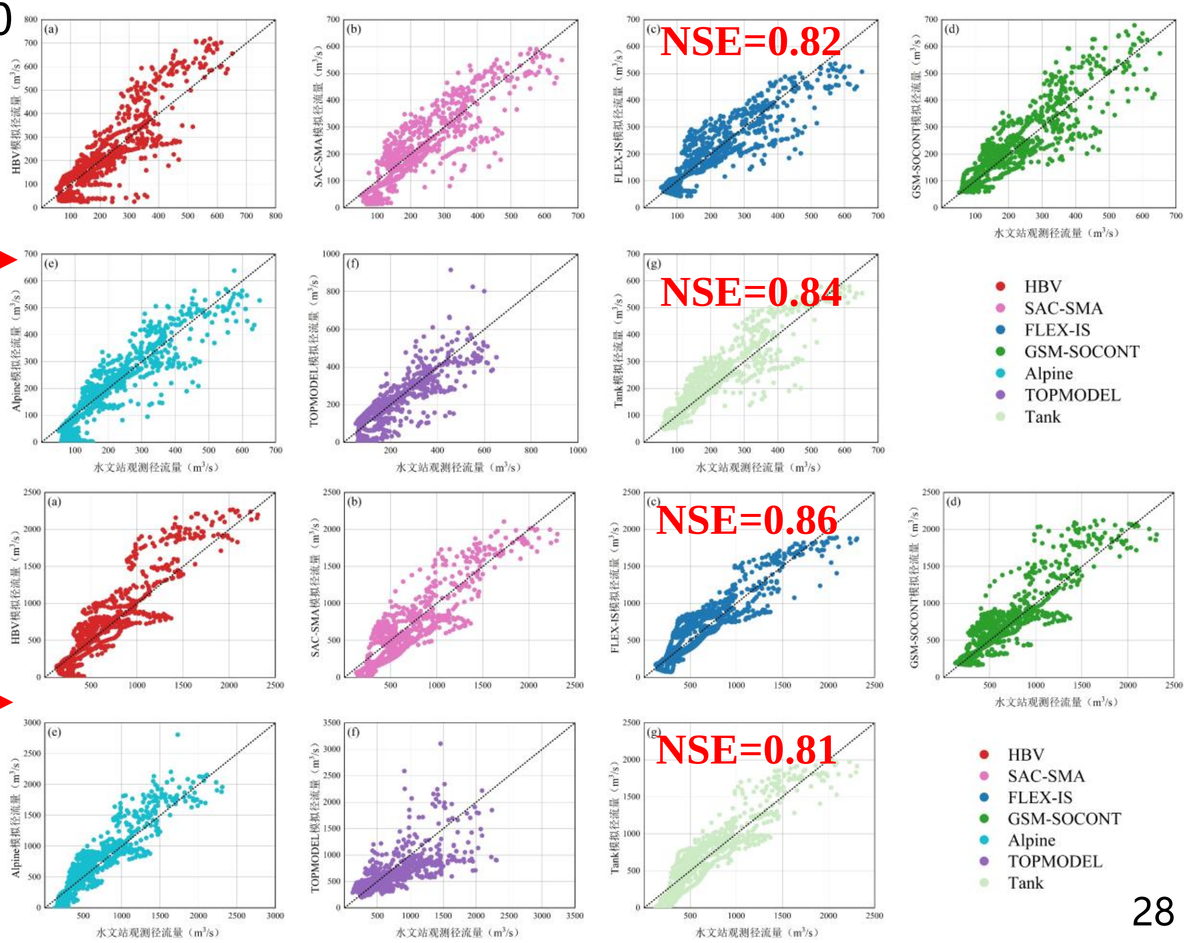
Model Type		Hydrological Station			
		Jimai	Maqu	Jungong	Tangnaihai
Origin	Alpine	-0.29	0.03	-0.05	-0.02
	TOPMODEL	-0.08	-0.20	-0.30	-0.28
	Tank	-0.47	-0.15	-0.21	-0.25
Improv-ement	Alpine	0.68	0.78	0.75	0.77
	TOPMODEL	0.59	0.46	0.44	0.48
	Tank	0.77	0.80	0.79	0.83

5 Rainfall-Runoff Modeling Based on Hydrological Models

5.2 Rainfall-Runoff Modeling in the SRYR

- **FLEX-IS** and the **improved Tank** models achieved NSE values over 0.80 for Jimai and Maqu stations during the validation period
- **TOPMODEL** showed weaker performance with an NSE<0.70

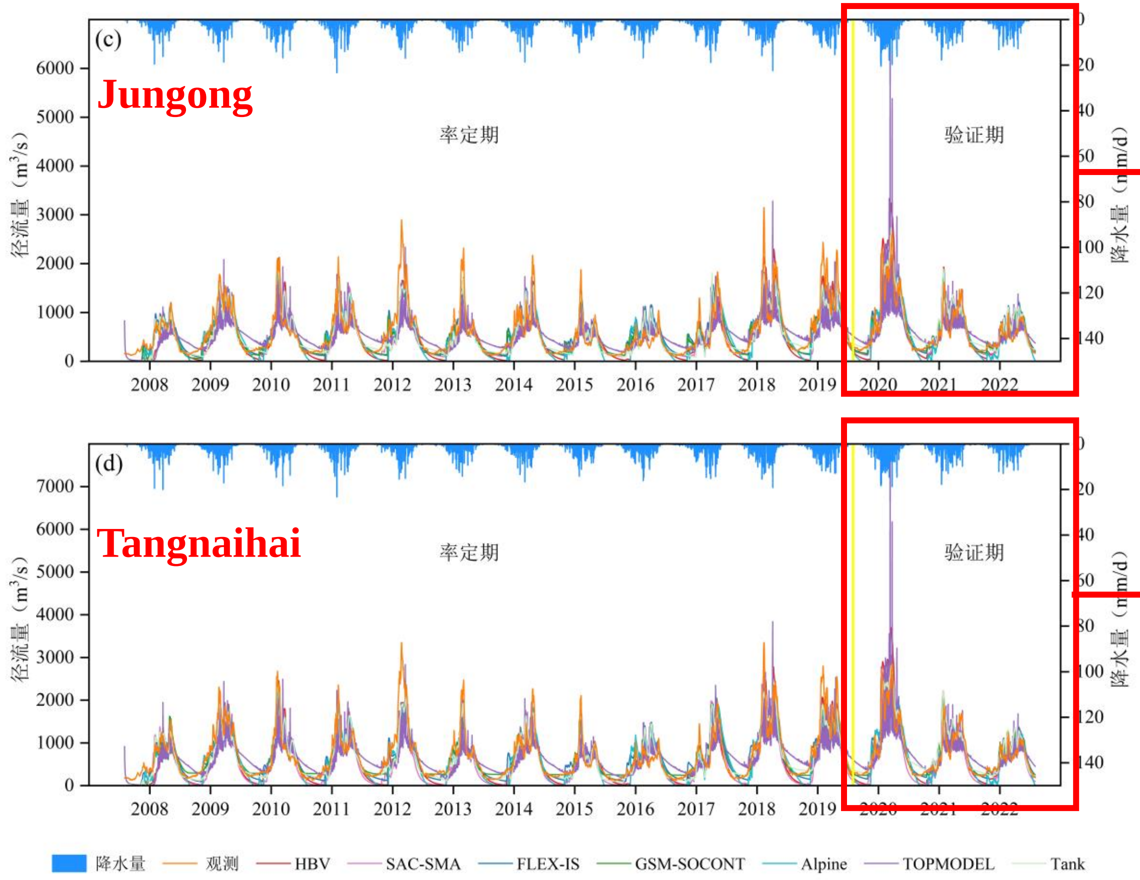


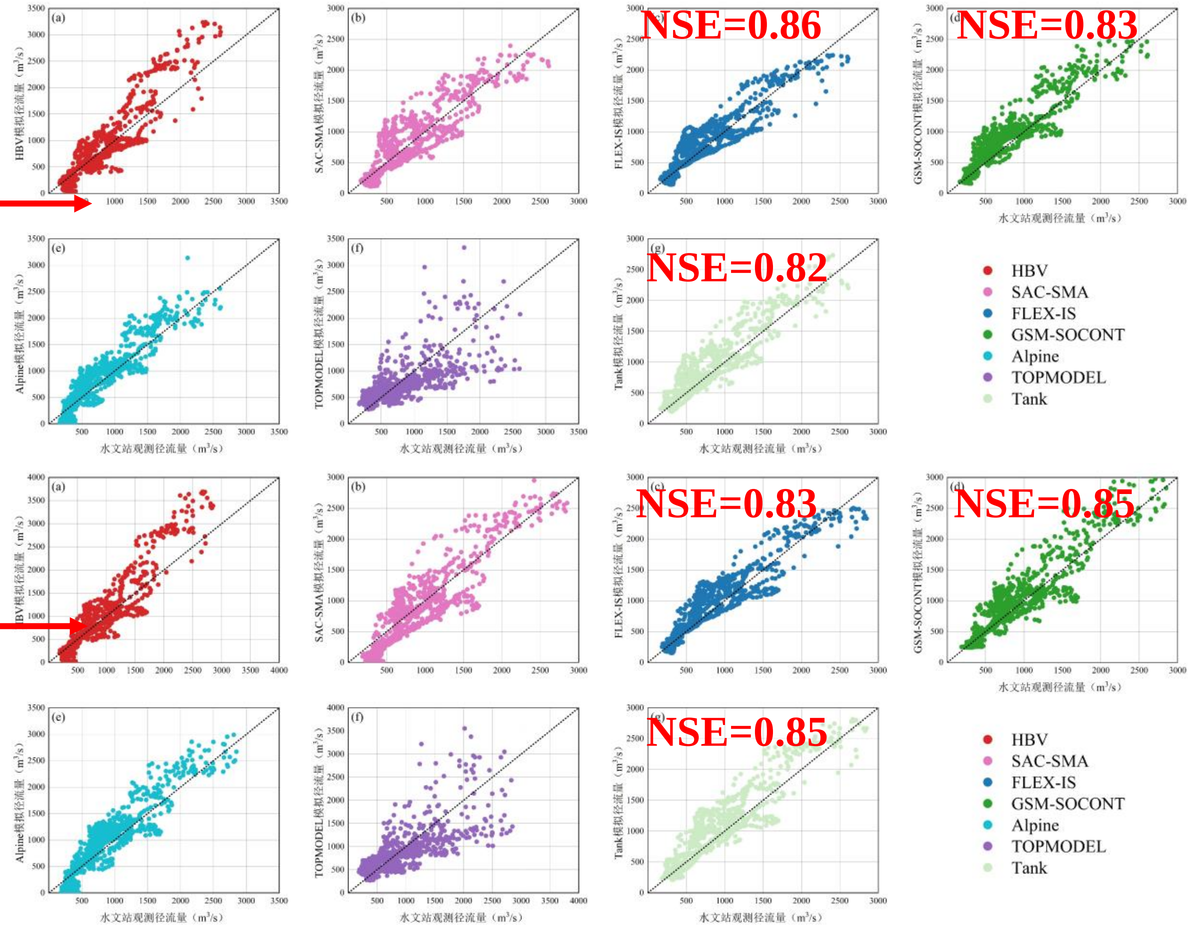


5 Rainfall-Runoff Modeling Based on Hydrological Models

5.2 Rainfall-Runoff Modeling in the SRYR

- **FLEX-IS**, **GSM-SOCONT**, and **improved Tank**models achieved NSE values greater than 0.80 for runoff simulations at Jimai and Maqu stations during the validation period
- **TOPMODEL** showed weaker performance with NSE < 0.50





Outline

6 Runoff Response Mechanisms Based on Precipitation Types

6.1 Precipitation Types in SRYR

IMERG-FInal

$$UDR = \frac{\sum_{x \in \Omega_U} P(x)}{\sum_{x \in \Omega_D} P(x)}$$

$$IDI = \frac{\sigma_p}{\mu_p}$$

$$PTT = f\left(I_p\right)$$

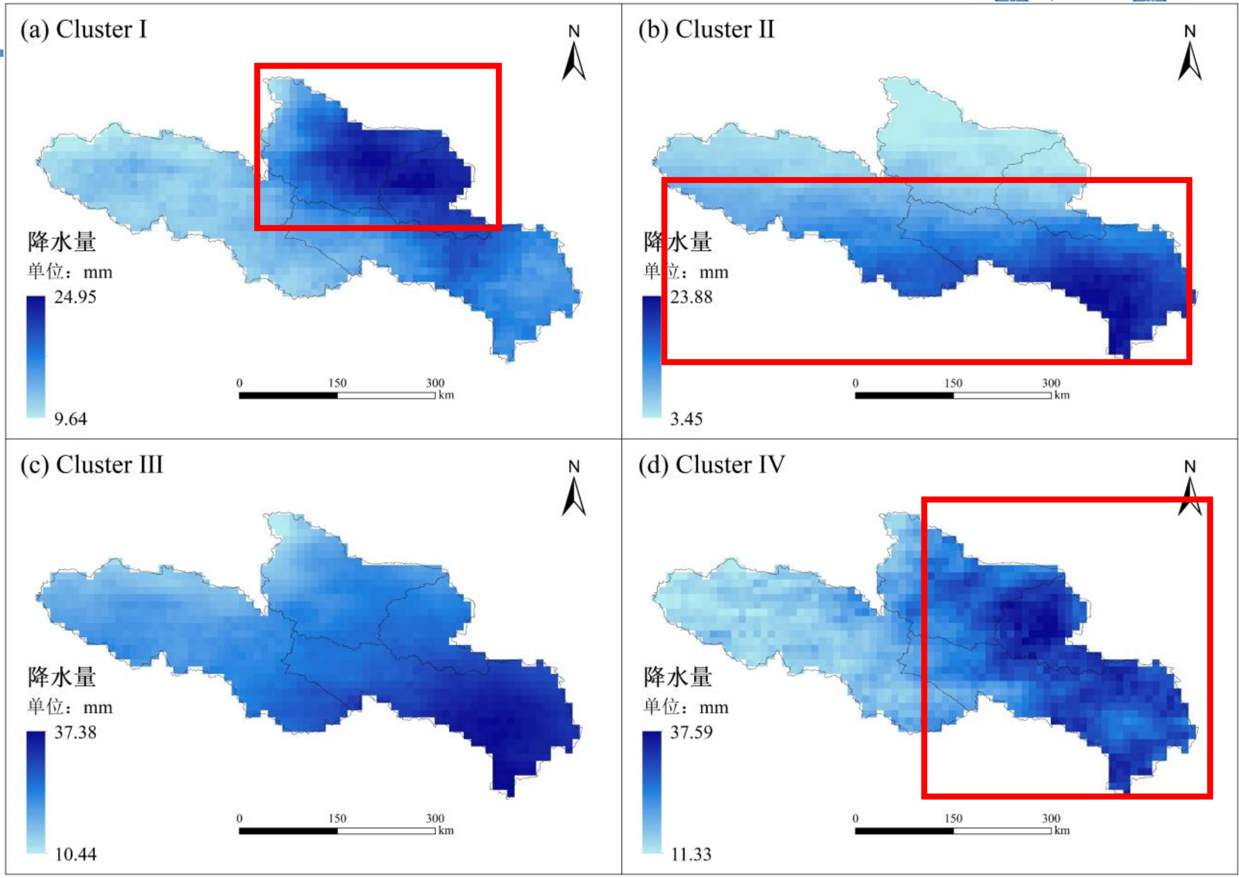
K-means

Cluster I
Northern regional precipitation events

Cluster II
Southern weak precipitation events

Cluster III
Regional strong precipitation events

Cluster IV
Eastern strong precipitation events



P Type	Average P (mm)	Average P Duration (d)	Average P Intensity (mm/d)
Cluster Ⅰ	15.9	3.9	3.7
Cluster Ⅱ	11.4	3.6	2.8
Cluster Ⅲ	23.1	5.0	4.1
Cluster IV	22.7	5.1	3.8

6 Runoff Response Mechanisms Based on Precipitation Types

6.2 Rainfall-Runoff Process for Different Precipitation Types

- Cluster I: Precipitation is small and concentrated in the northern part of the basin. Its overall impact on runoff is **weaker**, but the lag time from the precipitation peak to the formation of the peak flow at **Tangnaihai** station is relatively short (3.9 days)
- Cluster II: Precipitation is small but concentrated in the southern part of the basin. The peak flow at **Jimai** station responds more clearly to the precipitation peak, and the corresponding precipitation-runoff lag time is shorter (2.7 days).
- Cluster III: Precipitation is high and widely distributed, leading to the highest average and peak runoff values at the hydrological stations. However, the rainfall-runoff **lag time is longer** (4.5 days at Jimai station, 6.0 days at Tangnaihai station).
- Cluster IV: Precipitation is also relatively high, but the precipitation intensity shows a **gradual decreasing trend**. The corresponding runoff lag time is shorter compared to Cluster III.

Station	P Type	Average Runoff (m^3/s)	Peak Runoff (m^3/s)	Runoff lag time (d)
Jiamai	Cluster I	207	238	3.4
	Cluster II	251	286	2.7
	Cluster III	256	316	4.5
	Cluster IV	238	284	4.1
Tangnaihai	Cluster I	933	1056	3.9
	Cluster II	1022	1153	5.2
	Cluster III	1117	1308	6.0
	Cluster IV	1103	1261	5.1

6 Runoff Response Mechanisms Based on Precipitation Types

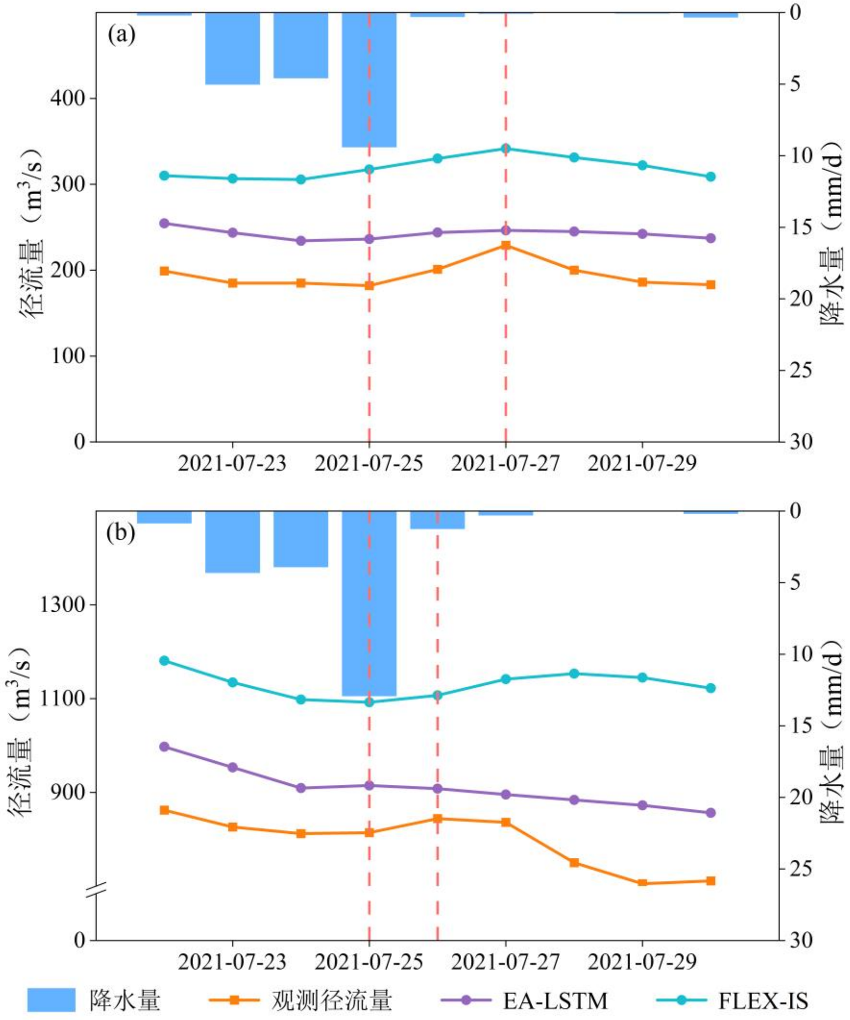
6.2 Rainfall-Runoff Process f

➢ Cluster I

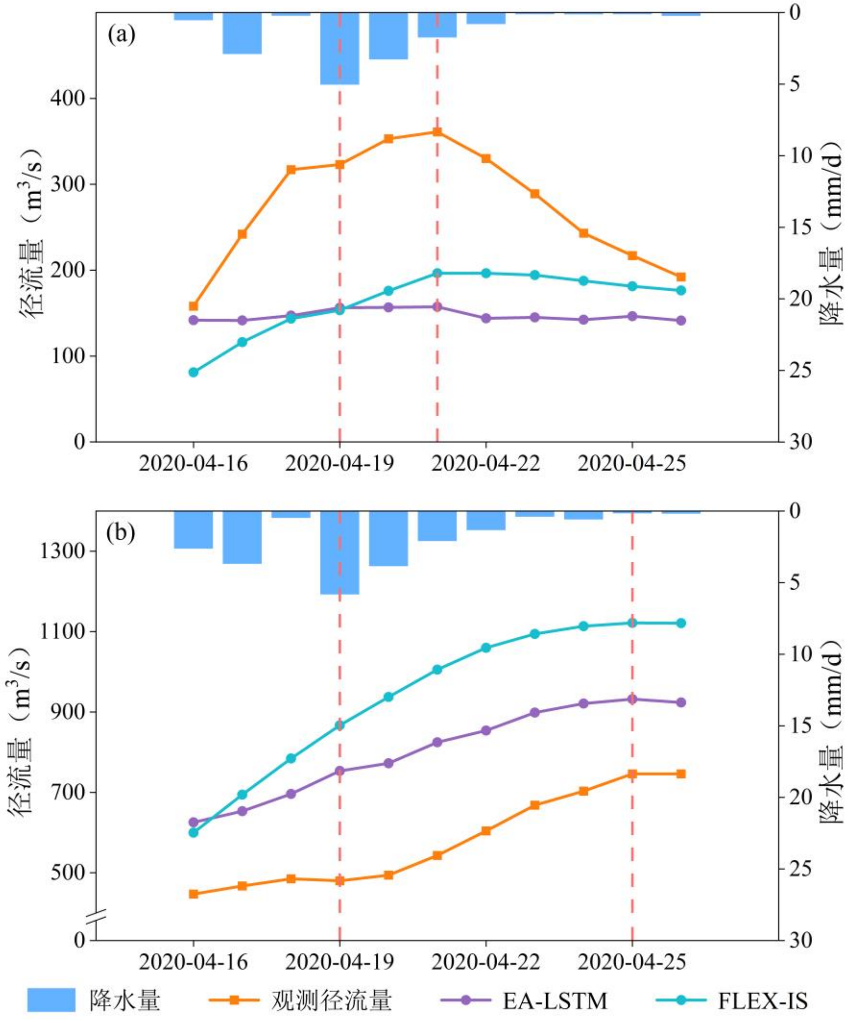
- the intensity of runoff increases significantly
- distribution of precipitation is concentrated in the upstream part of the basin
- At **Tangnaihai**, the precipitation-runoff lag time is only 1 day

➢ Cluster II

- precipitation is concentrated in the southern basin
- At **Jimai** , the response of runoff to precipitation is more significant. The observed runoff ranges from 158 m³/s to 361 m³/s, with a runoff duration of 2 days



Typical Cluster I
2021-07-23~2021-07-26



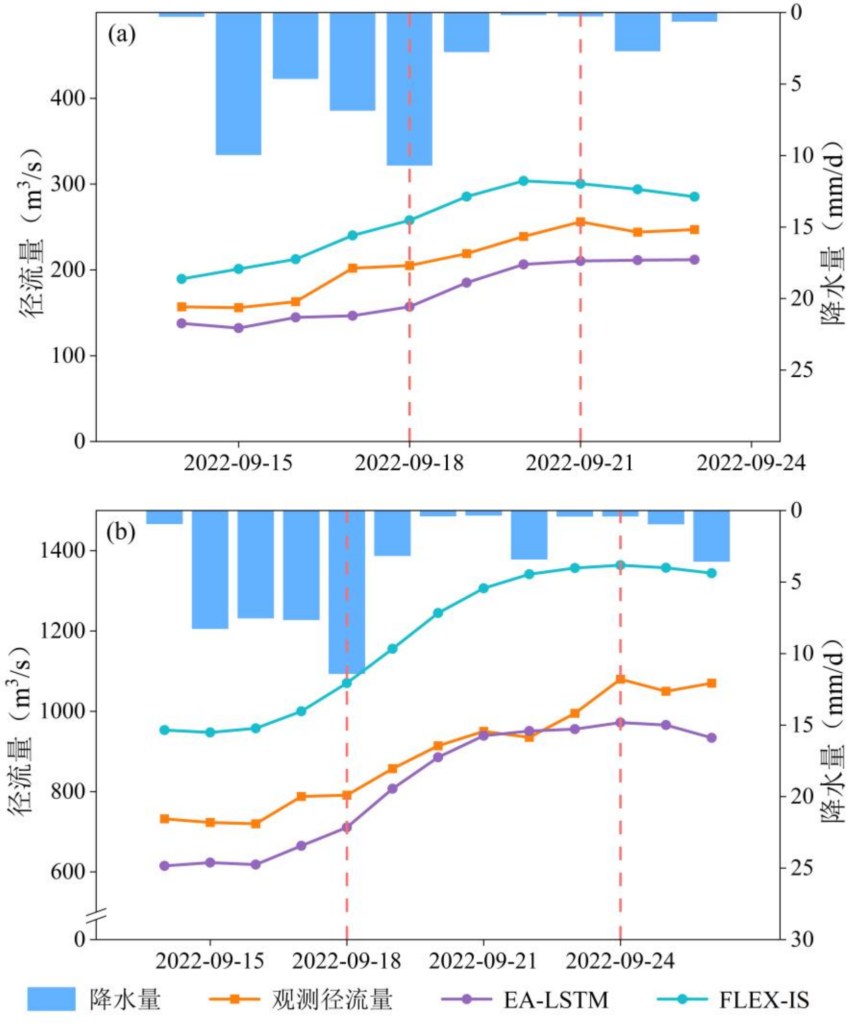
Typical Cluster II
2020-04-16~2020-04-22

6 Runoff Response Mechanisms Based on Precipitation Types

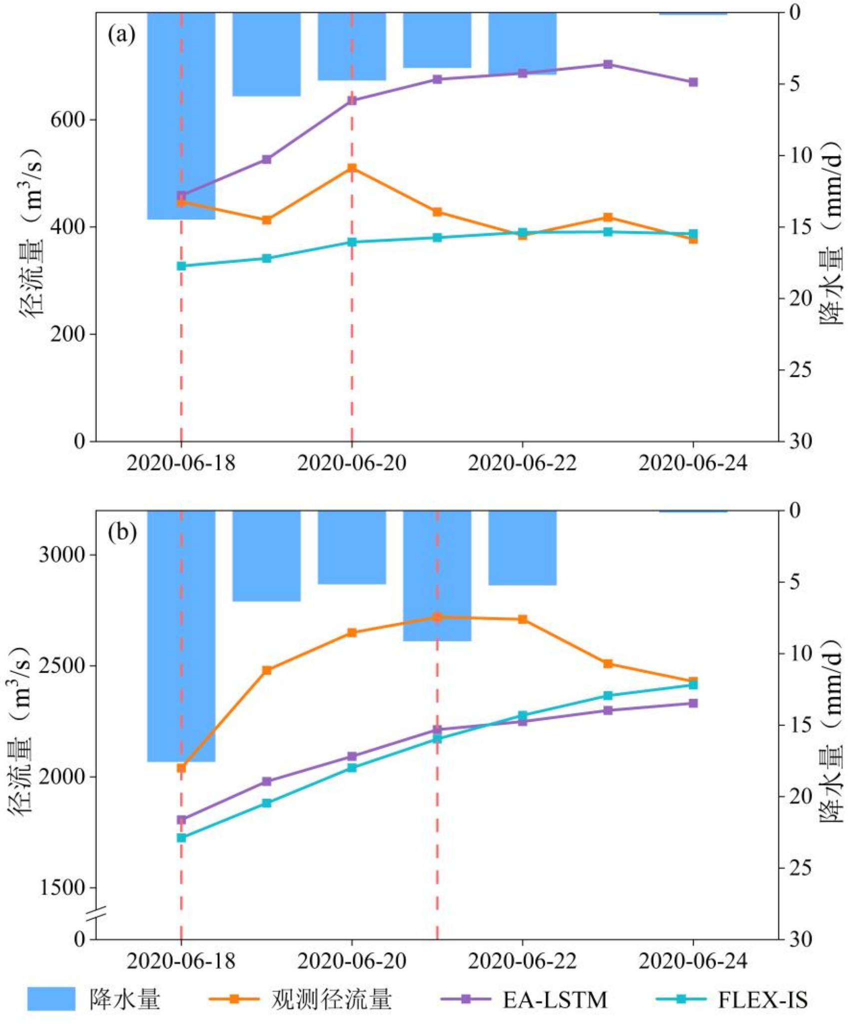
6.2 Rainfall-Runoff Process f

- Cluster III
  - the precipitation in the basin is high, and the precipitation intensity is large
  - The precipitation is evenly distributed across the basin, and the **rainfall-runoff lag time is relatively long**

- Cluster IV
  - the precipitation intensity in the basin gradually decreases
  - **Tangnaihai** station shows a significant runoff response. The runoff increases rapidly from 2040 m^3/s to 2720 m^3/s, and the precipitation-runoff lag time is also relatively short (3 days).



Typical Cluster III
2022-09-14~2022-09-19



Typical Cluster IV
2020-06-18~2020-06-22

Outline

7 Conclusions and Future Prospects

7.1 Main Conclusions

(1) The **IMF** product performed the best in the comprehensive evaluation, particularly in detecting extreme precipitation events, with an RSA score of 0.85, significantly higher than other products. This product was used to create the Caravan-SRYR hydrological dataset for the SRYR

(2) 过Both deep learning and traditional hydrological models simulated the hydrological processes in the SRYR, with **average NSE > 0.70** for all models. The **EA-LSTM** model, based on deep learning, showed significant advantages in rainfall-runoff simulation, with NSE values exceeding 0.85.

(3) The soil moisture constraint factor was incorporated into the **AET** calculation, **improving** the performance of the Alpine, TOPMODEL, and Tank models in simulating complex hydrological processes in the Yellow River source region

7 Conclusions and Future Prospects

7.1 Main Conclusions

(4) The runoff responses to different types of precipitation events varied significantly:

- Cluster I: Small precipitation, concentrated in the northern basin, with a short lag time of 3.89 days at **Tangnaihai** station
- Cluster II: Small precipitation, concentrated in the southern basin, with a short lag time of 2.67 days at **Jimai** station
- Cluster III: Large and widely distributed precipitation, with the highest average and peak runoff, but a **longer lag time** (4.46 days at Jimai station, 5.96 days at Tangnaihai station). Models captured the precipitation-runoff relationship most accurately for this cluster.
- Cluster IV: Higher precipitation, but with decreasing intensity and a **shorter lag time** compared to Cluster III

7 Conclusions and Future Prospects

7.2 Innovation Points

- Constructed the Caravan-SRYR hydrological modeling dataset based on the multidimensional **comprehensive quantitative evaluation** of SPPs
- Simulated the rainfall-runoff process in the SRYR using both **deep learning** and **traditional hydrological models**.
- Improved the Alpine, TOPMODEL, and Tank models by introducing a **soil moisture constraint factor** in the AET calculation module
- Classified precipitation events using K-means clustering, revealing the **runoff response characteristics** to different types of precipitation

7 Conclusions and Future Prospects

7.3 Limitations and Prospects

- High-accuracy SPPs are typically calibrated with ground rain gauge data, which have time delays in data release. Future research could explore the potential of **near-real-time** SPPs for hydrological forecasting.
- The EA-LSTM model has limited training samples and weak interpretability. Combining physical models and deep learning models could improve the model's ability to **explain** hydrological processes in the basin
- The lumped hydrological model has limitations in simulating **extreme runoff** events due to its simplifying assumptions. Future work could compare the application of different SPPs in distributed hydrological models to validate the performance of various precipitation data in high-accuracy hydrological models

Github repositories

◆ GitHub Repositories Used in This Study

- MARRMoT： https://github.com/wknoben/MARRMoT
- Caravan ： https://github.com/kratzert/Caravan
- Spotpy ： https://github.com/thouska/spotpy
- NeuralHydrology ： https://github.com/neuralhydrology/neuralhydrology

Master Thesis

Edit list

the repositories used in my Master thesis

4 repositories

wknoben / MARRMoT — Starred

Modular Assessment of Rainfall-Runoff Models Toolbox - Matlab code for 47 conceptual hydrologic models

MATLAB 120 56 Updated on Oct 3, 2024

kratzert / Caravan — Starred

A global community dataset for large-sample hydrology

Jupyter Notebook 208 42 Updated last month

thouska / spotpy — Sponsor Starred

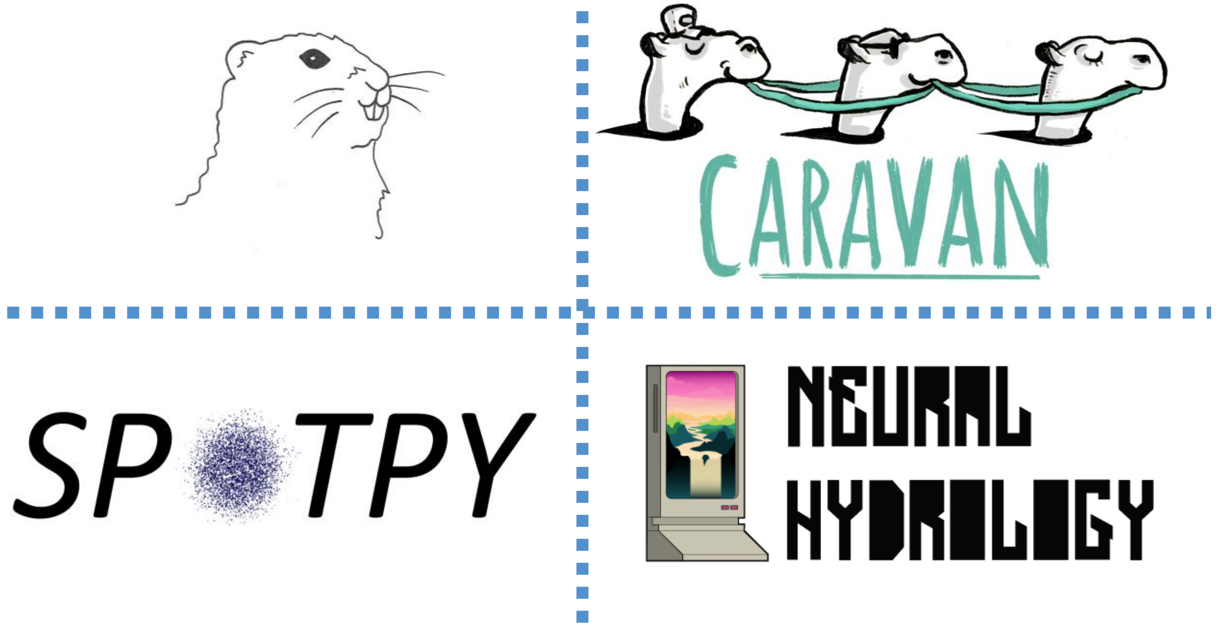
A Statistical Parameter Optimization Tool

Python 261 157 Updated on Feb 21

neuralhydrology / neuralhydrology — Starred

Python library to train neural networks with a strong focus on hydrological applications.

Python 418 215 Updated 3 days ago



Modular Assessment of Rainfall–Runoff Models Toolbox (MARRMoT) v2.1: an object-oriented implementation of 47 established hydrological models for improved speed and readability

Luca Trotter[1], Wouter J. M. Knoben[2], Keirnan J. A. Fowler[1], Margarita Saft[1], and Murray C. Peel[1]

Data Descriptor | Open access | Published: 31 January 2023

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Python Submitted 21 December 2021 • Published 04 March 2022

(Trotter et al., 2022; Kratzert et al., 2023; Houska et al., 2015; Kratzert et al., 2022)

Outline

8 Review and Revisions

◆ 8.1 Overall Review of the Thesis

- Reviewer 1:
- This paper focuses on the hydrological processes in the SRYR, addressing both theoretical frontiers and practical applications. The topic is well-chosen, relevant, and practical. Based on a review of domestic and international research, the paper quantitatively evaluates SPPs using multiple indicators. It also constructs a deep learning-based precipitation-runoff model for the SRYR, combining hydrological datasets and observed data, and performs case studies and comprehensive validation. Furthermore, the paper explores the runoff response mechanism in the SRYR based on precipitation classification. The research outcomes have certain theoretical and practical value and can provide theoretical and methodological references for basin hydrological process studies. The research approach is clear, the research plan is reasonable, and the technical approach is feasible. The case data is detailed and specific. The research work shows that the author has a solid and rich knowledge base in hydrological modeling and simulation and strong research capabilities. The writing is clear, well-organized, with a rigorous structure, and the figures and tables are well-presented, meeting the requirements for a master's thesis

8 Review and Revisions

◆ 8.1 Overall Review of the Thesis

- Reviewer 2:
- Hydrological simulation in the SRYR is of great significance for the water resource security of the Yellow River Basin. Given the difficulty of obtaining precipitation data for the source region, the use of SPPs in hydrological simulation is a good topic. This paper conducts comprehensive research on the application of satellite data, the selection of multiple hydrological models, and the optimization of hydrological parameters. The writing is standard, and the paper is a relatively excellent master's thesis.

- Reviewer 3:
- This paper addresses an important theoretical and practical issue, filling the research gap on the comprehensive evaluation of SPPs in cold regions. It provides a scientific basis for hydrological simulation and forecasting in these regions. The author has a comprehensive understanding of the relevant domestic and international literature, citing a large number of the latest research results, demonstrating a deep understanding of the cutting-edge developments in the field. The results and contributions of the paper are of high quality. The overall structure of the paper is clear, but the logical relationships between sections could be further refined.

Thank you