XVIII
World Water Congress
International Water Resources Association(IWRA)
Beijing, China | September 11-15, 2023

安徽理工大學
ANHUI UNIVERSITY OF SCIENCE & TECHNOLOGY

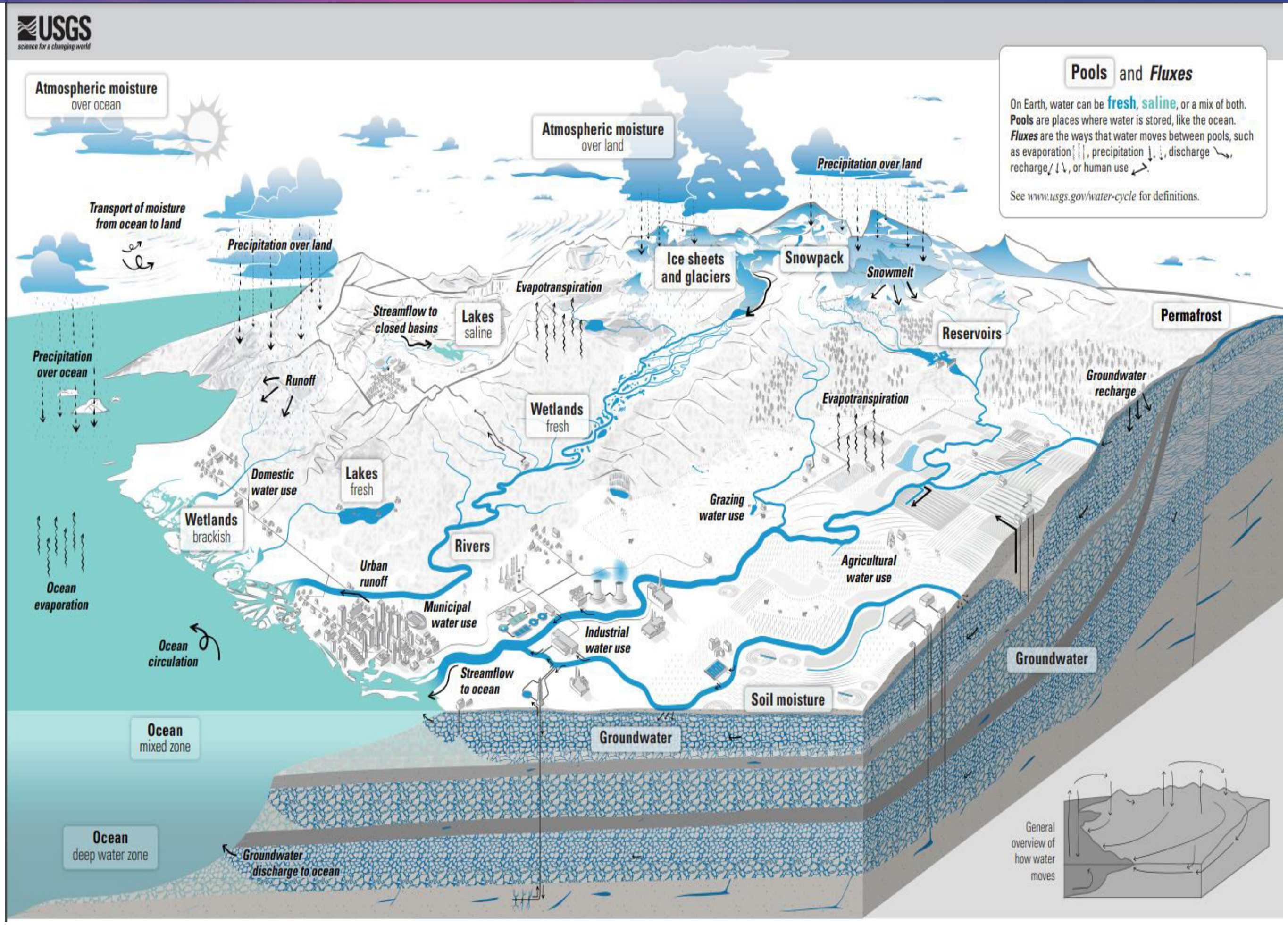
Comparative Study for Daily Streamflow Simulation with Different Machine Learning Methods

Ruonan Hao
Anhui University of Science and Technology

Zhixu Bai
Wenzhou University

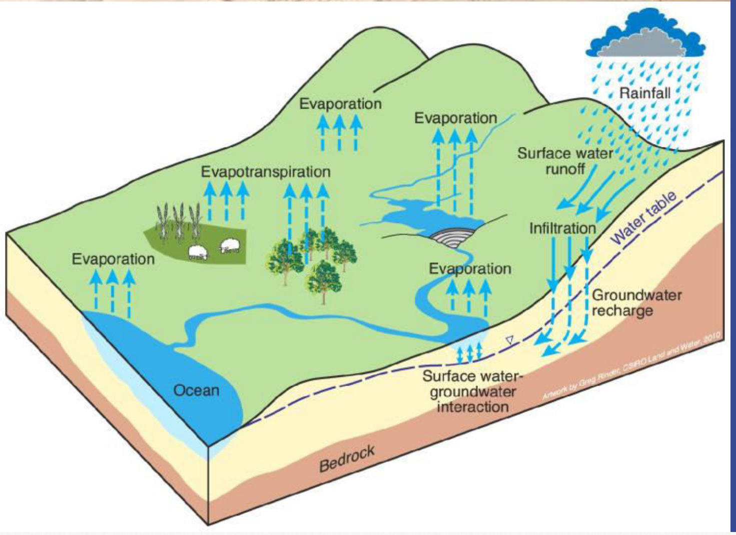
09/15 2023

Contents

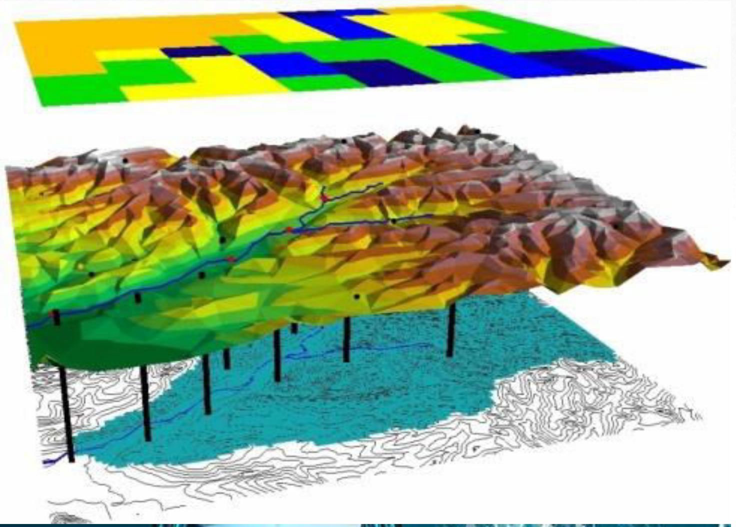


USGS
science for a changing world
Atmospheric moisture
over ocean
Atmospheric moisture
over land
Pools and Fluxes
On Earth, water can be fresh, saline, or a mix of both.
Pools are places where water is stored, like the ocean.
Fluxes are the ways that water moves between pools, such as evaporation, precipitation, discharge, recharge, or human use.
See www.usgs.gov/water-cycle for definitions.
Transport of moisture
from ocean to land
Precipitation over land
Precipitation over land
Ice sheets
and glaciers
Snowpack
Snowmelt
Evapotranspiration
Streamflow to
closed basins
Lakes
saline
Permafrost
Reservoirs
Precipitation
over ocean
Runoff
Groundwater
recharge
Wetlands
fresh
Evapotranspiration
Domestic
water use
Lakes
fresh
Grazing
water use
Wetlands
brackish
Rivers
Urban
runoff
Agricultural
water use
Ocean
evaporation
Municipal
water use
Industrial
water use
Ocean
circulation
Groundwater
Streamflow
to ocean
Soil moisture
Ocean
mixed zone
Groundwater
Ocean
deep water zone
Groundwater
discharge to ocean
General
overview of
how water
moves

Background



- ✓ Flood disasters in small watersheds in mountainous areas;
- ✓ Rainfall-runoff modelling;
- ✓ Machine learning;
- ✓ Rainfall runoff mechanism



Aims and Objectives

Aim: The performances of various **ML methods** with different input scenarios and training data for **simulating daily runoff over a mountainous river catchment**

Objectives:

1)the comparison of Support Vector Regression (**SVR**), eXtreme Gradient Boosting (**XGBoost**), and Long-Short Term Memory Neural Network (**LSTM**) models for daily streamflow forecasting

2) the impacts of **inputs** (rainfall and antecedent streamflow) on modeling accuracy

3)is there significant simulation differences during **different seasons** and for different machine learning methods?

Study Area

The north tributary of the Ao River (**ARNT**)

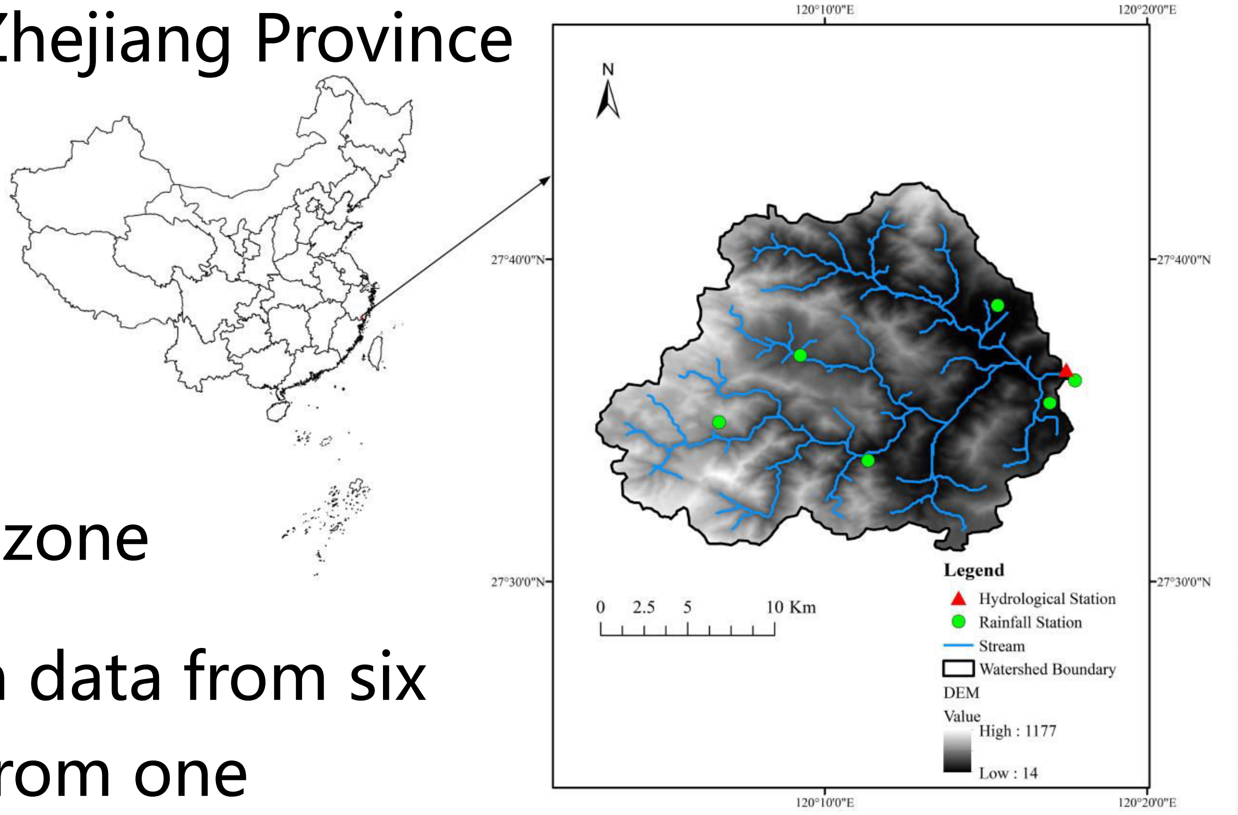
A small mountainous catchment in Zhejiang Province

Basin area: 346 km^2

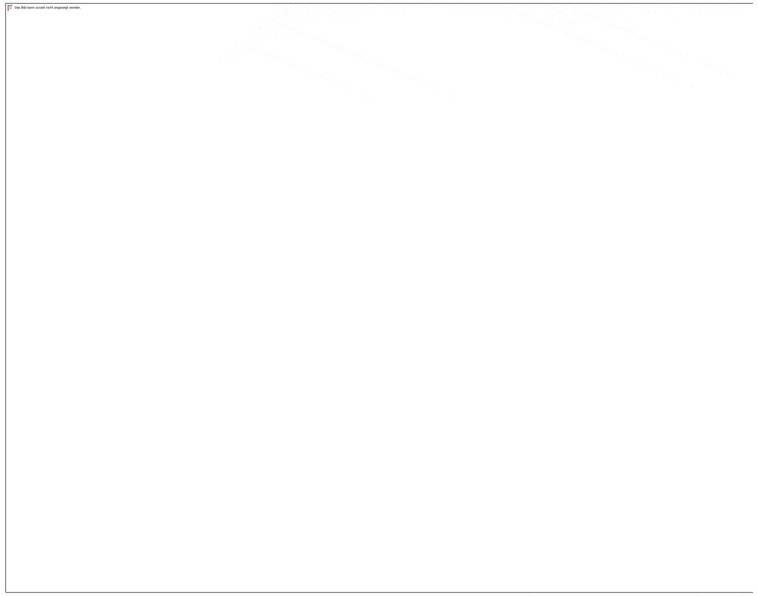
Mean annual discharge at the Daitou Station is 16.33 m^3/s

Subtropical oceanic monsoon climate zone

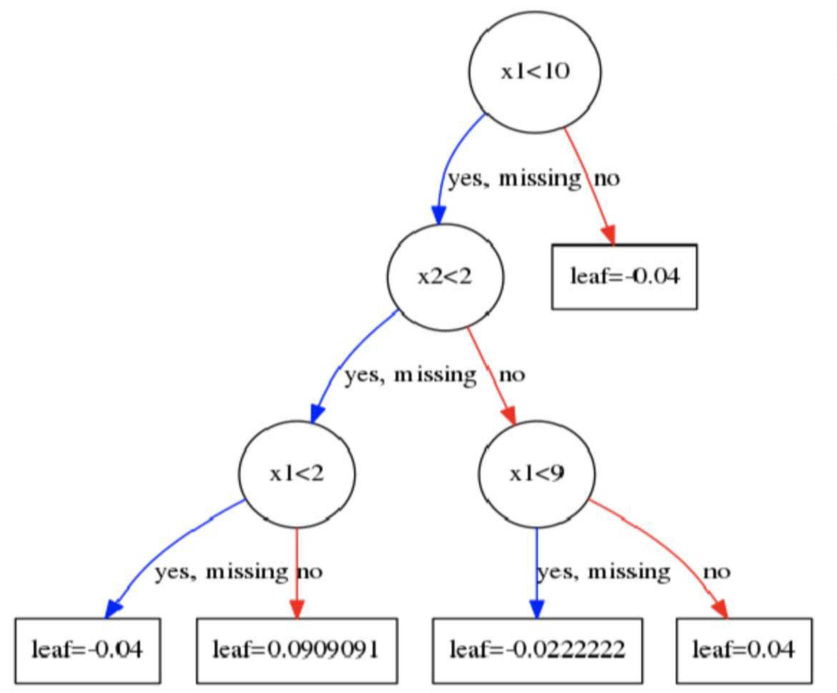
Data: 1991 to 2013, daily precipitation data from six rainfall stations, daily discharge data from one hydrological station



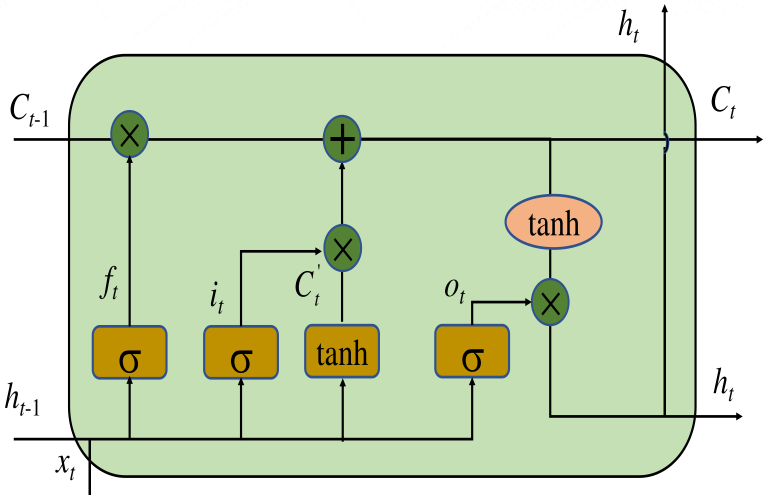
Methods



SVR



XGBoost



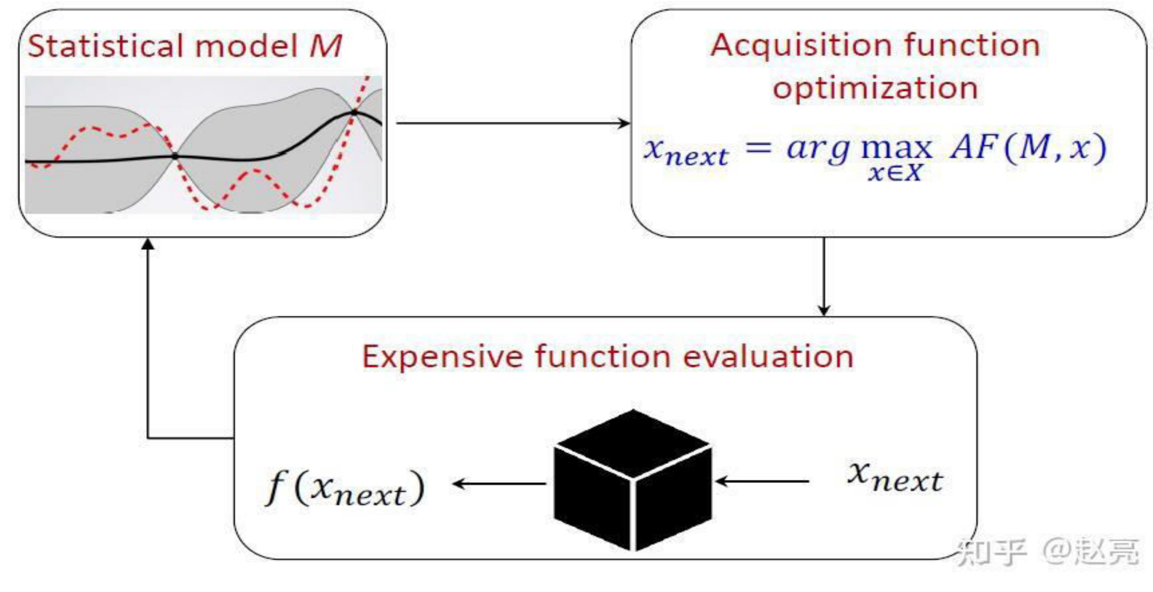
LSTM

Methods

Single and Multiple inputs

Input Scenarios	Input Variables
I	Q_{t-1}
II	$\overline{P}_t$
III	$P_{1,t}, P_{2,t}, P_{3,t}, P_{4,t}, P_{5,t}, P_{6,t}$
IV	$\overline{P}_t$, Q_{t-1}
V	$P_{1,t}, P_{2,t}, P_{3,t}, P_{4,t}, P_{5,t}, P_{6,t}, Q_{t-1}$

Bayesian Optimization



Evaluation Criteria

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}(d_i - y_i)^2}{\sum_{i=1}^{n}(d_i - \bar{d})^2}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(d_i - y_i)^2}$$

$$\mathrm{CC} = \frac{\sum_{i=1}^{n}(d_i - \bar{d})(y_i - \bar{y})}{\sqrt{\sum_{i-1}^{n}(d_i - \bar{d})^2}\sqrt{\sum_{i-1}^{n}(y_i - \bar{y})^2}}$$

Simulation Performances with Single-Input Scenarios

Input Scenario	Model	Training			Validation			Testing		
		NSE	RMSE (m^3/s)	CC	NSE	RMSE (m^3/s)	CC	NSE	RMSE (m^3/s)	CC
Ⅰ	SVR	0.26	31.55	0.51	0.22	63.08	0.47	0.23	27.79	0.48
	XGBoost	**0.32**	**30.21**	**0.56**	**0.23**	**62.69**	**0.50**	**0.27**	**26.95**	**0.53**
	LSTM	0.09	34.83	0.31	0.04	69.97	0.21	0.08	30.34	0.29
Ⅱ	SVR	0.11	34.46	0.47	0.13	66.46	0.63	0.09	30.12	0.37
	XGBoost	0.22	32.29	0.47	0.22	63.01	0.55	0.10	29.92	0.37
	LSTM	**0.69**	**20.42**	**0.83**	**0.68**	**40.10**	**0.83**	**0.64**	**19.09**	**0.83**

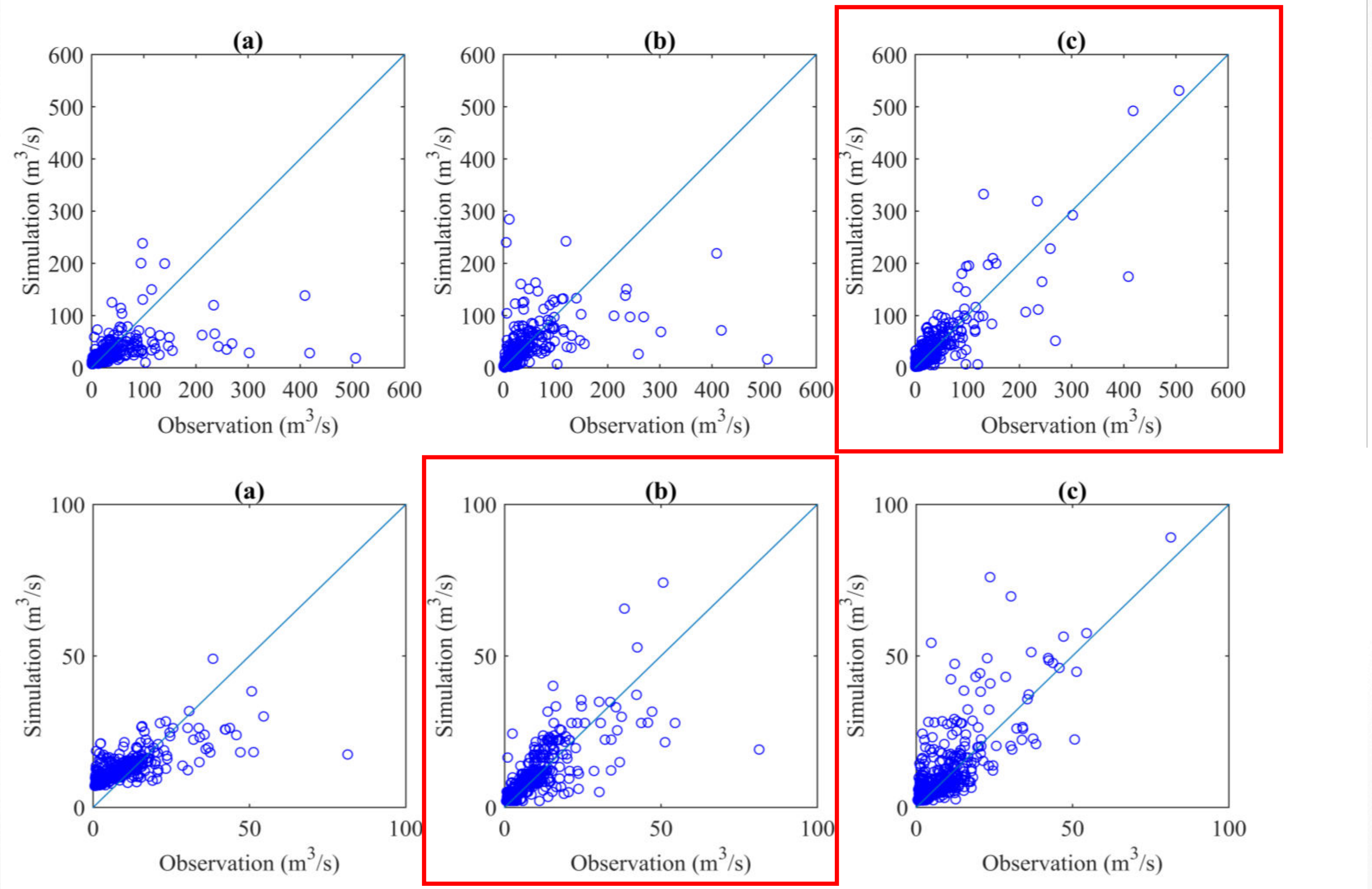
Simulation Performances with Multiple-Input Scenarios

InputScenario	Model	Training			Validation			Testing		
		NSE	RMSE (m^3/s)	CC	NSE	RMSE (m^3/s)	CC	NSE	RMSE (m^3/s)	CC
Ⅲ	SVR	0.12	34.34	0.48	0.14	66.25	0.63	0.10	30.03	0.37
	XGBoost	0.25	31.60	0.51	0.31	59.13	0.61	0.08	30.40	0.35
	LSTM	**0.70**	**20.08**	**0.84**	**0.72**	**38.09**	**0.85**	**0.67**	**18.22**	**0.84**
IV	SVR	0.35	29.57	0.60	0.32	58.70	0.58	0.31	26.34	0.56
	XGBoost	0.48	26.36	0.70	0.40	55.07	0.70	0.37	25.02	0.62
	LSTM	**0.72**	**19.30**	**0.85**	**0.68**	**40.32**	**0.83**	**0.70**	**17.27**	**0.85**
V	SVR	0.35	29.56	0.60	0.32	58.91	0.57	0.31	26.31	0.56
	XGBoost	0.61	22.82	0.78	0.54	48.58	0.75	0.33	25.85	0.60
	LSTM	**0.75**	**18.23**	**0.87**	**0.72**	**37.96**	**0.85**	**0.74**	**16.29**	**0.87**

Simulation Performances during Wet and Dry Seasons

Wet Seasons

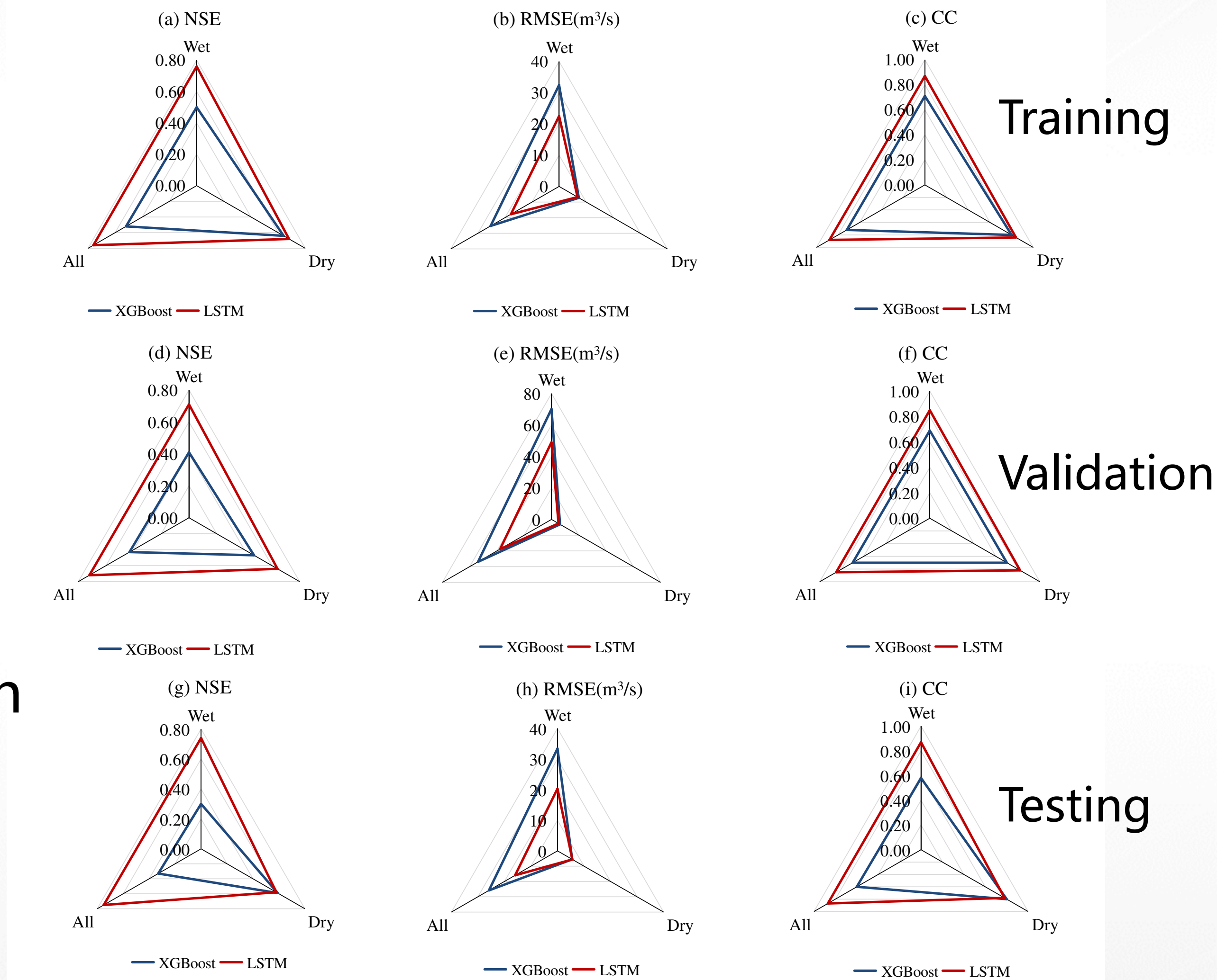
Dry Seasons



(a) SVR (b) XGBoost (c) LSTM

Classification of Wet and Dry Seasons for Simulation

- **XGBoost** trained with datasets during **dry** seasons > XGBoost for wet seasons;
- **LSTM** trained with datasets during **wet** seasons > LSTM for dry seasons;
- **LSTM** models **trained with different datasets** > the LSTM model trained with all datasets, especially during the dry seasons.



Comparison of LSTM and XGBoost models trained with different datasets

Conclusions

- ✓ The performance of LSTM models was always better than that of XGBoost, followed by that of SVR. XGBoost showed relatively high accuracy compared with LSTM during dry seasons.

- ✓ The impacts of input variables were different for SVR, XGBoost, and LSTM. LSTM:Rainfall, XGBoost: Antecedent Steamflow

- ✓ The classification of datasets according to wet and dry seasons improved the performances of LSTM especially for dry seasons.

Future Work

- Streamflow forecasting **at a fine temporal scale** over a mountainous river catchment

- Advancing the understanding of runoff processes by **Interpretable Machine Learning**

- **Uncertainty** of streamflow forecasting by machine learning

Thanks

rhn2019@aust.edu.cn