

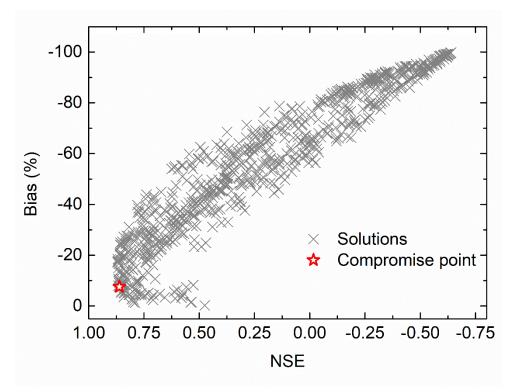
2018 HEPEX Workshop Melbourne, Australia

The potential application of hydrological ensemble prediction in forecasting flood and its components over the Yarlung Zangbo River Basin, China

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1. Motivations

1.1 Compromised solution



The trade-offs between Bias and NSE from algorithm epsilon-NSGA II

Multi-objective optimization

- Result in a set of solutions
- Single parameter set is used, and the compromise is necessary
- Improvement in one objective can cause deterioration in at least one other objective
- It is difficult to cause the two-objective trade-off to collapse to one single point

More than one parameter set is selected for simulation and forecasts Advantage vs Disadvantage ??

1. Motivations

1.2 Complex streamflow components

Climate change

- Increasing temperature
- Glacier retreat
- Permafrost degradation
- Increasing precipitation
- Frequent natural disasters urge the improvement in flood forecasting

Multi-sources of streamflow

- Rainfall
- Snowmelt
- Glacier melt
- Evaluate and quantify the components for better understanding the sources for predictability

Tibetan Plateau 90°0'0"E 70°0'0"E





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2. Methodology

2.1 Method to select limited parameter sets

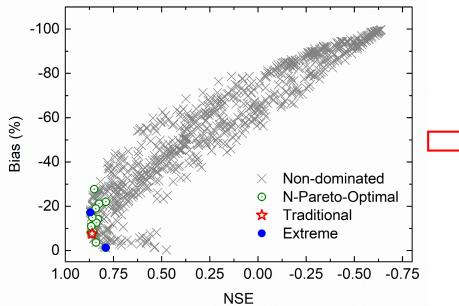
Preference Ordering Routine (POR) developed by Khu (2005).

Two theorems:

The efficiency of k order (or k-Pareto-optimal points)
 Point is not dominated by any other points in any of the k-dimensional subspaces.

The efficiency of order k with degree p (or [k,p]-Pareto-optimal points)

Points is not dominated by any other points for exactly p out of the possible k-dimensional subspaces.



Two simulation modes

N-simulations

The POR selected points (green circles) + extreme points(blue circles) + the compromise point (red star) S-simulation

The compromise point (red star)



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To find the points which are not dominated by as many k-dimensional subspaces as possible by reducing k and increasing p

2. Methodology

2.2 Method to separate streamflow components

 $Inflow = M_t + Rain_t$ Layer 0 Layer 1 Layer 2 $Inflow = M_t + Rain_t$ $R_{snow,t} = R_t \frac{M_t}{M_t + Rain_t}$ $R_{rain,t} = R_t \frac{Rain_t}{M_t + Rain_t}$ $R_{rain,t} = R_t \frac{Rain_t}{M_t + Rain_t}$ $R_{rain,t} = B_t f_{W,snow,t}$ $R_{rain,t} = B_t f_{W,rain,t}$ • Assuming that snowmelt M_t and rainfall $Rain_t$ exhibit identical infiltration and runoff ratios
• The fraction of baseflow induced by snowmelt $B_{snow,t} = B_t f_{W,rain,t}$ • Streamflow is separated into snowmelt- and rainfall-induced streamflow in surface runoff and baseflow

Iteration
$$\begin{cases} f_{W,snow,t}W_t = f_{W,snow,t-1}W_{t-1} + f_{i,snow,t-1}i_t\Delta t - f_{W,snow,t-1}(ET_t - Sub_t)\Delta t - f_{W,snow,t-1}B_t\Delta t \\ f_{W,rain,t}W_t = f_{W,rain,t-1}W_{t-1} + f_{i,rain,t-1}i_t\Delta t - f_{W,rain,t-1}(ET_t - Sub_t)\Delta t - f_{W,rain,t-1}B_t\Delta t \\ f_{W,snow,t} + f_{W,rain,t} + f_{W,unkown,t} = 1 \\ SWE_t = SWE_{t-1} + Snowfall_t\Delta t - Melt_t - Sub_t\Delta t \end{cases}$$

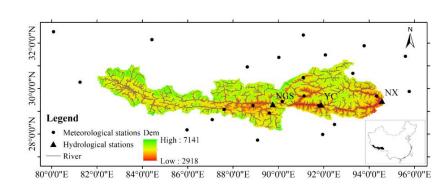
Snowmelt Tracking Algorithm by Li et al. (2017)

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3.1 Study area, model and data

Yarlung Zangbo River basin

- Observed meteorological data spanning 1998 to 2015 from CMA
- Forecasts (P/Tmax/Tmin) from **ECMWF** up to 15 days, and post-processed by QM coupled with Shaake Shuffle
- Interpolated by IDW considering elevation

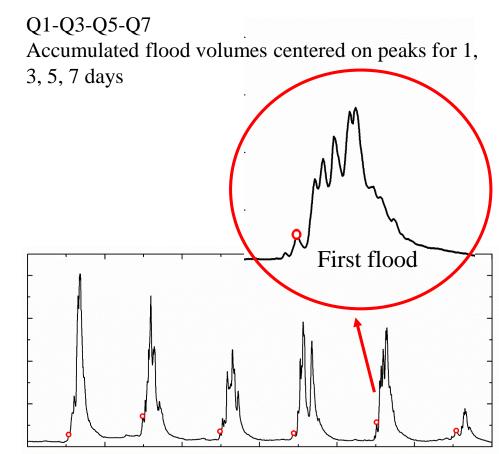


VIC

- Snow module and frozen soil algorithm is active
- Glacier-melt is not considered
- Calibrated by epsilon-NSGA II
- NSE and Bias for daily flows and for high flows (top 10%)

Flood events

- MF: the annual Maximum Flood events
- FF: the First Flood event before July in each year



3.2 Results for simulated streamflow

Station	Numbers	Mode -	Calibration/Evaluation				
			NSE	Bias(%)	NSE10%	Bias10%(%)	
Nugesha	16	N-	0.77~0.87/	-27.75~-1.30/	0.06~0.51/	-8.83~8.05/	
		simulations	0.77~0.88	-21.72~6.37	-0.05~0.48	-9.29~16.38	
		S-simulation	0.86/0.86	-7.55/-2.74	0.51/0.48	-3.02/1.29	
Yangcun	15	N- simulations	0.71~0.88/ -0.07~0.65	-34.03~-10.52/ -17.72~6.37	-1.11~0.34/ -1.41~0.73	-14.21~2.60/ -9.29~16.38	
		S-simulation	0.88/0.56	-13.54/-8.81	0.32/0.73	-7.43/-9.29	
Nuxia	11	N- simulations	0.65~0.77/ 0.58~0.79	-44.33~-34.82/ -46.53~-34.45	-1.27~-0.45/ -0.87~0.23	-27.83~-20.06/ -16.36~-4.17	
		S-simulation	0.77/0.74	-35.03/-35.51	-0.45/0.06	-20.06/-5.33	

• Information of N-simulations and S-simulation

- S-simulation behaves well in calibration but sometimes lose advantage in evaluation (bold values)
- Negative bias at Nuxia is caused by underestimation in observed meteorological data

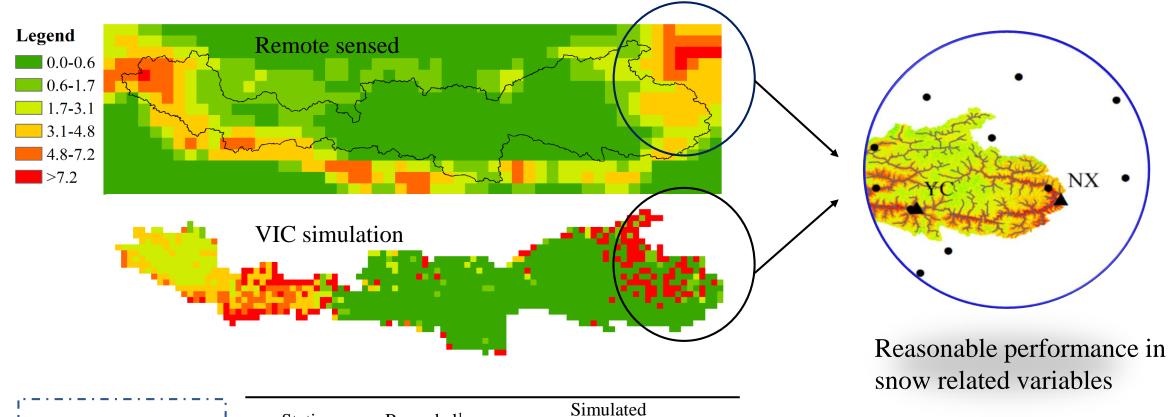
• MAE and CRPS of flood volumes during evaluation

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Events	Volumes	MAE/CRPS			
Events		Nugesha	Yangcun	Nuxia	
	Q1	107.65/96.42	258.64/230.82	315.74/379.21	
FF	Q3	297.30/266.81	714.26/636.85	795.62/998.83	
ГГ	Q5	461.82/409.22	1089.45/976.46	1181.44/1517.56	
	Q7	611.13/530.84	1412.74/1274.65	1524.84/2010.17	
	Q1	537.88/467.14	818.24/731.23	1824.27/2025.75	
MF	Q3	1497.96/1267.92	2280.90/2021.00	5125.15/5608.94	
IVIT	Q5	2304.14/1919.31	3471.46/3081.09	7820.15/8514.79	
	Q7	3016.17/2514.06	4438.17/3975.66	10091 79/10940 98	

• N-simulations behaves better than Ssimulation for flood volumes except Nuxia

3.3 Results for snow depth



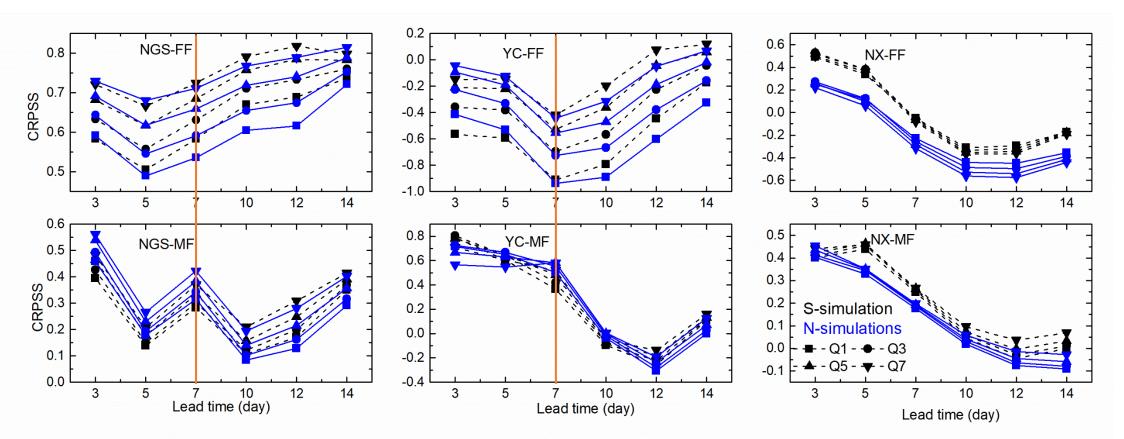
Proportion ofN-simulationsS-simulationsnowmelt inducedNGS18%14%~25%16%YC20%11%~30%25%		Station	Recorded ¹	Simulated	
streamflow YC 20% 11%~30% 25%	Proportion of	Station		N-simulations	S-simulation
	snowmelt induced	NGS	18%	14%~25%	16%
NX 38% 20%~37% 35%	streamflow	YC	20%	11%~30%	25%
$\frac{1121}{1121} \frac{3070}{2070} \frac{2070}{3770} \frac{3570}{3570}$	streamnow	NX	38%	20%~37%	35%

¹Liu et al (1999); Cuo et al. (2014)

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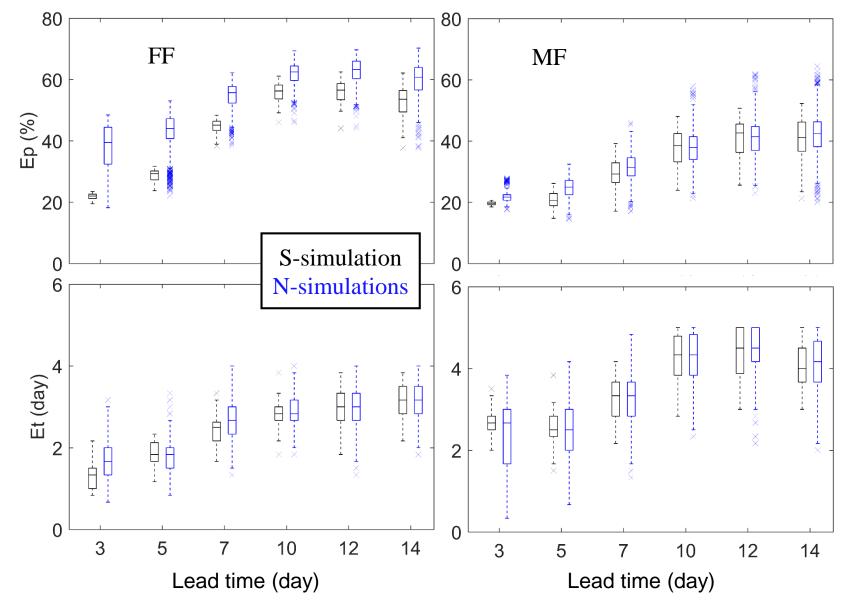
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3. Application 3.4 Flood volume forecasts

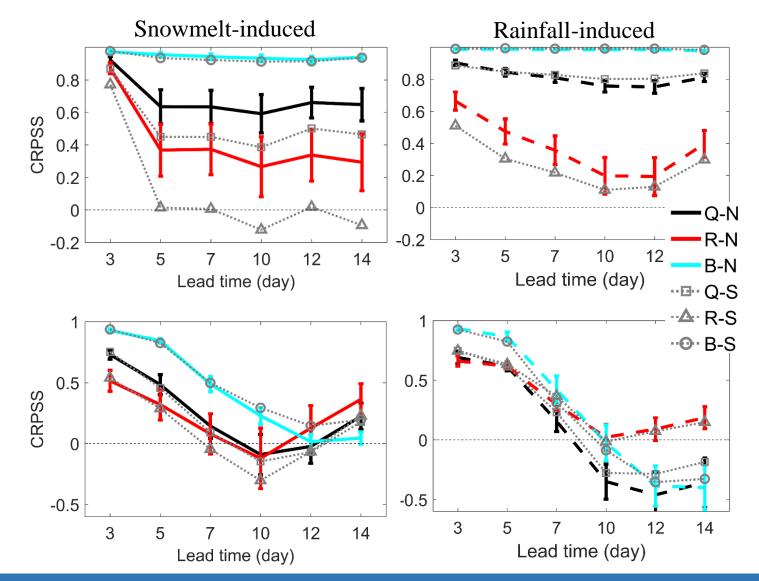


N-simulations behaves better at lead time less than 7 days Q7 is better predicted than Q1 MF can be predicted in longer lead time, about 10-14 days

3.5 Flood peak errors and peak time errors at Nuxia station



3.6 Performance in streamflow components



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4. Conclusions

□ N-simulations mode has been proven to be superior in model simulation

□ For flood forecasting, the performance of N-simulations and S-simulation varies with lead time and basin scale, and the N-simulations generally lose advantage in longer lead time

□ The forecasting system provides better forecasts for MF with a lead time of 10-14 days

Components in the surface runoff are the toughest part to capture

Thank you for your attention Question?

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