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Introduction

Precipitation is an important component of water circulation and an essential input for various hydrological models. A high quality, high spatial resolution, and long-term precipitation dataset would benefit hydrological investigations, particularly for regions having insufficient precipitation records. The UHRB was selected as the research location for this study, and the accuracy and performance of the high-resolution daily gridded precipitation dataset for China (HRLT), Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Climate Data Record (PERSIANN-CDR), and the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center Global precipitation dataset (CPC) in the hydrological simulation were evaluated by comparing with GP and the hydrological data for the period of 2000–2019.

Technical flow

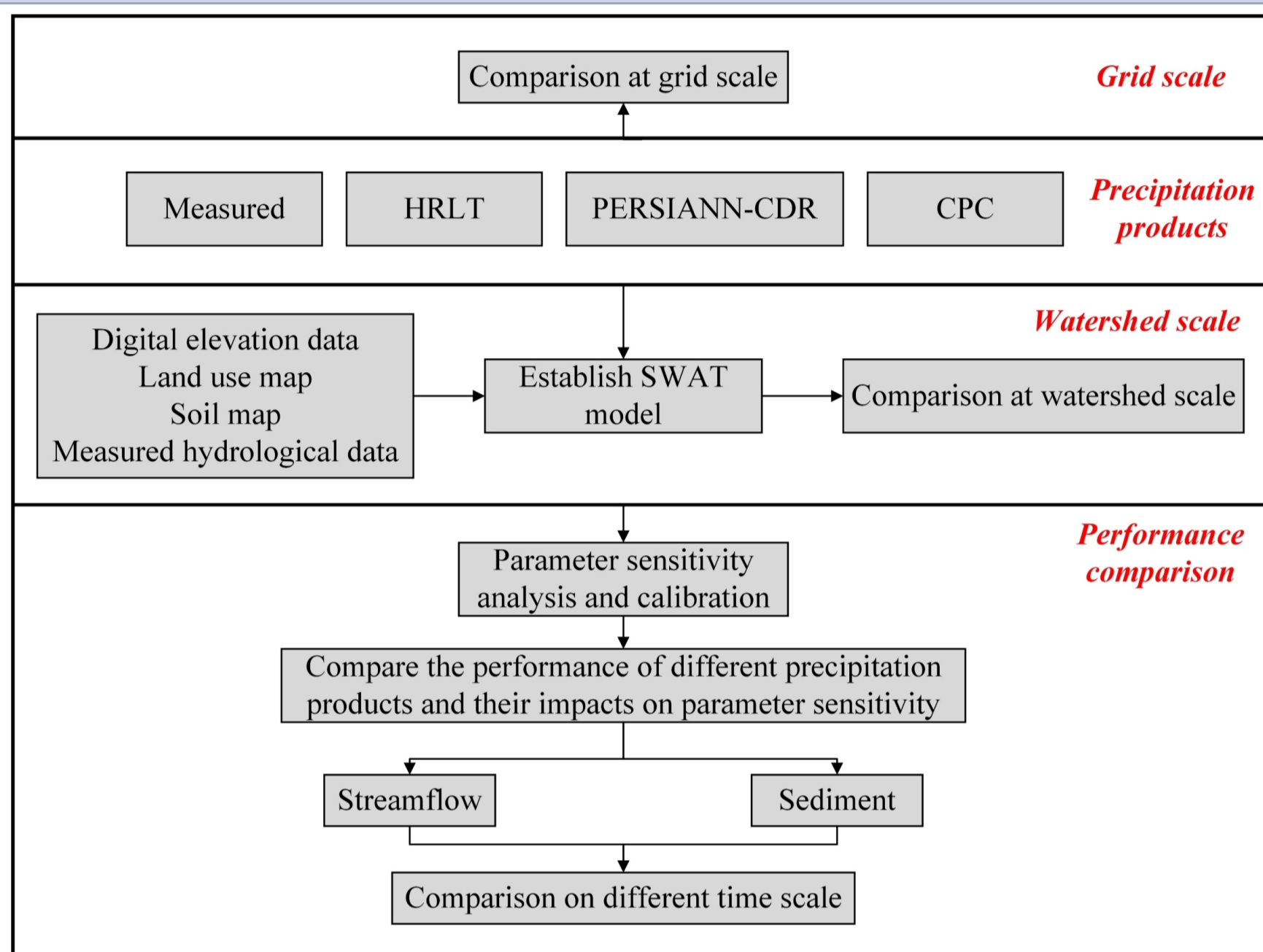


Fig 1. Technical flow of this study.

Results

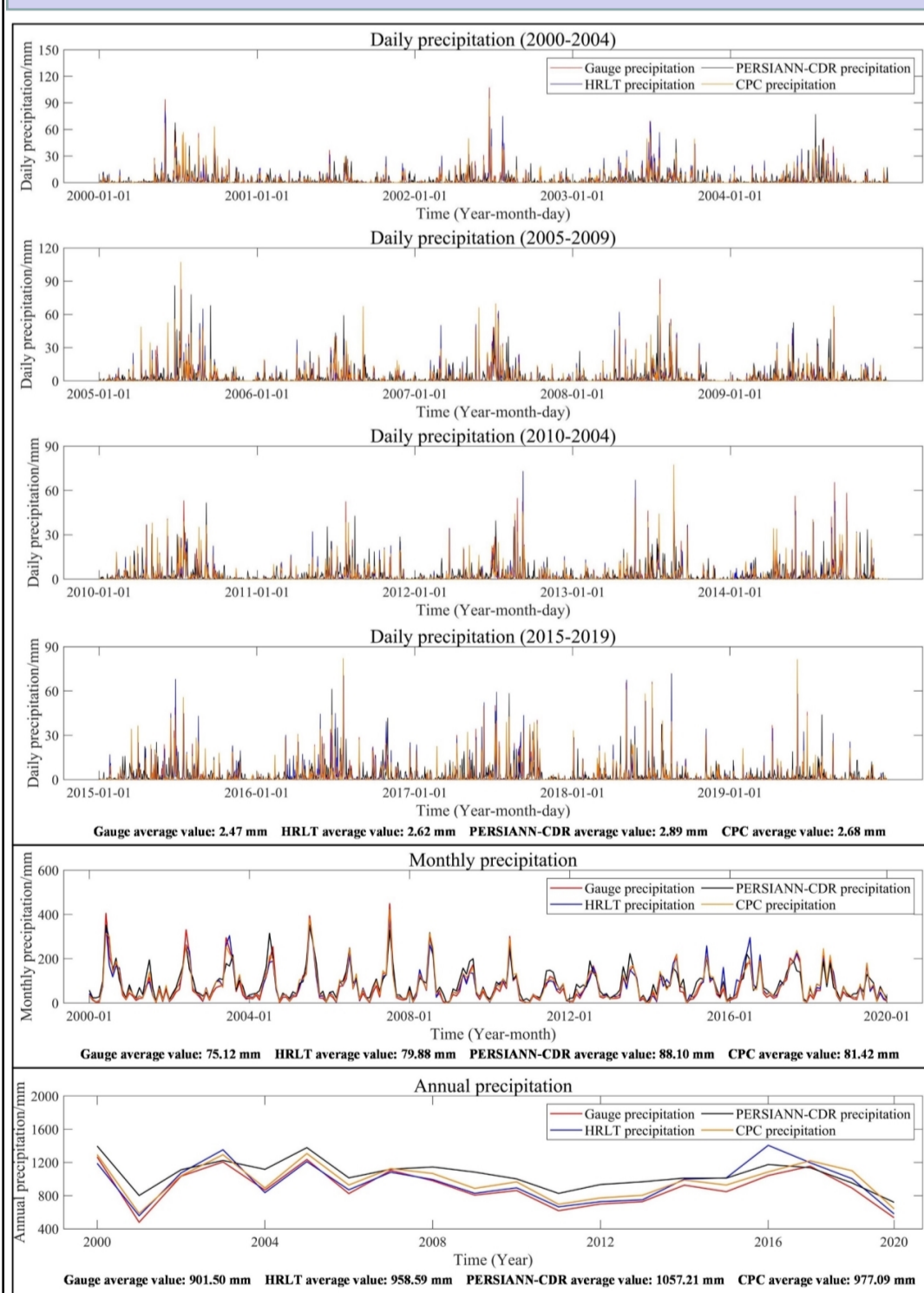


Fig 2. Comparison of the PPs and GP at daily, monthly, and annual scales.

Table 1. Continuous statistics indicators of the three PPs against GP at a watershed scale in the UHRB.

PPs	Scales	CC	RMSE/mm	BIAS/%	NSE
HRLT	Daily	0.63	6.22	6.22	0.28
	Monthly	0.97	20.59	6.22	0.93
	Annual	0.92	106.35	6.22	0.77
PERSIANN-CDR	Daily	0.67	5.59	16.69	0.42
	Monthly	0.93	31.09	16.69	0.84
	Annual	0.93	175.51	16.69	0.37
CPC	Daily	0.94	2.46	8.38	0.89
	Monthly	0.98	17.73	8.38	0.95
	Annual	0.98	86.76	8.38	0.84

Table 2. Continuous statistics indicators of the three PPs against the GP grid-to-point in the UHRB.

PPs	Scales	CC	RMSE/mm	BIAS/%	NSE
HRLT	Daily	0.45	9.43	9.26	0.05
	Monthly	0.86	47.87	9.26	0.7
	Annual	0.79	224.4	9.26	0.12
PERSIANN-CDR	Daily	0.53	8.35	20.46	0.23
	Monthly	0.85	47.12	20.46	0.68
	Annual	0.82	240.05	20.46	-0.05
CPC	Daily	0.78	5.78	10.78	0.6
	Monthly	0.91	37.41	10.78	0.81
	Annual	0.90	161.33	10.78	0.51

Table 3. Continuous statistics indicators of the three PPs against the GP grid-to-point in the UHRB.

Index	Watershed scale			Grid to point		
	HRLT	PERSIANN-CDR	CPC	HRLT	PERSIANN-CDR	CPC
POD	0.78	0.79	0.95	0.73	0.76	0.91
FAR	0.31	0.55	0.16	0.51	0.67	0.32
CSI	0.58	0.4	0.81	0.41	0.30	0.64
FBI	1.14	1.76	1.12	1.56	2.44	1.40
ETS	0.46	0.23	0.74	0.31	0.16	0.57

The accuracy of the three PPs were ranked as CPC > HRLT > PERSIANN-CDR on the watershed average scale, HRLT would underestimate the extreme precipitation; and PERSIANN-CDR would overestimate the annual precipitation. On the grid-to-point scale, PERSIANN-CDR was found to be the most stable with high accuracy, followed by CPC and HRLT on all temporal scales.

The ability of these PPs to detect rainfall events was ranked as CPC > HELT > PERSIANN-CDR.

Table 4. Performances of Q and SY for the SWAT forced by different PPs under parameter set of GP.

Variables	PPs	Calibration (2000-2011)				Validation (2012-2019)			
		R ²	NSE	PBIAS	KGE	R ²	NSE	PBIAS	KGE
Q	GP	0.91	0.89	4.5	0.88	0.81	0.81	-0.3	0.83
	HRLT	0.9	0.59	-45.3	0.42	0.7	-0.35	-103.4	-0.14
	PERSIANN-CDR	0.72	0.6	-25.9	0.68	0.45	0.41	-21.9	0.53
	CPC	0.89	0.86	-9.7	0.85	0.81	0.79	-19.2	0.78
SY	GP	0.62	0.59	-0.7	0.8	0.79	0.74	10.2	0.63
	HRLT	0.62	0.19	-50.4	0.37	0.79	0.17	-115.8	-0.22
	PERSIANN-CDR	0.47	0.39	-16.9	0.63	0.46	0.43	5.1	0.4
	CPC	0.57	0.53	-4.9	0.74	0.68	0.68	-8.8	0.7

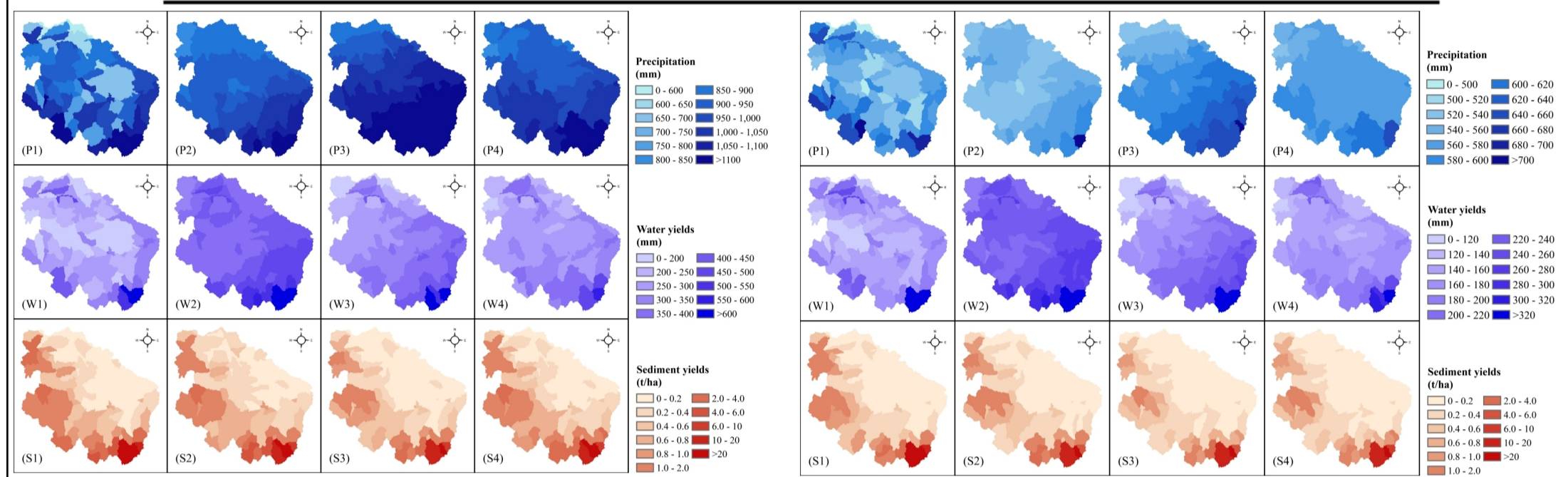


Fig 3. Annual average precipitation, WY, and SY at sub-watershed scale simulated by SWAT during the flood season (June – September) at the sub-watershed scale simulated by SWAT driven by different PPs under parameter set of GP.

Among all the PPs, the performance of CPC in the Q and SY simulations was found to be the best, followed by HRLT and PERSIANN-CDR.

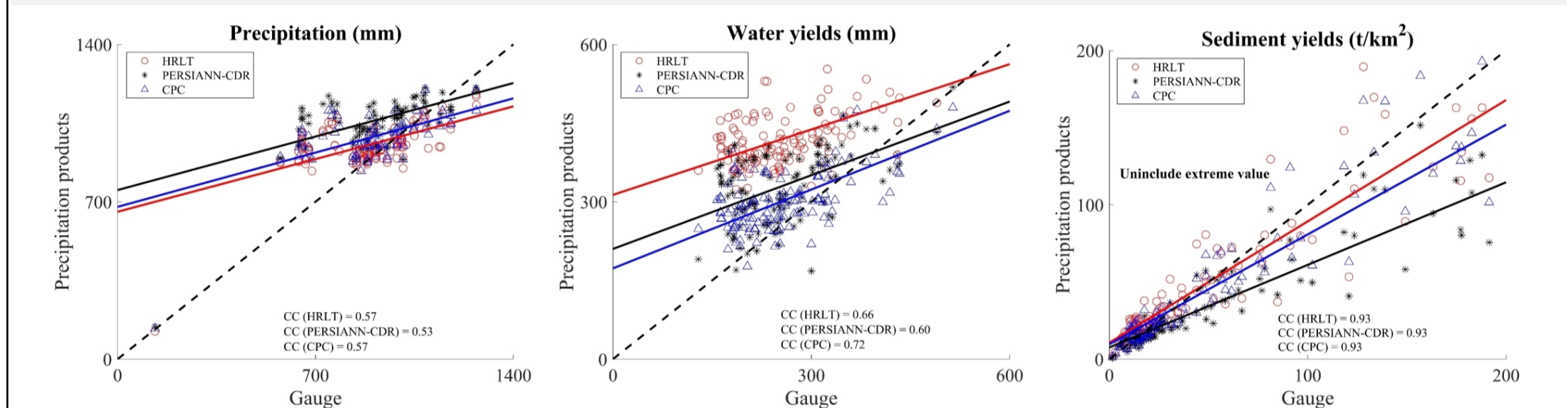


Fig 5. Correlation between the annual average precipitation, WY, and SY simulated by SWAT driven by different PPs and GP under parameter set of GP at subwatershed scale.

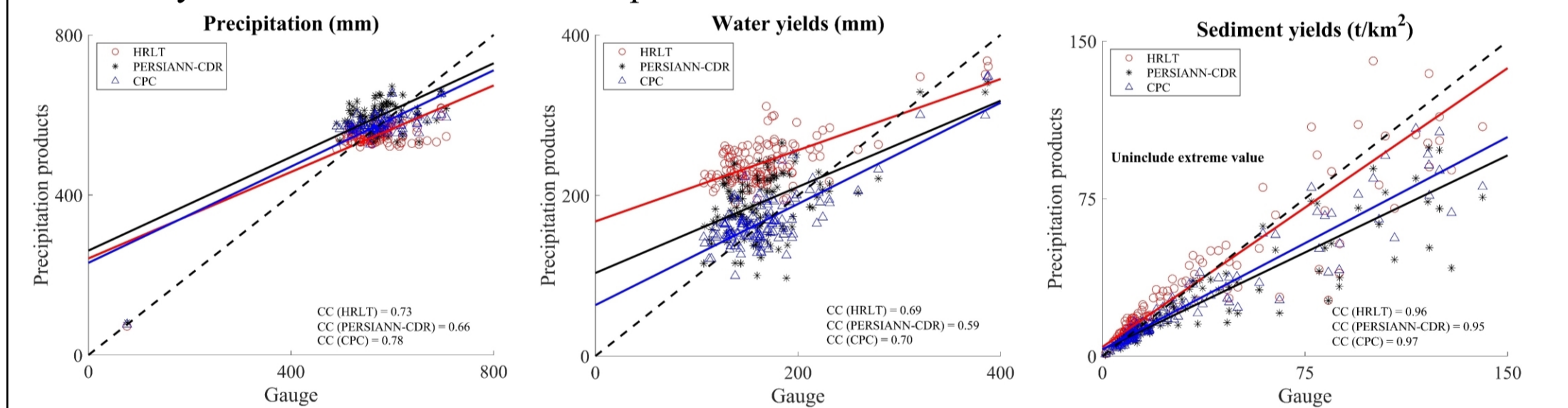


Fig 6. Correlation between average precipitation, WY, and SY during the flood season (June – September) simulated by SWAT forced by different PPs and GP at the subwatershed scale.

Compared to the sub-watershed SY simulated forced by GP, the sub-watershed SY simulated forced by CPC was closest, while that simulated forced by HRLT and PERSIANN was overestimated and underestimated, respectively.

Table 5. Performances of Q and SY for SWAT forced by different PPs under parameter set calibrated based on various PPs.

Variables	PPs	Calibration (2000-2011)				Validation (2012-2019)			
		R ²	NSE	PBIAS	KGE	R ²	NSE	PBIAS	KGE
Q	GP	0.91	0.89	4.5	0.88	0.81	0.81	-0.3	0.83
	HRLT	0.85	0.84	1.6	0.92	0.69	0.49	-36.5	0.56
	PERSIANN-CDR	0.7	0.65	-7	0.82	0.56	0.5	22	0.46
	CPC	0.88	0.86	0.8	0.91	0.8	0.79	-10.9	0.78
SY	GP	0.62	0.59	-0.7	0.8	0.79	0.74	10.2	0.63
	HRLT	0.57	0.49	3.1	0.75	0.77	0.62	-45.8	0.49
	PERSIANN-CDR	0.42	0.3	-4.4	0.65	0.54	0.34	43.6	0.18
	CPC	0.62	0.57	-0.9	0.78	0.76	0.72	10.3	0.65

The performance of PPs on forcing SWAT model has been improved after calibrating the parameters for each PPs. And the streamflow parameter sensitivity has been changed.

Conclusions

1. The accuracy of the three PPs were ranked as CPC > HRLT > PERSIANN-CDR.
2. The ability of these PPs to detect rainfall events was ranked as CPC > HELT > PERSIANN-CDR.
3. The sensitivity of the Q parameters changed with the variation in the precipitation input.
4. The performance of CPC in the Q and SY simulations was found to be the best, followed by HRLT and PERSIANN-CDR, and all the PPs could simulate SY better than Q in spatial distribution.