

Supplementary materials

S1 Density of precipitation station

Daily precipitation of 13 meteorological stations from the national weather station network, which is sparse and distributed unevenly, are selected for this study. The contributions of each station to the basin rainfall can be measured by the density map of precipitation stations over the region. The Kernel Density (“KD”) function is adopted to create a smooth surface evaluating the density of precipitation stations. The KD function calculates the density of features in a neighbourhood around those features and expresses the result as magnitude per unit area [1]. The density map of precipitation stations is generated using the kernel density estimation provided by ArcGIS Spatial Analyst [2]. The search radius (bandwidth) is set to 100 km and the population field is set to none. The output cell size (grid resolution) is set to 1000 m. The low density (particularly in the south) results in local ‘hot spots’ in the density map. The mean density of precipitation station (units: gauges per 10^4 km²) is 0.91.

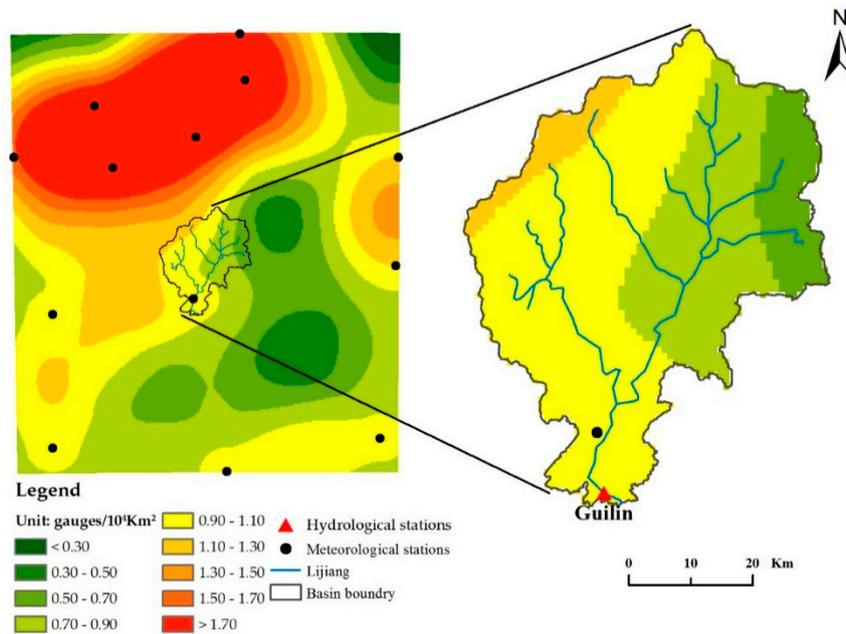


Figure S1. Density map of precipitation stations over the region (units: gauges per km²).

S2 Cross-validation statistics

The cross-validation statistics were applied to evaluate the overall predictive error of the fitted spline surface in this study. The ANUSPLIN enabled a robust detection of error using cross validation statistics that were applied to evaluate the overall predictive error of the fitted spline surface in this study. In each interpolation, the ANUSPLIN performs cross-validation by implicitly holding out each station in turn and calculating the individual difference between the observed and the fitted surface values at that station’s location [3].

The mean absolute error (MAE), root mean square error (RMSE) and relative error (the RMSE divided by the daily observed precipitation at the cross-validation station) of these individual unweighted differences can be used to evaluate the overall predictive error of the fitted spline surface. The MAE, RMSE and relative error as well as error bars for RMSE and relative error for these individual unweighted residuals are shown below (Table S1).

Table S1. Mean absolute error (MAE), root mean square error (RMSE) and relative error of cross-validation for daily interpolated precipitation grids.

	Annual	Spring	Summer	Autumn	Winter
MAE(unit: mm)	4.18	4.52	6.79	2.76	1.54
RMSE(unit: mm)	6.35	6.67	10.54	4.31	2.18
Relative Error	13.85%	9.47%	26.99%	10.96%	4.59%

The error statistics showed that annual average of MAE and RMSE were 4.18mm and 6.35mm for daily precipitation. The MAE and RMSE of the summer were higher than those of other seasons. The annual average error of the relative error was within 13.85% for daily precipitation. The study proved that the distributed precipitation surface grid interpolated by ANUSPLIN can provide a reliable precipitation grid for the input of hydrologic model.

S3 Calibrated using NSE_{log} as an objective function

There is an underestimations of flood peak in simulation, especially for daily streamflow. The reason for this phenomenon is probably these models are calibrated using the Nash-Sutcliffe Efficiency on logarithmic-transformed streamflows (NSE_{log}) that puts more weight on low flows as the objective function. The model calibrated using Nash-Sutcliffe Efficiency on non-transformed streamflows (NSE) that gives more weight to high flows. See this Supplement for the model performance calibrated using NSE as an objective function.

Setting one year as the warm-up period, selecting 2012–2016 as the calibration period, and NSE as the objective function, the Shuffled Complex Evolution algorithm is used to calibrate the parameter values of hydrologic models. Using the calibrated parameters, the overall performance (NSE) of observed value and simulated value for precipitation datasets and models for the period 2008–2016 are as follows (TableS2).

Table S2. Overall performance (daily NSE_{log} (monthly NSE)) of precipitation datasets for models using NSE_{log} as the objective function for calibration.

	IHACRES	Sacramento
Gauge-interpolated	0.77(0.74)	0.72(0.75)
TRMM	0.77(0.79)	0.76(0.81)
CMADS	0.82(0.86)	0.84(0.87)

Selecting 2012–2016 as the calibration period and 2008–2012 as the validation period, the daily and monthly model performance of the IHACRES model and Sacramento model for different precipitation products are shown in Table S3 and Table S4.

Table S3. Model performance of IHACRES model (calibrated using NSE_{log}) for the calibration period and validation periods.

	Datasets	<i>rel.bias</i>	NSE	NSE_{sq}	NSE_{log}	Monthly NSE
Calibration period	Gauge-interpolated	-0.18	0.48	0.67	0.75	0.75
Validation period	Gauge-interpolated	-0.24	0.48	0.71	0.78	0.73
Calibration period	TRMM	-0.18	0.52	0.69	0.74	0.79
Validation period	TRMM	-0.16	0.45	0.70	0.78	0.78
Calibration period	CMADS	-0.12	0.65	0.80	0.84	0.91
Validation period	CMADS	-0.26	0.56	0.76	0.80	0.81

Table S4. Model performance of Sacramento model (calibrated using NSE_{log}) for the calibration period and validation periods.

	Datasets	<i>rel.bias</i>	<i>NSE</i>	NSE_{sq}	NSE_{log}	<i>Monthly NSE</i>
Calibration period	Gauge-interpolated	-0.12	0.45	0.63	0.68	0.75
Validation period	Gauge-interpolated	-0.14	0.46	0.69	0.75	0.75
Calibration period	TRMM	-0.14	0.59	0.72	0.73	0.80
Validation period	TRMM	-0.07	0.51	0.73	0.77	0.82
Calibration period	CMADS	-0.11	0.70	0.81	0.83	0.90
Validation period	CMADS	-0.16	0.61	0.81	0.85	0.84

When the models calibrated using NSE_{log} as the objective function, similar conclusion can be reached with the models calibrated using NSE as the objective function. The CMADS precipitation datasets performs best in all the three precipitation datasets, followed by TRMM precipitation, and then gauge-interpolated precipitation.

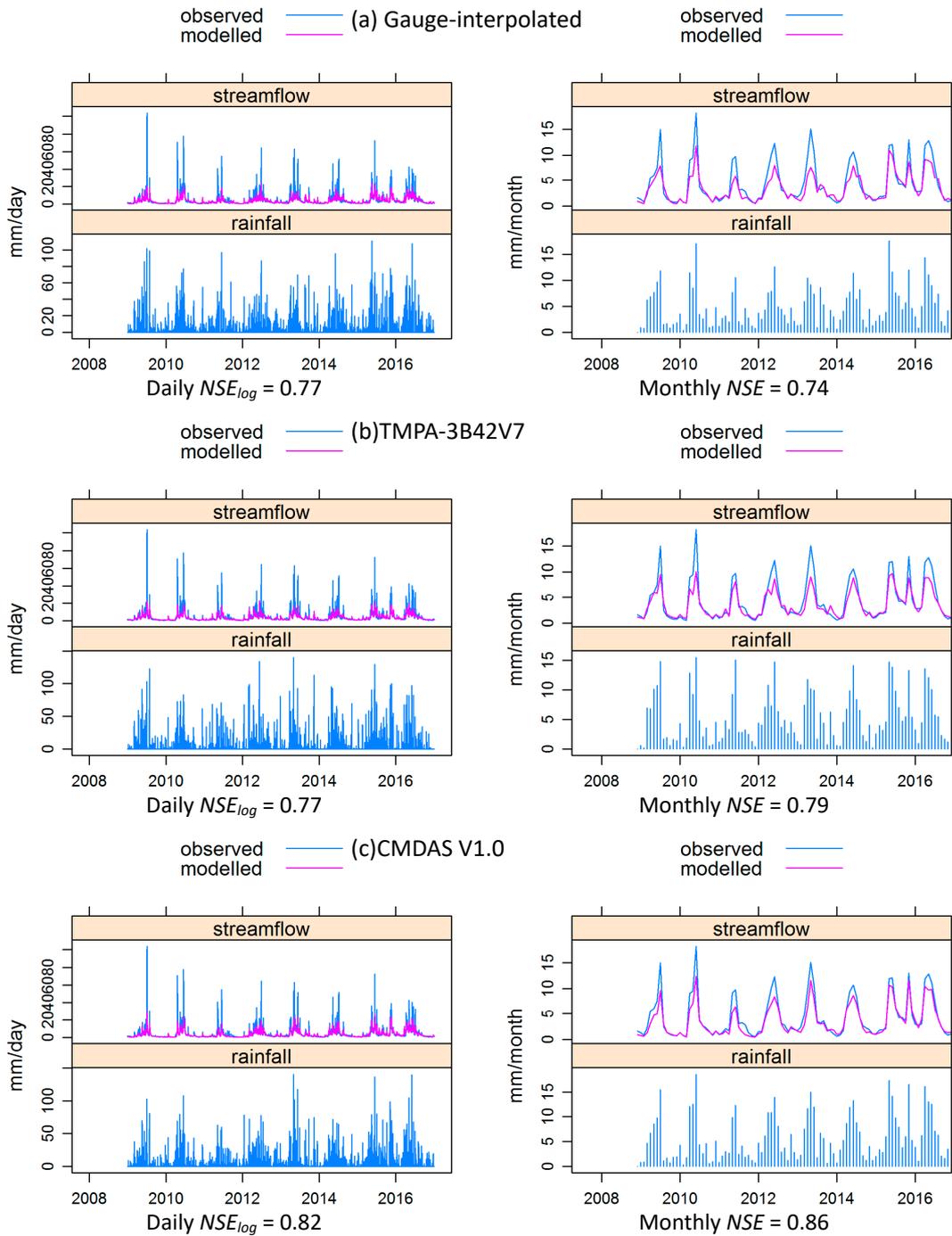


Figure S2. Observed and IHACRES-model-simulated daily and monthly runoffs for (a) Gauge-interpolated, (b) TMPA-3B42V7 and (c) CMDAS rainfall datasets (for the IHACRES model calibrated using NSE_{log} as the objective function).

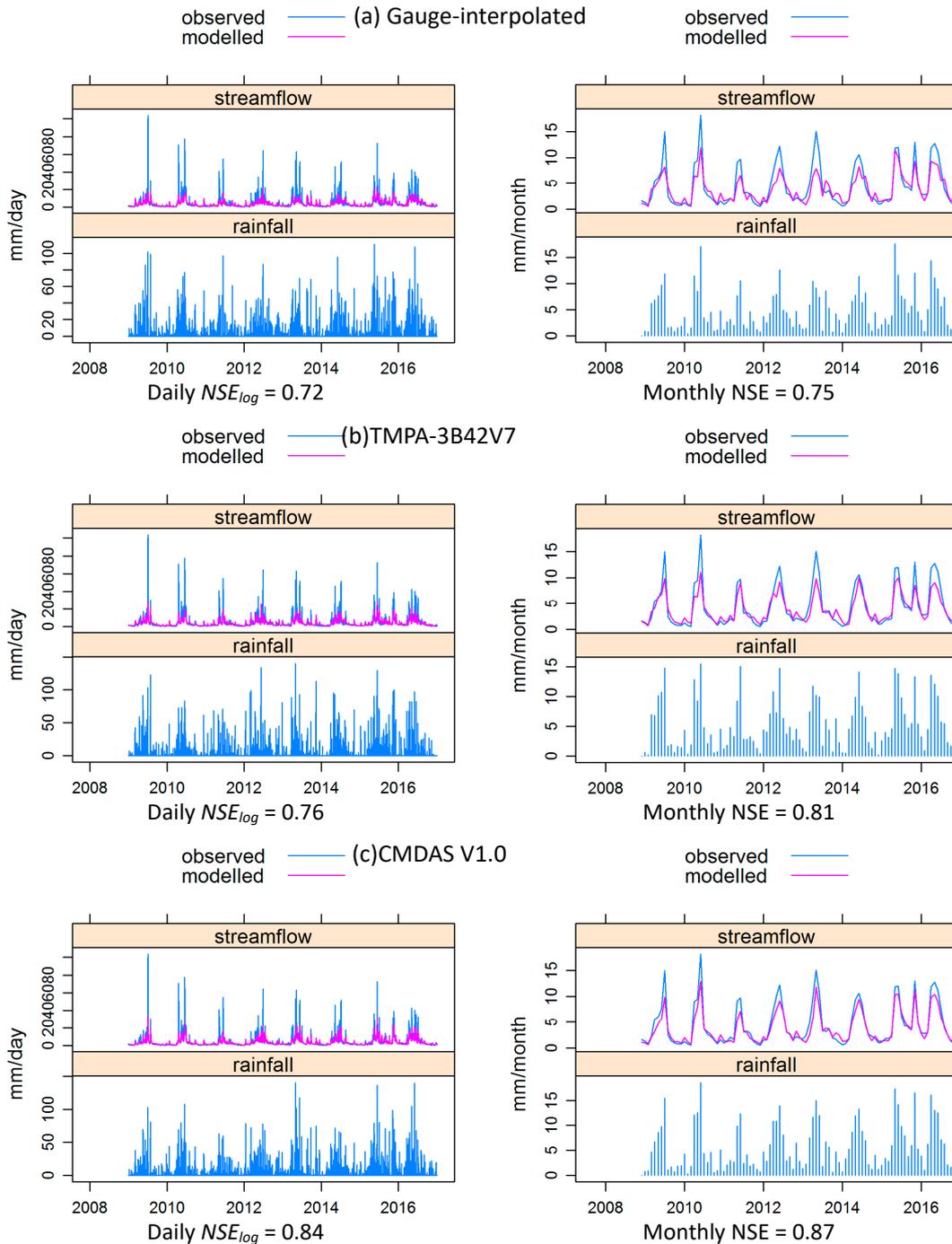


Figure S3. Observed and Sacramento-model-simulated daily and monthly runoffs for (a) Gauge-interpolated, (b) TMPA-3B42V7 and (c) CMDAS rainfall datasets (for the Sacramento model calibrated using NSE_{log} as the objective function).

Figure S2 and Figure S3 shows the IHACRES-model-simulated runoff and Sacramento-model-simulated runoff using the gauge-interpolated product, the TMPA-3B42V7 product and CMDAS product. The discharge modelling using the CMDAS precipitation datasets has a better performance in capturing the flow peaks during the simulation period.

Comparing the model performance of using NSE_{log} and NSE as the objective function for calibration, the model calibrated using NSE performed better in simulating peak flows while underestimate the low flow. While the model calibrated using NSE_{log} performed well in simulating low flow while underestimate the flood peak in simulation.

References

1. Szczęśniak, M.; Piniewski, M. Improvement of Hydrological Simulations by Applying Daily Precipitation Interpolation Schemes in Meso-Scale Catchments. *WATER-SUI* **2015**, *7*, 747–779.
2. ESRI ArcGIS desktop: release 10.1, Environmental Systems Research Institute: Redlands, California, 2012.
3. Hutchinson, M.F.; Xu, T. *Anusplin version 4.4 user guide; fenner school of environment and society*; The Australian National University: Canberra, Australia, 2013.