

A new Xin'anjiang and Sacramento combined rainfall-runoff model and its application

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ABSTRACT

The Xin'anjiang model and the Sacramento model are two widely used short-term watershed rainfall-runoff forecasting models, each with their own unique model structure, strengths, weaknesses and applicability. This paper introduces a weight factor to integrate the two models into a combined model, and uses the cyclic coordinate method to calibrate the weight factor and the parameters of the two models to explore the possibility of the complementarity between the two models. With application to the Yuxiakou watershed in Qingjiang River, it is verified that the cyclic coordinate method, although simple, can converge rapidly to a satisfactory calibration accuracy, mostly after two iterations. Also, the results in case studies show that the forecast accuracy of the new combined rainfall-runoff model can improve the forecast precision by 4.3% in a testing period, better in runoff process fitting than the Xin'anjiang model that performs better than the Sacramento model.

Key words: combined Xin'anjiang and Sacramento model, cyclic coordinate method, rainfall-runoff modeling, runoff forecast

HIGHLIGHT

- This paper introduces a weight factor to integrate the two models into a combined model, and uses the cyclic coordinate method to calibrate the weight factor.
- It is verified that the cyclic coordinate method can converge fast to a satisfactory calibration accuracy.
- The results show that the forecast accuracy of the new combined rainfall-runoff model can improve the forecast precision.

1. INTRODUCTION

Stream flow, a major part in the water cycle, plays an essential role in managing and planning water resources systems (Hansen & Hallam 1991), and the objective existence of the lead time between the rainfall and its then caused runoff in river networks opens an opportunity for us to reduce the uncertainty of stream flows by forecasting the runoff based on rainfall observed (Anderson *et al.* 2002). Many efforts have long been made in previous works to address this engineering problem by modeling the relationship between rainfall and runoff (Todini 1988; Ayttek *et al.* 2008; Asadi *et al.* 2019). Among these rainfall and runoff models, the physically based models are best used when precise data are available, physical properties of the hydrological processes are accurately understood, and applied on fine scales due to computational time, while conceptual models have gained popularity in the modeling community because they are easy to use and calibrate (Sitterson *et al.* 2018). The Xin'anjiang and Sacramento models are two lumped conceptual hydrological models extensively studied and applied in forecasting runoffs from rainfall (Jaiswal *et al.* 2020).

Professor Zhao is well known as the founder of the Xin'anjiang rainfall-runoff model based on the conception of hillslope hydrology (Ren-Jun 1992), which has since been widely applied in China (Bai *et al.* 2016). The model has been improved in its structure and simulation procedure by previous works, including the following: Jayawardena & Zhou (2000) modified the spatial distribution curve of soil moisture storage capacity from the traditional single parabolic to a general double parabolic in order to differentiate the wet from dry condition; Meng *et al.* (2018) included both the infiltration and saturation excess runoff mechanisms, coupled to a two-source potential evapotranspiration model (TSPE), to simulate the hydrological process; Yao *et al.* (2014) coupled the Xin'anjiang model with the geomorphologic instantaneous unit hydrograph to achieve better flood predictions in ungauged catchments; and Liao *et al.* (2016) employed the antecedent precipitation to correct the real-time forecast. The sensitivity of forecasting accuracy to the parameters was investigated by, for example, Zhang

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et al. (2012), who used the generalized likelihood uncertainty estimation to investigate the sensitivity of parameters of the Xin'anjiang model, and Song *et al.* (2013), who presented a two-step statistical evaluation framework using global techniques to reduce the computational cost in sensitivity analysis of the Xin'anjiang model. The parameter calibration has attracted the interest of many researchers, including the genetic algorithm in the work by Cheng *et al.* (2006), the shuffle complex evolution (Zhijia *et al.* 2013), and the multi-objective artificial bee colony algorithm (Huo & Liu 2019), to mention a few. The previous applications of the model show that the Xin'anjiang rainfall-runoff model was more applicable to humid and semi-humid regions than any other regions.

The Sacramento model was originally developed for the United States National Weather Service and State of California, Department of Water Resources by Burnash *et al.* (1973), and then widely applied worldwide. Efforts were also made to improve its performance by structurally modifying the model in previous works. Koren *et al.* (2014), for example, presented two physically based modifications in order to take into account the effects of freezing and thawing soil on the runoff generation process. The parameters in the model can be calibrated with various optimization methods, including the shuffled complex evolution (Sorooshian *et al.* 1993), the direct search algorithm that Hendrickson *et al.* (1988) showed as being more robust than the Newton-type algorithm, which is more susceptible to poor conditioning of the response surface, as well as the multi-objective particle swarm optimization in a previous work (Ahirwar *et al.* 2018) that took into account two criteria, root mean square error and bias, to calibrate parameters. The Sacramento model has been used in humid, arid, and semi-arid areas with good results.

To date, due to differences in the modeling concepts and simulation procedure, such as water source division, runoff yield and confluence, different hydrological models will have large differences in the forecast accuracy when even applied to the same watershed for the same forecast period (Mathevet *et al.* 2020). It is difficult for a single hydrological model to cover various possible factors that affect the forecast results, as it often strengthens individual modules and ignores some factors, resulting in certain limitations of the model to adapt to different engineering backgrounds, as shown by Gill *et al.* (2006).

Shamseldin *et al.* (1997) presented a combined forecasting method, which was helpful in improving the accuracy of the model forecast since it might amplify the simulation effects of the superior modules in the hydrological models, while at the same time, reduce the impact of its own defects on the forecast results. Xiong *et al.* (2001) showed that better runoff estimates can be obtained by combining the outputs of different models. Bates & Granger (2001) compared four methods in combining the simulation results from the different models to produce better combination forecasts. These previous works all made efforts in processing only the results obtained by different models independently so as to produce a better runoff ensemble.

This work introduces a weight factor to combine the Xin'anjiang with the Sacramento model, which, instead of only processing the simulation results obtained separately by the two models, optimizes the weight factor and involved parameters all together. Also, to the best of our knowledge, the complementarity between the Xin'anjiang and Sacramento models in forecasting runoffs has never been investigated in previous works.

2. THE RAINFALL-RUNOFF MODEL

2.1. Combine Xin'anjiang with Sacramento

The runoff from the combined model is simply defined as the weighted runoffs from both the well-known Xin'anjiang and Sacramento models, expressed as:

$$Q_t^{\text{COM}} = \lambda \cdot Q_t^{\text{XAJ}}(\mathbf{I}^{\text{XAJ}} | \mathbf{S}^{\text{XAJ}}, \boldsymbol{\mu}^{\text{XAJ}}) + (1 - \lambda) \cdot Q_t^{\text{SAC}}(\mathbf{I}^{\text{SAC}} | \mathbf{S}^{\text{SAC}}, \boldsymbol{\mu}^{\text{SAC}}) \quad (1)$$

where, λ is the weight factor between 0 and 1 introduced to combine the Xin'anjiang with the Sacramento model. 'COM', 'XAJ', and 'SAC' are tags used to indicate the combined, Xin'anjiang, and Sacramento models, respectively; Q_t represents the runoff at time t ; \mathbf{I} , \mathbf{S} , and $\boldsymbol{\mu}$ represent vectors of inputs that mainly include rainfalls and evaporation capacities, initial states, and parameters, respectively. The schematic diagrams involving the inputs, states, and parameters, as well as the mathematical relationships between them, can be found in previous works for both the Xin'anjiang model (Ren-Jun 1992) and the Sacramento model (Burnash *et al.* 1973). The structure of this combined model allows the inclusion of more individual models.

2.2. Initial states and parameters to be calibrated

The parameters that need to be calibrated include the weight factor as well as all the parameters involved in both the Xin'anjiang and Sacramento models. The calibration is inevitably based upon certain performance criteria to be quantified by model simulation, which depend on, among others, the initial states, including, for example, the initial soil moisture storage and runoff in the river. It is very difficult, if not impossible, to observe or measure any of these initial states, which, when artificially set to certain values, may have negative impacts on model calibration. For example, the initial moisture storages, when far above their real values, are very likely to result in false runoffs much greater than the real ones, especially during the early stage of simulation or prediction.

Table 1 gives the parameters to be calibrated for the Xin'anjiang model, as well as the eight initial states, which will also be equally regarded as parameters to be calibrated so as to improve the accuracy of the model in simulating the rainfall-runoff process. Table 2 gives all the 12 initial soil moisture and river flow states, as well as 23 parameters in the Sacramento model. The initial states will also be calibrated all together with the parameters. Most of the parameters are conceptually defined in the tables and can be determined by field measurement, which, however, would be a very laborious yet unnecessary task to yield only an initial estimation on the parameters, that can instead be easily optimized by starting with initial parameters enforced within the empirical range given in the tables as a reference for future research.

Table 1 | Parameters to be calibrated for the Xin'anjiang model

Symbol	Meaning	Empirical	Type
WU	Soil moisture storage in the upper layer		State
WL	Soil moisture storage in the lower layer		State
WD	Soil moisture storage in the deep layer		State
S	Surface-free water capacity		State
QI	Interflow		State
QG	Base flow		State
QU	Outflow of the catchment		State
Q ^{XAJ}	Stream flow at the downstream gauge site		State
KC	Conversion coefficient of evapotranspiration capacity	[0, 1.0]	Parameter
UM	Soil moisture capacity in the upper layer	[10, 20]	Parameter
LM	Soil moisture capacity in the lower layer	[60, 90]	Parameter
DM	Soil moisture capacity in the deep layer	[50, 90]	Parameter
C	Coefficient of deep layer evapotranspiration	[0.1, 0.2]	Parameter
IM	Impervious area ratio	[0.01, 0.04]	Parameter
B	Coefficient in the distribution curve of soil moisture capacity	[0.1, 0.4]	Parameter
SM	Surface-free water storage capacity	[60, 180]	Parameter
EX	Index of the free water capacity distribution	[1.0, 1.5]	Parameter
KI	Interflow discharge coefficient of the free water	[0, 1.0]	Parameter
KG	Base flow discharge coefficient of free water	[0, 1.0]	Parameter
N	Number of linear reservoirs for surface runoff	[1, 20]	Parameter
CS	Recession coefficient of the surface runoff	[0, 1.0]	Parameter
CI	Interflow recession coefficient	[0, 1.0]	Parameter
CG	Base flow recession coefficient	[0, 1.0]	Parameter
L	Time lag	0	Parameter
KE	Storage constant in Muskingum routing method	[0 h, 72 h]	Parameter
XE	Flow ratio in Muskingum routing method	[0, 0.5]	Parameter

Table 2 | Parameters to be calibrated for the Sacramento model

Symbol	Meaning	Empirical	Type
QI	Interflow		State
QGS	Supplemental runoff		State
QGP	Primary runoff		State
QU	Outflow of the catchment		State
Q ^{SAC}	Stream flow at the downstream gauge site		State
LZFS	Lower zone free supplemental water content		State
LZFP	Lower zone free primary water content		State
AUZW	Upper zone tension water content on additional impervious area		State
ALZW	Lower zone tension water content on additional impervious area		State
UZTW	Upper zone tension water content		State
UZFW	Upper zone free water content		State
LZTW	Lower zone tension water content		State
KC	Conversion coefficient of evapotranspiration capacity	[0, 1.0]	Parameter
UZTWM	Upper zone tension water capacity	[10,30]	Parameter
UZPWM	Upper zone free water capacity	[15, 30]	Parameter
LZTWM	Lower zone tension water capacity	[80, 130]	Parameter
LZFSM	Lower zone free supplemental water capacity	[10, 30]	Parameter
LZPFM	Lower zone free primary water capacity	[50, 150]	Parameter
UZK	Fractional daily upper zone free water withdrawal rate	[0.01, 0.04]	Parameter
ZPERC	Maximum percolation rate coefficient	[8, 25]	Parameter
CGS	Recession coefficient of supplemental water	[0, 1.0]	Parameter
CGP	Recession coefficient of primary water	[0, 1.0]	Parameter
CR	Fractional withdraw rate of water in river networks	[0, 1.0]	Parameter
KE	Storage constant in Muskingum routing method	[1 h, 72 h]	Parameter
PCTIM	Minimum impervious area	0.01	Parameter
ADIMP	Additional impervious area	0.01	Parameter
RSERV	Fraction of lower zone-free water not transferrable to lower zone tension water	[0, 0.3]	Parameter
RIVA	Riparian vegetation area	0.01	Parameter
LZSK	Fractional daily supplemental withdrawal rate	[0.1, 0.3]	Parameter
LZPK	Fractional daily primary withdrawal rate	[0.005, 0.05]	Parameter
CI	Interflow recession coefficient	[0, 1.0]	Parameter
REXP	Percolation equation exponent	[0.1, 1.0]	Parameter
XE	Flow ratio in Muskingum routing method	[0, 0.5]	Parameter
LR	Time lag	0	Parameter
PFREE	Conversion coefficient of evapotranspiration capacity	[0.2, 0.5]	Parameter

3. PARAMETER CALIBRATION

3.1. Assessment criterion

Usually, the simulated and observed runoffs are compared to evaluate the accuracy of a forecast model. To evaluate the calibration accuracy, the present work employs the well-known Nash–Sutcliffe efficiency (NSE), the closer whose value is to 1,

the better the calibration. The NSE is expressed as:

$$NSE = 1 - \frac{\sum_{t=1}^n (Q_t^{\text{COM}} - Q_t)^2}{\sum_{t=1}^n (Q_t - \bar{Q})^2} \quad (2)$$

where, n is the number of time intervals during the simulation period; Q_t^{COM} is the stream flow at time t , simulated by the combined model; Q_t is the stream flow observed at time t ; and the \bar{Q} is the average over Q_t .

3.2. The cyclic coordinate method to calibrate parameters and initial states

Combining more than one rainfall-runoff model has been practiced in previous works, most of which, however, calibrate parameters independently for each model and then process the results from all individual models to produce better forecast accuracy. The present work calibrates the parameters and the initial states of the two models, as well as the weight factor to combine the models all together by using the cyclic coordinate method (CCM), which is popular with practitioners owing to its simplicity.

The CCM is an optimization algorithm that successively optimizes along coordinate directions to find the optimum of a function. This procedure, although very simple, is very effective in finding a KKT solution for unconstrained optimization or one with only box constraints. Obviously, the calibration problem in this work is a nonlinear optimization with box constraints on each parameter or initial state, which is only constrained with an upper and a lower bound.

Let a solution of parameters and initial states to the calibration problem be:

$$\begin{aligned} X &= [\lambda, \mathbf{I}^{XAJ}, \mathbf{S}^{XAJ}, \boldsymbol{\mu}^{XAJ}, \mathbf{I}^{\text{SAC}}, \mathbf{S}^{\text{SAC}}, \boldsymbol{\mu}^{\text{SAC}}]^T \\ &= [x_1, x_2, \dots, x_n]^T \end{aligned} \quad (3)$$

and start with an initial solution denoted as:

$$X^{(0)} = [x_1^{(0)}, x_2^{(0)}, \dots, x_n^{(0)}]^T \quad (4)$$

The procedure of the CCM is illustrated in [Figure 1](#).

For an optimization with box constraints on decision variables $X \in \mathbb{R}^n$, the CCM starts with the initial solution $(X(0))$ at the beginning of the first cycle, searches along the first coordinate direction

$$\bar{e}_1 = [1, 0, 0, \dots, 0]^T \quad (5)$$

to derive the optimal solution () on the direction, then searches along

$$\bar{e}_2 = [0, 2, 0, \dots, 0]^T \quad (6)$$

to obtain the optimum () on the direction, and continues in this way but let

$$X_0^{(k+1)} = X_n^{(k)} \quad (7)$$

every time after the last coordinate rotated. The procedure repeats

$$\begin{cases} NST(X_i^{(k)}) = \min_{\lambda} NSE(X_{i-1}^{(k)} + \lambda \bar{e}_i) \\ \text{s.t. } \underline{X} \leq X_{i-1}^{(k)} + \lambda \bar{e}_i \leq \bar{X} \end{cases} \quad (8)$$

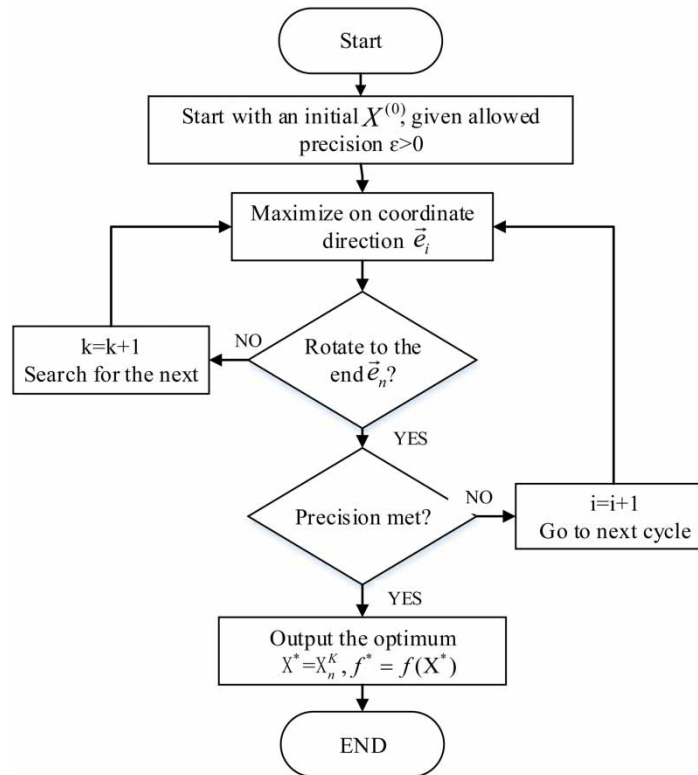


Figure 1 | Cyclic coordinate method in calibrating parameters.

until reaching the convergence

$$\|X_n^{(k)} - X_1^{(k)}\| \leq \varepsilon \quad (9)$$

which also determines the optimal parameters and initial states as: $X^* = X_n^{(k)}$.

4. CASE STUDIES

4.1. The watershed background

The Qingjiang River Basin is located at the eastern end of the Yunnan-Guizhou Plateau, China. The terrain is high in the west and low in the east, with the total length of the mainstream being 423 km, and the total drainage area about 16,700 km². The basin belongs to a subtropical monsoon climate zone, with an average annual relative humidity of 70–80% and an average annual rainfall of 1,460 mm, which is unevenly distributed throughout the year, with more than 75% of the annual rainfall concentrated in the rainy season from April to September. The basin is rich in hydropower resources, with a large drop in water head, a small submerged area, making it easy to be developed. A three-level of cascaded hydropower stations ‘Shuibuya-Geheyan-Gaobazhou’ has been built in the middle and lower reaches of the mainstream. The map of Qingjiang River Basin and its sub-basins is shown in [Figure 2](#).

The hydrological data available for Qingjiang Yuxiakou Basin include rainfall, evaporation, runoff data from 1990 to 1991. Part of the data with a long time interval are processed with linear interpolation so that all the data are at 6-hour intervals. Thus, each year can be divided into 1,460 6-hour intervals, with those in 1990 used for training the models, and 1991 for testing the model. It is worth noting that this work does not take into account the impacts of hydro-plants Gaobazhou and Shuibuya on the stream flow since they were constructed later, in 2001 and 2009, respectively.

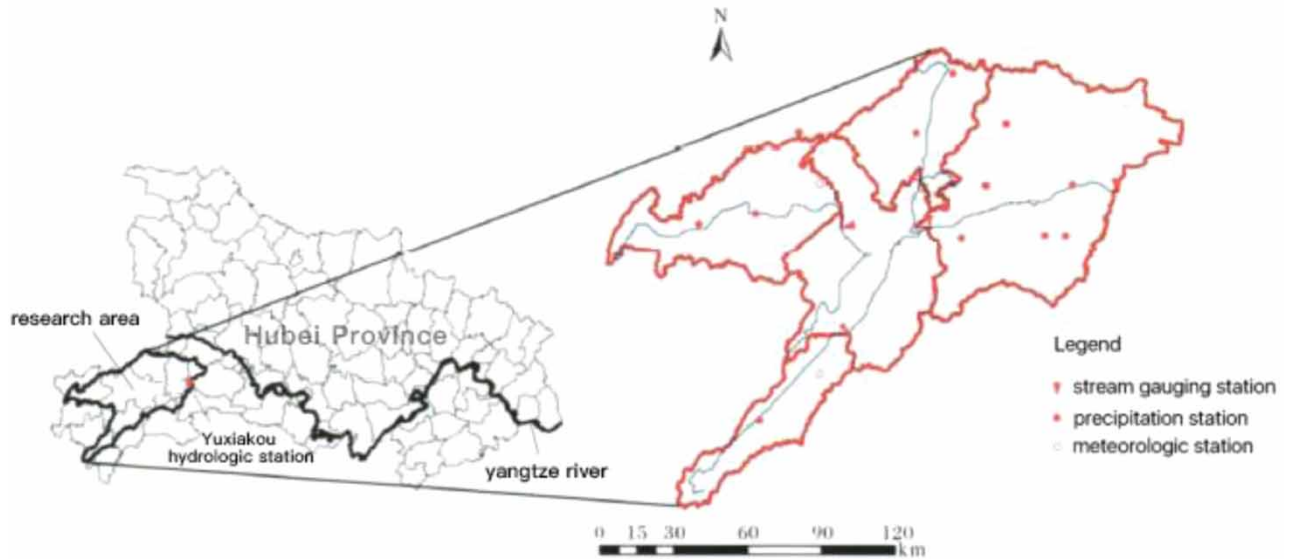


Figure 2 | Map of the watershed and its sub-watersheds.

4.2. The performance of the cyclic coordinate method

The initial values set for the parameters and initial states will affect the calibration results. Here, the experiments are done by starting the CCM at different initial solutions, selected out one by one from 1,600 sets of values randomly and reasonably generated for parameters, including initial states for the model.

Figure 3 illustrates the convergence of the NSE in the Xin'anjiang model from part of the experiment results derived by starting the CCM at different initial values generated for the parameters and initial states of the model. The NSE, although quite different at the starting points, will mostly rise to around 0.8 through about two cycles of coordinate rotation, indicating that the CCM for parameter calibration converges fast and has excellent performance. Similar conclusions can be drawn when applied to the Sacramento model.

4.3. Results in the training period

As mentioned above, the observed data in 1990 are used for training the model. To explore more local optimums, 1,600 sets of initial values for the parameters are randomly generated for each model separately, serving as their own starting solutions of the CCM. When applied to all three models, the Sacramento, Xin'anjiang, and present combined model, the best estimations give a low, high, and the highest simulation accuracy for the three models respectively, with $NSE = 0.763$ for the Sacramento, $NSE = 0.875$ for the Xin'anjiang, and $NSE = 0.916$ for the new combined model in the training period, as summarized in Table 3. The weight factor to combine the Xin'anjiang with the Sacramento model is calibrated to its best value, equal to 0.874, which suggests the Xin'anjiang model is more weighted in the present combined model.

Figure 4 illustrates the comparison of stream flows between the Xin'anjiang and Sacramento models, simulated at the best estimated parameters. The results show that the runoff in the Yuxiakou Basin of Qingjiang River is mainly concentrated during the 400–900th periods, and the rest of the periods have relatively small runoff, especially with the average of observed flow over the 1,400–1,600th periods being only $53.6 \text{ m}^3/\text{s}$. In the first 400 time periods, the runoff changing trends of the Xin'anjiang and Sacramento models are basically consistent with the observed values, but the simulated runoffs are all smaller than the observed ones. The 400–900th periods, with frequent rainfalls, are in the wet season, when the Sacramento model simulates a higher peak flow in a flood event than the observed value, and runoffs during the recession limb after the flood peak lagging behind both the observed value and the value simulated by the Xin'anjiang model. The Xin'anjiang model has a better curve fitting between the simulated runoffs and their observed values, with the peaks and valleys basically coinciding with each other. The 900–1,400th periods are in the dry season in the basin, with the average runoff only being $103 \text{ m}^3/\text{s}$. The simulated value of the Sacramento model is larger than the observed value, while that of the Xin'an River model is slightly smaller than the observed value, showing a higher simulation accuracy of the Xin'anjiang model than the Sacramento model.

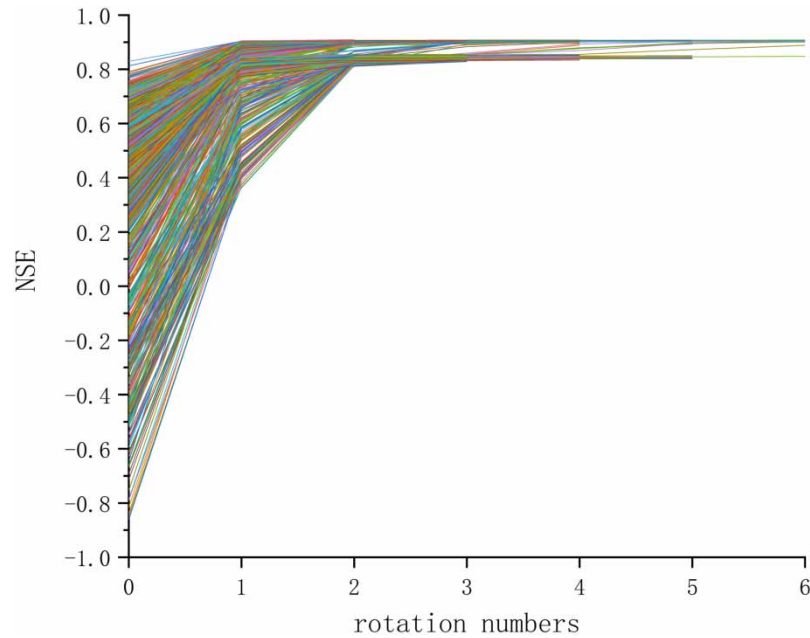


Figure 3 | Convergence of the NSE in parameter calibration of the Xin'anjiang model.

Table 3 | NSE in the training period

Model	NSE
Xin'anjiang	0.875
Sacramento	0.763
Combined	0.916 (with $\lambda = 0.874$)

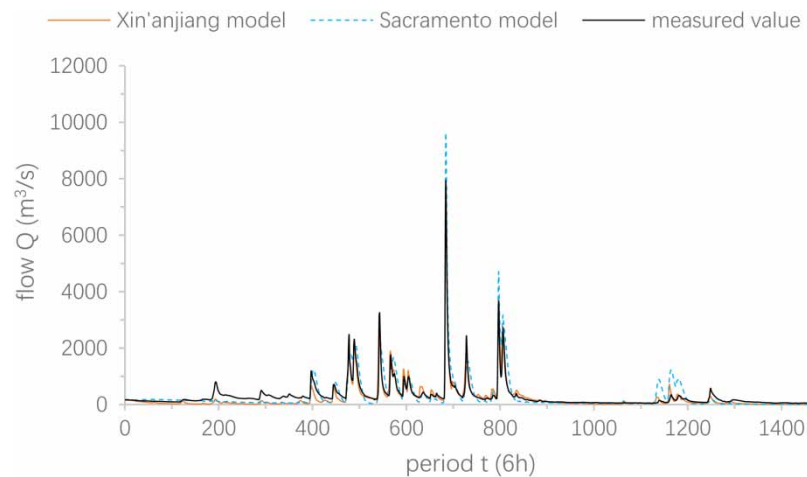


Figure 4 | Comparison between the Xin'anjiang and SAC models in the training period.

4.4. Results in the testing period

Applying the same parameters and initial states calibrated from the data in the training period (1990) to the testing period (1991) gives $NSE = 0.881$, $NSE = 0.745$, and $NSE = 0.919$ for the Xin'anjiang and Sacramento, and the new combined

models respectively, as summarized in Table 4. The combined model improves the NSE by 4.3% compared with the Xin'anjiang model, the better one when individually applied.

The NSE of the combined forecast model is greater than that of the two models when forecasting separately, indicating a higher forecast accuracy than the two single models when forecasting the runoffs in 1991 of the Yuxiakou watershed, Qingjiang River. The weight factor can be seen as the contribution ratio to the runoff simulated by the combined model, then in this way the contribution from the Sacramento model is only 12.6%, which is small and reduces the influence of the model's own defects on the forecast results to a certain extent.

The comparison between the simulated and observed runoffs during the testing period is given in Figure 5 for both the Xin'anjiang and Sacramento models. The forecast results show that in the first 400 periods when it is relatively dry, the forecast values of the two models are lower than the observed values with a certain forecast error. During the 400–900th wet period, three major floods occurred in the Qingjiang Basin. The average error of the Xin'anjiang model for the peak discharge simulation is 4.87%, while the peak discharge forecast values of the SAC model are all greater than the actual observed values, with the average error reaching 27.89%, which is a large deviation, indicating that the Xin'anjiang model has higher accuracy in forecasting the peak flood during the wet season. In the recession limb, the Sacramento model is more accurate in simulation, while the Xin'anjiang model simulates too large runoffs, indicating the existence of complementarity between the two models. In the 900–1,400th periods of the dry season, the forecast difference between the Xin'anjiang model and the Sacramento model is not significant.

The comparison between the simulated runoff by the combined model and the observed runoff during the testing period is shown in Figure 6. The combined model is better than any of the two models in either fitting the flood peak flow or the recession limb, with simulated runoffs closer to the observed values. The results show that the combined forecast model can take the advantages of both the Xin'anjiang and Sacramento models to dynamically modify the forecast value when forecasting runoff so as to improve the forecast accuracy and enhance the adaptability of the model. For the first 400 periods in the dry season, the forecast values of the two models are smaller than the observed runoffs when the two models are separately applied, making the combined model forecast runoffs smaller than the observed values too.

Table 4 | NSE in the testing period

Model	NSE
Xin'anjiang	0.881
Sacramento	0.742
Combined	0.919 (with $\lambda = 0.874$)

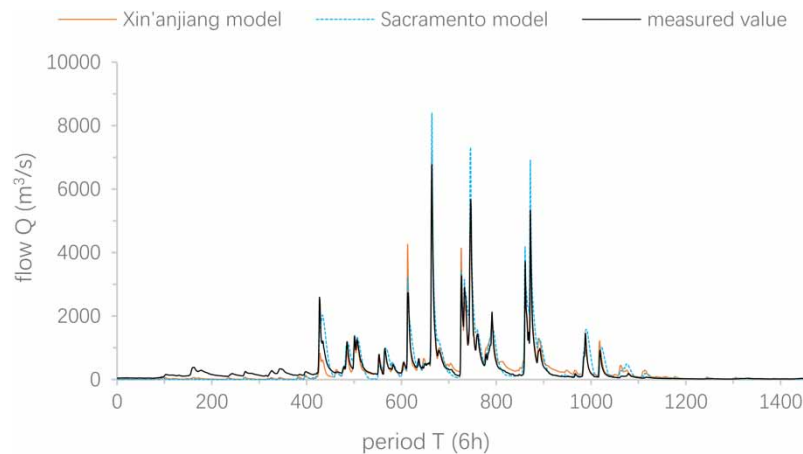


Figure 5 | Comparison between the Xin'anjiang and SAC models in the testing period.

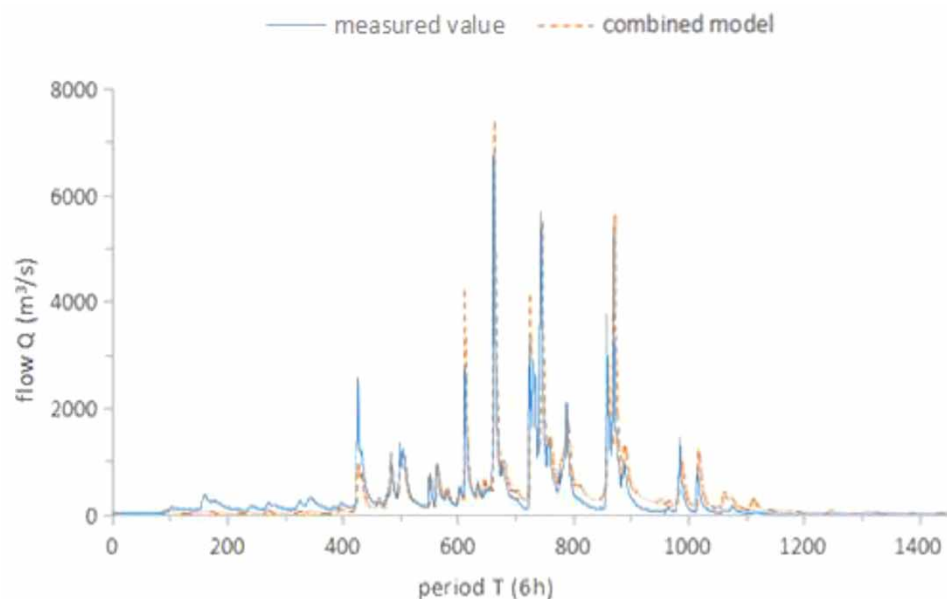


Figure 6 | Comparison among three models in the testing period.

5. DISCUSSION

Obviously, the combined model is a general one that is adaptive to its particular models and theoretically guarantees better performance than any of its particular models, either the Xin'anjiang or the Sacramento model. Physically, however, there are still some mechanisms remaining open to be explored, including, but not limited to, the long range dependence (LRD) (Dimitriadis *et al.* 2021) that the present combined model may have enhanced so as to decrease the uncertainty when translating the rainfalls to stream flows, as well as the surface, inter, and base flows that may be more connective (Keesstra *et al.* 2018) because of combining the Xin'anjiang with the Sacramento model on more diverse runoff yields. The sensitivity of the results to parameters is yet to be analyzed to give a more comprehensive assessment on the combined model by using, for example, different sensitivity indexes (Ballinas-González *et al.* 2020).

6. CONCLUSIONS

This work introduces a weight factor to combine the Xin'anjiang with the Sacramento model to explore the complementarity between the two models. Instead of only combining the results derived from the two models separately to produce better forecast, this work optimizes the weight factor, the parameters, and initial states in the two models all together by the cyclic coordinate method. Case studies in the Yuxiakou catchment of Qingjiang River in China show that the CCM converges very fast, with the Nash–Sutcliffe efficiency, though quite different at the starting points, mostly rising to around 0.8 through about two cycles of coordinate rotation. The application also reveals that the combined model performs much better than either the Xin'anjiang or Sacramento model alone, improving the NSE by 4.7% in the training period and 4.3% in the testing period compared with the Xin'anjiang model that has higher NSEs than the Sacramento model.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

REFERENCES

- Ahirwar, A., Jain, M. K. & Perumal, M. 2018 *Performance of the Xinanjiang Model*. Springer Singapore, Singapore, pp. 715–731.
- Anderson, M. L., Chen, Z.-Q., Kavvas, M. L. & Feldman, A. 2002 Coupling HEC-HMS with atmospheric models for prediction of watershed runoff. *Journal of Hydrologic Engineering* 7 (4), 312–318.
- Asadi, H., Shahedi, K., Jarihani, B. & Sidle, R. C. 2019 Rainfall-runoff modelling using hydrological connectivity index and artificial neural network approach. *Water* 11 (2), 212.

- Aytek, A., Asce, M. & Alp, M. 2008 An application of artificial intelligence for rainfall-runoff modeling. *Journal of Earth System Science* **117** (2), 145–155.
- Bai, P., Liu, X., Liang, K., Liu, X. & Liu, C. 2016 A comparison of simple and complex versions of the Xinanjiang hydrological model in predicting runoff in ungauged basins. *Hydrology Research* **48** (5), 1282–1295.
- Ballinas-González, H. A., Alcocer-Yamanaka, V. H., Canto-Rios, J. J. & Simuta-Champo, R. 2020 Sensitivity analysis of the rainfall-runoff modeling parameters in data-scarce urban catchment. *Hydrology* **7**, 75. <https://doi.org/10.3390/hydrology7040073>.
- Bates, J. M. & Granger, C. W. J. 2001 The combination of forecasts. In: *Essays in Econometrics: Collected Papers of Clive W. J. Granger. Volume 1, Spectral Analysis, Seasonality, Nonlinearity, Methodology, and Forecasting* (Ghysels, E., Swanson, N. R. & Watson, M. W., eds). Cambridge University Press, Cambridge, UK, pp. 391–410.
- Burnash, R. J., Ferral, R. L. & McGuire, R. A. 1973 A generalized streamflow simulation system – conceptual modelling for digital computers. U.S. Department of Commerce, National Weather Service, Silver Springs, MD and State of California, Department of Water Resources, Sacramento, CA.
- Cheng, C.-T., Zhao, M.-Y., Chau, K. W. & Wu, X.-Y. 2006 Using genetic algorithm and TOPSIS for Xinanjiang model calibration with a single procedure. *Journal of Hydrology* **316** (1), 129–140.
- Dimitriadis, P., Koutsoyiannis, D., Iliopoulou, T. & Papanicolaou, P. 2021 A global-scale investigation of stochastic similarities in marginal distribution and dependence structure of key hydrological-cycle processes. *Hydrology* **8** (2), 59.
- Gill, M. K., Kaheil, Y. H., Khalil, A., McKee, M. & Bastidas, L. 2006 Multiobjective particle swarm optimization for parameter estimation in hydrology. *Water Resources Research* **42** (7), 257–271.
- Hansen, L. T. & Hallam, A. 1991 National estimates of the recreational value of streamflow. *Water Resources Research* **27** (2), 167–175.
- Hendrickson, J. D., Sorooshian, S. & Brazil, L. E. 1988 Comparison of Newton-type and direct search algorithms for calibration of conceptual rainfall-runoff models. *Water Resources Research* **24** (5), 691–700.
- Huo, J. & Liu, L. 2019 Application research of multi-objective Artificial Bee Colony optimization algorithm for parameters calibration of hydrological model. *Neural Computing and Applications* **31** (9), 4715–4732.
- Jaiswal, R. K., Ali, S. & Bharti, B. 2020 Comparative evaluation of conceptual and physical rainfall-runoff models. *Applied Water Science* **10** (1), 48.
- Jayawardena, A. W. & Zhou, M. C. 2000 A modified spatial soil moisture storage capacity distribution curve for the Xinanjiang model. *Journal of Hydrology* **227** (1), 93–113.
- Keesstra, S., Nunes, J. P., Saco, P., Parsons, T., Poepl, R., Masselink, R. & Cerdà, A. 2018 The way forward: can connectivity be useful to design better measuring and modelling schemes for water and sediment dynamics? *Science of the Total Environment* **644**, 1557–1572.
- Koren, V., Smith, M. & Cui, Z. 2014 Physically-based modifications to the Sacramento soil moisture accounting model. Part A: modeling the effects of frozen ground on the runoff generation process. *Journal of Hydrology* **519**, 3475–3491.
- Liao, S.-L., Li, G., Sun, Q.-Y. & Li, Z.-F. 2016 Real-time correction of antecedent precipitation for the Xinanjiang model using the genetic algorithm. *Journal of Hydroinformatics* **18** (5), 803–815.
- Mathevet, T., Gupta, H., Perrin, C., Andréassian, V. & Le Moine, N. 2020 Assessing the performance and robustness of two conceptual rainfall-runoff models on a worldwide sample of watersheds. *Journal of Hydrology* **585**, 124698.
- Meng, C., Zhou, J., Zhong, D., Wang, C. & Guo, J. 2018 An improved grid-Xinanjiang model and its application in the Jinshajiang Basin, China. *Water* **10** (9), 1265.
- Ren-Jun, Z. 1992 The Xinanjiang model applied in China. *Journal of Hydrology* **135** (1), 371–381.
- Shamseldin, A. Y., O'Connor, K. M. & Liang, G. C. 1997 Methods for combining the outputs of different rainfall-runoff models. *Journal of Hydrology* **197** (1), 203–229.
- Sitterson, J., Knightes, C., Parmar, R., Wolfe, K., Mucbe, M. & Avant, B. 2018 An overview of rainfall-runoff model types. In *9th International Congress on Environmental Modelling and Software*, Fort Collins, CO, USA.
- Song, X.-m., Kong, F.-z., Zhan, C.-s., Han, J.-w. & Zhang, X.-h. 2013 Parameter identification and global sensitivity analysis of Xin'anjiang model using meta-modeling approach. *Water Science and Engineering* **6** (1), 1–17.
- Sorooshian, S., Duan, Q. & Gupta, V. K. 1993 Calibration of rainfall-runoff models: application of global optimization to the Sacramento soil moisture accounting model. *Water Resources Research* **29** (4), 1185–1194.
- Todini, E. 1988 Rainfall-runoff modeling – past, present and future. *Journal of Hydrology* **100** (1), 341–352.
- Xiong, L., Shamseldin, A. Y. & O'Connor, K. M. 2001 A non-linear combination of the forecasts of rainfall-runoff models by the first-order Takagi-Sugeno fuzzy system. *Journal of Hydrology* **245** (1), 196–217.
- Yao, C., Zhang, K., Yu, Z., Li, Z. & Li, Q. 2014 Improving the flood prediction capability of the Xinanjiang model in ungauged nested catchments by coupling it with the geomorphologic instantaneous unit hydrograph. *Journal of Hydrology* **517**, 1035–1048.
- Zhang, D., Zhang, L., Guan, Y., Chen, X. & Chen, X. 2012 Sensitivity analysis of Xinanjiang rainfall-runoff model parameters: a case study in Lianghui, Zhejiang province, China. *Hydrology Research* **43** (1–2), 123–134.
- Zhijia, L., Penglei, X. & Jiahui, T. 2013 Study of the Xinanjiang model parameter calibration. *Journal of Hydrologic Engineering* **18** (11), 1513–1521.

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