

Article

Improving Efficiency of Hydrological Prediction Based on Meteorological Classification: A Case Study of GR4J Model

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Abstract: Distribution of hydrological parameters is varied under contrasting meteorological conditions. However, how to determine the most suitable parameters on a predefined meteorological condition is challenging. To address this issue, a hydrological prediction method based on meteorological classification is established, which is conducted by using the standardized runoff index (SRI) value to identify three categories, i.e., the dry, normal and wet years. Three different simulation schemes are then adopted for these categories. In each category, two years hydrological data with similar SRI values are divided into a set; then, one-year data are used as the calibration period while the other year is for testing. The Génie Rural à 4 paramètres Journalier (GR4J) rainfall-runoff model, with four parameters x_1 , x_2 , x_3 and x_4 , was selected as an experimental model. The generalized likelihood uncertainty estimation (GLUE) method is used to avoid parameter equifinality. Three basins in Australia were used as case studies. As expected, the results show that the distribution of the four parameters of GR4J model is significantly different under varied meteorological conditions. The prediction efficiency in the testing period based on meteorological classification is greater than that of the traditional model under all meteorological conditions. It is indicated that the rainfall-runoff model should be calibrated with a similar SRI year rather than all years. This study provides a new method to improve efficiency of hydrological prediction for the basin.

Keywords: rainfall-runoff model; standardized runoff index; parameter distribution; meteorological classification; GR4J model



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1. Introduction

Rainfall-runoff model is a mathematical model based on the physical law between rainfall and runoff in nature, which takes the catchment as the research object [1]. Because the rainfall-runoff system is a complex nonlinear system affected by many factors such as meteorology, geology and geomorphology, the different meteorological and underlying surface conditions will inevitably change the relationship between rainfall and runoff [2]. For example, runoff generation in humid areas is mainly saturation excess runoff, while in arid areas, it is infiltration excess runoff; however, the humid and arid areas depend on the precipitation [3,4]. When it is assumed that the model parameters do not change with time, the hydrological cycle process cannot be fully reflected in the model, especially the dynamic changes of the basin meteorological conditions. Therefore, under the influence of climate change, it is more realistic to think that the rainfall-runoff model parameters have the characteristics of changing with time, i.e., time varying [5–7]. The change of basin climate and underlying surface conditions is very likely to cause the change of rainfall-runoff model parameters [8–12].

The parameter uncertainty of the rainfall-runoff model, as the main source of model simulation error, has been widely discussed in recent years [13]. The general practice is to establish a time-varying parameter for the rainfall-runoff model based on Kalman filter technology [14–17] or split calibration [18,19]. However, the time-varying law of

multi-dimensional parameter group is complex, and the correlation between each non-independent parameter is difficult to be modeled, which further increases the uncertainty of the rainfall-runoff model system [20]. Therefore, it is more practical to use the constant value parameters to predict in the experiment.

To obtain a fixed parameter in the previous research, the flowchart of rainfall-runoff model prediction is as follows [21]: (1) select the appropriate rainfall-runoff model; (2) select the training period in the historical data based on researcher experience; (3) calculate the unique parameter group by using the parameter optimization algorithm under the condition of the optimal solution of the objective function; and (4) bring the group of parameter values into the testing period for simulation. Obviously, the above process has the following shortcomings: due to the different rainfall-runoff modes under different climatic conditions, training period data that are subjectively judged and unselected are often underrepresented, which leads to the phenomenon of “over fitting” [22] between the training period parameters and the special meteorological conditions of periodic data, thereby further increasing the uncertainty of the rainfall-runoff model parameters. As a result, the simulation efficiency during the validation period does not match expectations.

In order to classify the hydrological data reasonably, Broderick [23] used the differential split sample testing (DSST) method to divide the hydrological data into two types of non-continuous “wettest” and “driest” years based on the total annual precipitation of the experimental basin. However, this method only considers rainfall as the criterion; it ignores the runoff characteristics of the basin during this period and cannot fully and accurately reflect the hydrological characteristics of the basin under different meteorological conditions.

SRI is a drought index commonly used in hydrological drought monitoring and evaluation. It is proposed by Shukla and Wood [24], referring to the standardized precipitation index (SPI), and can comprehensively reflect the hydrological and meteorological processes of the watershed. Khedun [25] pointed out that SRI comprehensively reflects hydrological and meteorological processes and is better than SPI in describing drought phenomena. Keskin et al. [26] pointed out that the standardized runoff index is a powerful tool to evaluate hydrological drought. Xiang Y Y et al. [27] used the standardized runoff index (SRI) with a three-month timescale (SRI-3) to analyze hydrological drought risk in two arid river basins characterized by different runoff regimes. Therefore, this study chooses the SRI indicator to classify the historical data of the river basin.

Based on the above discussion, a rainfall-runoff model for meteorological classification is established; GR4J model was used as the experimental model, and three basins in southeastern Australia, which were less affected by human activities, were used as the experimental basins to explore whether the distribution of rainfall-runoff model parameters was consistent under different meteorological conditions. In addition, the prediction method based on the classification of meteorological conditions was compared with the model simulation effect obtained by the traditional prediction method.

2. Methods

2.1. Rainfall-Runoff Model Based on Meteorological Classification

As shown in Figure 1, the main steps of the rainfall-runoff model based on meteorological classification are as follows:

- (1) The annual SRI value of the study area is calculated.
- (2) The hydrological data in the study basin are divided into three categories: dry (D), normal (N) and wet (W).
- (3) The corresponding verification mechanism is formulated by meteorological classification.
- (4) The corresponding parameter verification results are substituted into the corresponding similar classification period for testing.

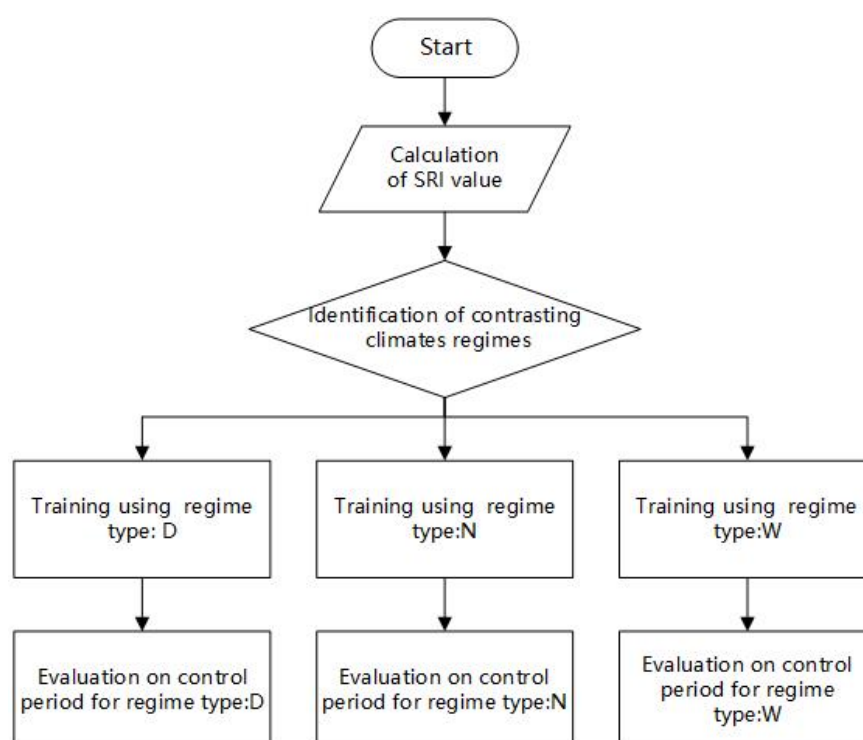


Figure 1. Flow diagram of the meteorological classification prediction model.

2.2. Standardized Runoff Index (SRI)

The standardized runoff index (SRI) is a hydrological drought index constructed based on the principle of the standardized precipitation index (SPI). It is similar to SPI, assuming that the inner diameter flow conforms to a suitable probability distribution type in a certain period of time, and the SRI is obtained after normal standardization of runoff. The calculation method is to assume that the runoff in a certain period is x , and the probability density function of runoff (P—III distribution) is as follows [28]:

$$f(x) = \frac{\beta^\alpha}{\Gamma(\alpha)} (x - a_0)^{(\alpha-1)} e^{-\beta(x-a_0)} \quad (x > a_0) \quad (1)$$

$$\Gamma(\alpha) = \int_0^\infty t^{\alpha-1} e^{-t} dt \quad (2)$$

where α , β and a_0 are shape, scale and position parameters, respectively, and $\alpha, \beta > 0$; $\Gamma(\alpha)$ is gamma function. The L-moment method is used to calculate the values of α , β and a_0 , which are brought into the formula and integrated, and the cumulative frequency $F(x)$ of each item is normalized to obtain the SRI value:

$$SRI = S \frac{k - (c_2 k + c_1)k + c_0}{[(d_3 k + d_2)k + d_1]k + 1.0} \quad (3)$$

$$k = \sqrt{2 \ln(F)} \quad (4)$$

$$F(x) = \frac{1}{\Gamma(\alpha)} \int_0^{\beta(x-a_0)} t^{\alpha-1} e^{-t} dt \quad (5)$$

where: when $F \leq 0.5$, $S = -1$; when $F > 0.5$, $S = 1$; $d_1 = 1.43279$, $d_2 = 0.18927$, $d_3 = 0.00131$, $c_0 = 2.51552$, $c_1 = 0.80285$, $c_2 = 0.010323$.

In this study, the hydrological drought situation of the study basin was divided into three grades [29] according to SRI value (Table 1).

Table 1. Hydrological drought classification based on SRI.

Drought Level	SRI Value Range	Drought Degree
W	$SRI \geq 1$	Wet
N	$-0.5 \leq SRI < 0.5$	Normal
D	$SRI < -1$	Dry

2.3. GR4J Model

Génie Rural à 4 paramètres Journalier (GR4J) [30] is a conceptual rainfall-runoff model which has 4 free parameters only. In the model, two nonlinear reservoirs are used for runoff generation and confluence calculation. The first routing applies a single unit hydrograph and the second a unit hydrograph and nonlinear storage function. Groundwater exchanges with deeper aquifers and/or adjoining catchments are represented using a gain/loss function applied to each routing channel.

GR4J model consists of four parameters: x_1 , x_2 , x_3 and x_4 . Its value range and specific meaning are listed in Table 2.

Table 2. Parameters of GR4J model.

Parameter	Unit	Meaning	Range
x_1	mm	Capacity of runoff-producing reservoir	50~1000
x_2	mm	Groundwater exchange coefficient	−10~10
x_3	mm	Capacity of confluence reservoir	10~200
x_4	d	Confluence time of instantaneous unit hydrograph (IUH)	0.7~10

In this study, the Nash–Sutcliffe efficiency (NSE) criterion [31] was used to assess performance of models between training and testing periods. The NSE is defined as follows:

$$NSE = 1 - \frac{\sum_{t=1}^T (Q_i^o - Q_i^m)^2}{\sum_{t=1}^T (Q_i^o - \overline{Q_i^o})^2} \quad (6)$$

where Q_i^m and Q_i^o represent simulated and observed daily runoff, respectively; $\overline{Q_i^o}$ is the mean observed streamflow for the estimation period, t is the time step and T is the length of the estimation period.

2.4. Parameter Selection

Previous studies suggest that parameter values sampled from different regions of the parameter space can provide equally effective simulation of system behavior [32]. However, parameter sets may perform quite well in the training period, but their test performance may be degraded under different conditions [33]. In addition, the parameters may show different distributions and sensitivities according to the different meteorological conditions experienced during the training period; these factors will affect the final prediction effect of the model.

In order to better sample the parameters and improve the effect of calibration and test, the uncertainty analysis of parameters should be carried out first. In this paper, the generalized likelihood uncertainty estimation (GLUE) method is adopted, which is a widely used Monte-Carlo-based model training and uncertainty evaluation method. The specific principle and steps of the GLUE method are detailed in reference [34]. In this study, uniform distribution is used as the prior distribution of parameters. In each experimental watershed, 10,000 groups of random parameter values are generated and brought into the model for calculation. In this paper, NSE value is used as the likelihood function, and

the feasible likelihood function threshold is set to further screen the posterior distribution of parameters.

3. Study Catchments and Data

In this study, three watersheds in southeastern Australia were used. There was no hydraulic structure or human intervention in the three watersheds. Daily precipitation, potential evapotranspiration and streamflow time series records were taken from the national dataset of Australia [35], covering 1976–2011. Due to some data being missing, the data from 1976 to 2010 were used in the catchment ID 405264 and 405219 and the data from 1976 to 2005 were used in the catchment ID 225219, with acceptable data quality. The attributes of southeastern Australian catchments are shown in Figure 2 [36]:

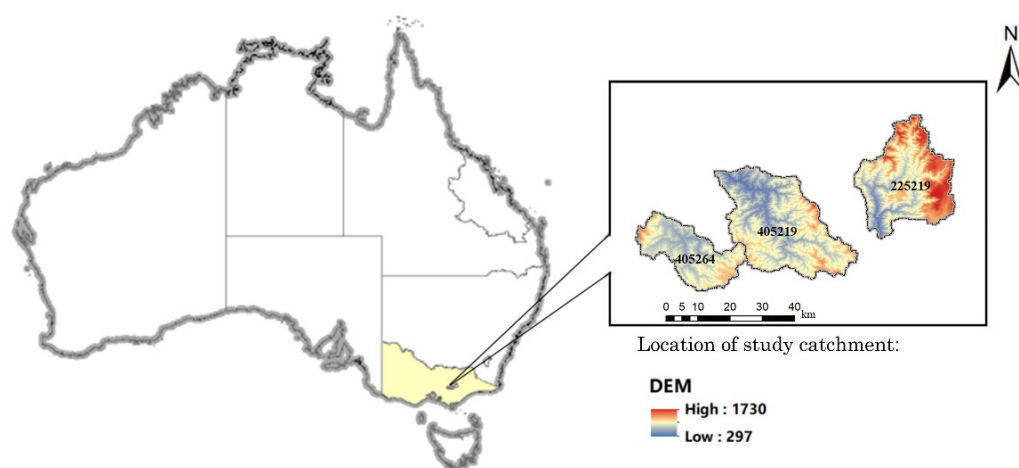


Figure 2. Locations of study catchments in Victoria, Australia.

4. Results

4.1. Meteorological Classification

SRI values are used to identify a meteorological pattern in the historical data of three basins in Australia. In application, when the testing year was determined, the corresponding training period can be selected according to the closest SRI value:

$$f = \min(|\text{SRI}_{\text{testing}} - \text{SRI}_{\text{training}}|) \quad (7)$$

According to this standard, the years with the closest SRI value under three patterns, most Wet/Normal/Dry, were set in one group, as shown in Figure 3. Taking the catchment ID 405264 as an example (Figure 3a), the two driest years screened by the meteorological classification algorithm are 1982 and 2006, the two wettest years are 1993 and 1996 and the two most normal years are 1988 and 2004.

The data period closest to SRI value is selected as a pair of tests target. Taking catchment ID 405219 as an example, since the annual SRI value of 1993 is the closest to 1996, which determined that the two-year meteorological conditions are consistent, they are set as a group. Thus, 1993 is the training period, while 1996 is the testing period. The obtained parameter group from 1993 is used for simulation in 1996; other grouping results of three experimental basins in Australia are shown in Table 3.

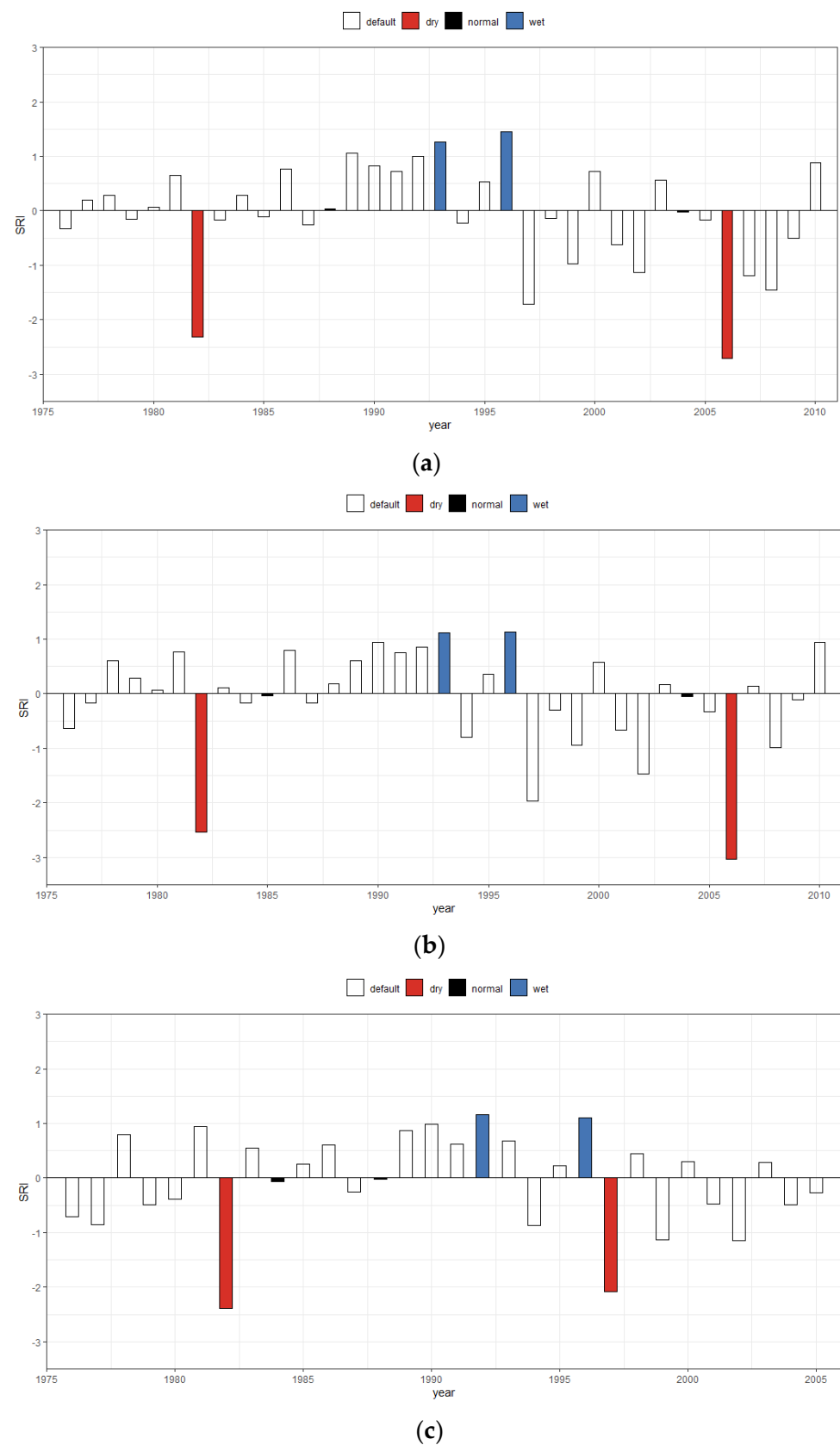


Figure 3. Classification of experimental watersheds under most W/N/D meteorological conditions based on SRI. (a) SRI (total year) value of the catchment ID 405264 (b) SRI (total year) value of the catchment ID 405219 (c) SRI (total year) value of the catchment ID 225219.

Table 3. Data segmentation results of three experimental watersheds.

Category	ID: 405264				ID: 405219				ID: 225219			
	Training	SRI	Testing	SRI	Training	SRI	Testing	SRI	Training	SRI	Testing	SRI
Wet	1993	1.26	1996	1.44	1993	1.11	1996	1.13	1992	1.16	1996	1.10
Normal	1988	0.04	2004	−0.02	1985	−0.04	2004	−0.06	1984	−0.06	1988	−0.03
Dry	1982	−2.31	2006	−2.71	1982	−2.53	2006	−3.03	1982	−2.39	1997	−2.08

4.2. Comparison of the Posterior Distribution of Model Parameters under Different Meteorological Conditions

Figures 4 and 5 show the variation of rainfall-runoff model posterior parameters distribution under contrasting meteorological conditions inferred by the GLUE method, and these figures are the density heat map drawn in R language, using the “denscols” function to identify the scatter distribution density by different colors. When the color of the scatter points is darker (red color), the parameter density in this area is higher. On the contrary, when the scatter color is lighter (yellow color), the parameter density in this area is lower.

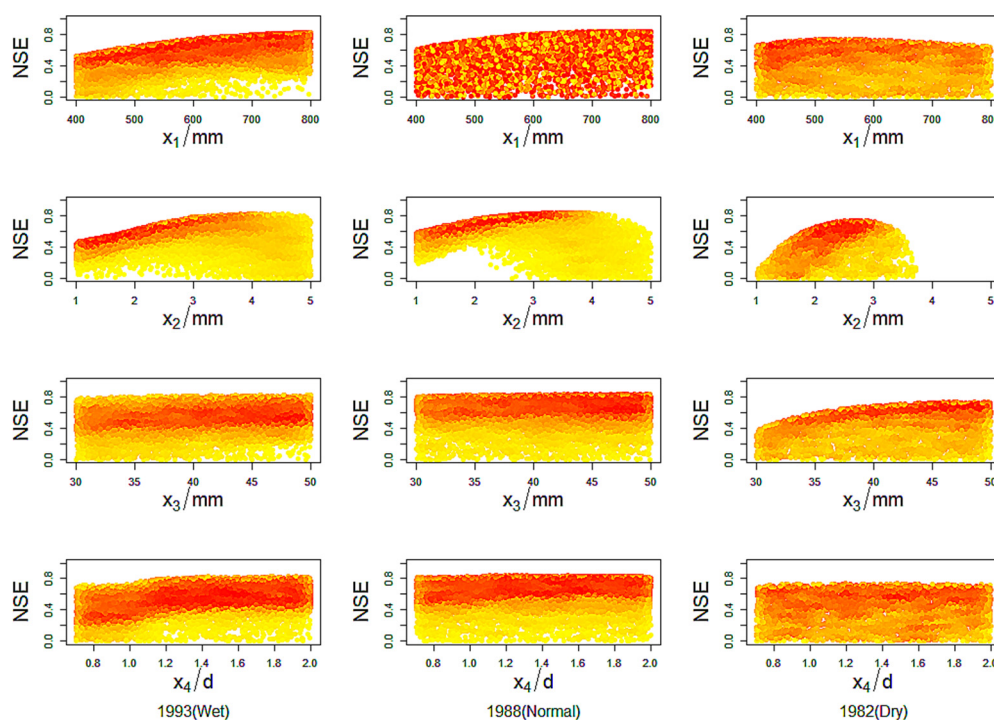


Figure 4. The density heat map of parameter distribution of GR4J under different meteorological conditions (catchment ID 405264, training period).

Comparing Figure 4 with Figure 5, the distribution of the four parameters is significantly different under three meteorological conditions (i.e., wet, normal and dry), and the sensitivity performance of the parameters is also different. In the same meteorological condition, the parameter distribution is close. In wet condition, the high-density area of parameter x_1 (capacity of runoff-producing reservoir) value is higher (400~800) in both the training and the testing period. In normal conditions, the parameter distribution is relatively uniform without an obvious clustering phenomenon, and the high-density area of x_1 value in the dry period is lower (400~500). The distribution of parameter x_2 (groundwater exchange coefficient) is similar in wet and normal conditions, and there is an obvious high-density area of x_2 value (1~3). In the dry condition, the parameter distribution is significantly different from other patterns, the range of the feasible parameter area is reduced and the high-density area of parameter x_2 value is increased (2~3). Parameter x_3 (capacity of confluence reservoir) is not sensitive in W/N/D and has no obvious clustering

phenomenon, but its distribution is slightly different from the W/N condition in the dry condition. The NSE value is low in the low-value area (0.7~1.2) of parameter x_4 (confluence time of IUH), and high in the high-value area (1.2~2) in wet condition, while the NSE values corresponding to the high-density area of the normal year parameter x_4 are consistently in the feasible range, and the clustering phenomenon of the parameters in the arid period is not obvious.

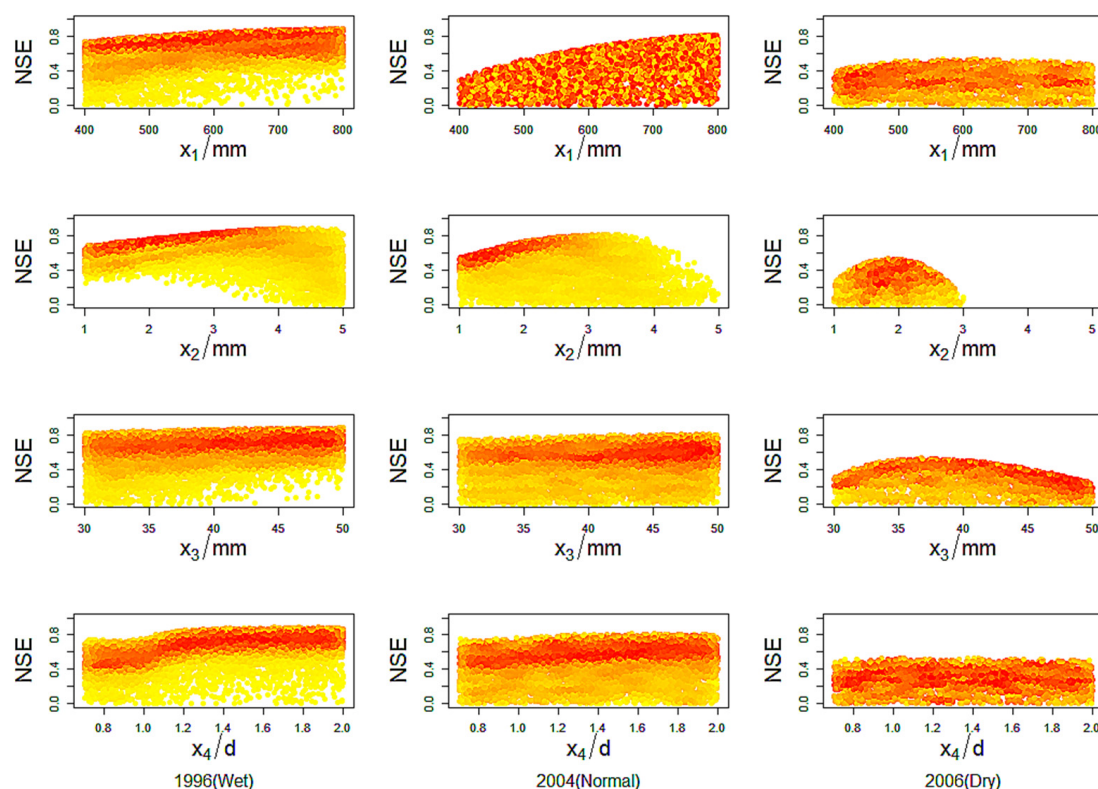


Figure 5. The density heat map parameter distribution of GR4J under different meteorological conditions (catchment ID 405264, the testing period).

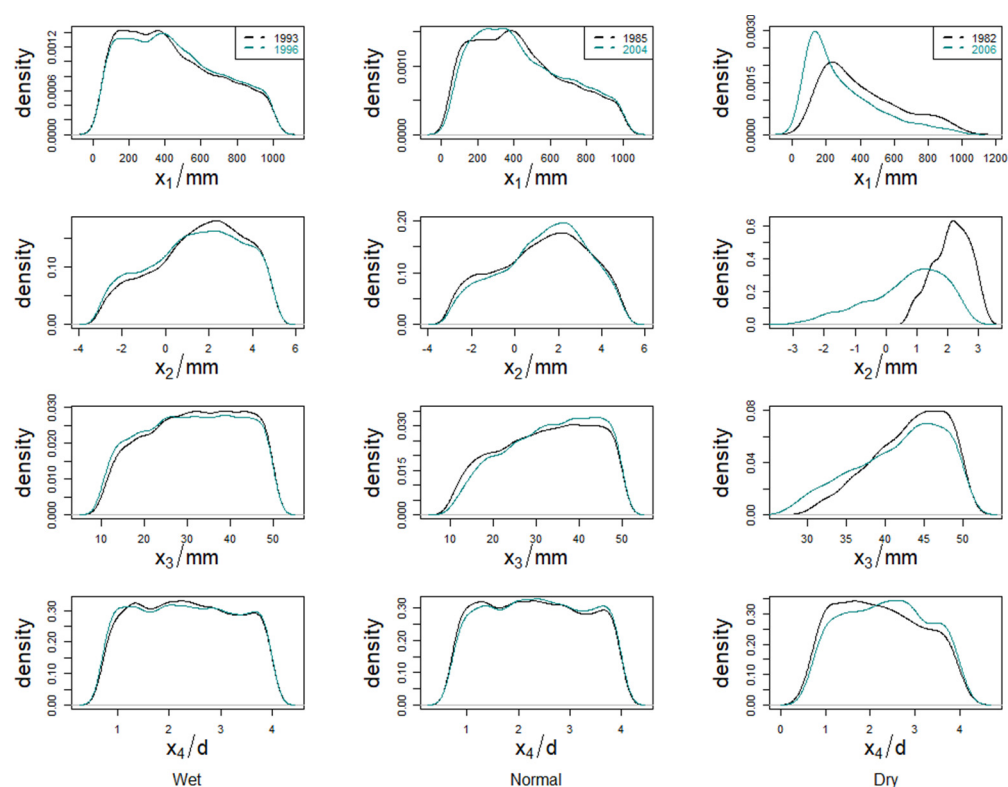
Through analysis, it is considered that in the wet period, the runoff-producing reservoir capacity (x_1) of the basin will increase compared with the normal and dry period. The groundwater exchange coefficient (x_2) will decrease due to the decrease of runoff recharge to groundwater caused by the non-closure of the basin. Because the runoff generation mode is saturation excess runoff generation in the wet period, the confluence time (x_4) will increase slightly. On the contrary, in the dry period, due to the reduction of runoff-producing reservoir capacity, runoff replenishment of groundwater increases, and the groundwater exchange coefficient (x_2) increases. Because the runoff-producing mode of the basin in the dry period is infiltration excess runoff, the confluence time (x_4) decreases. The analysis of the experimental results further proves that the parameters of the rainfall-runoff model are non-fixed and change with the change of meteorological conditions.

To verify the consistency of model parameters under similar meteorological conditions, the Mann–Whitney U independent sample nonparametric test is further adopted for the distribution fitting test of two groups of parameters, where the null hypothesis (H_0) is that the two independent samples have the same distribution. As listed in Table 4, the test results show that the parameter distribution of the two periods is highly consistent under similar meteorological conditions at the 0.05 level of significance.

Table 4. P-values of Mann–Whitney U distribution fitting test on the catchment ID 405264.

Paired Conditions	x_1	x_2	x_3	x_4
Wet	0.247	0.152	0.291	0.615
Normal	0.154	0.121	0.963	0.87
Dry	0.658	0.000	0.158	0.79

In the comparative analysis of the posterior probability density distribution of the model parameters in periods with similar SRI values, it is further found that the posterior probability density distribution of the parameters is highly similar (Figure 6). It can therefore be concluded that using the group of data with the closest SRI value as the test object is more in line with objective reality.

**Figure 6.** Comparison of posterior distribution of training and testing period parameters under different meteorological classification conditions (catchment ID 405219).

It can be seen from Figures 4 and 5 that the feasible range of parameters changed with the difference of meteorological conditions in one basin. If the parameters of the basin rainfall-runoff model have clear physical meanings and there is a unique “true value”, then the actual distribution of the parameters should be a certain continuity area around this true value (high-density areas in Figures 4 and 5), and the parameters should be optimal within the feasible range of the parameters. The selection of the region is particularly critical in the range of feasible parameter area. Taking catchment ID 405264 as an example, under the approximate meteorological conditions of the same basin, the parameter values should be relatively close. The parameter group is calibrated with the hydrological data of the closest SRI value during the testing period, and the resulting parameter group is closer to the real situation of the watershed. The prediction performance of the model can be improved by selecting different parameter ranges under different meteorological conditions (Figure 7).

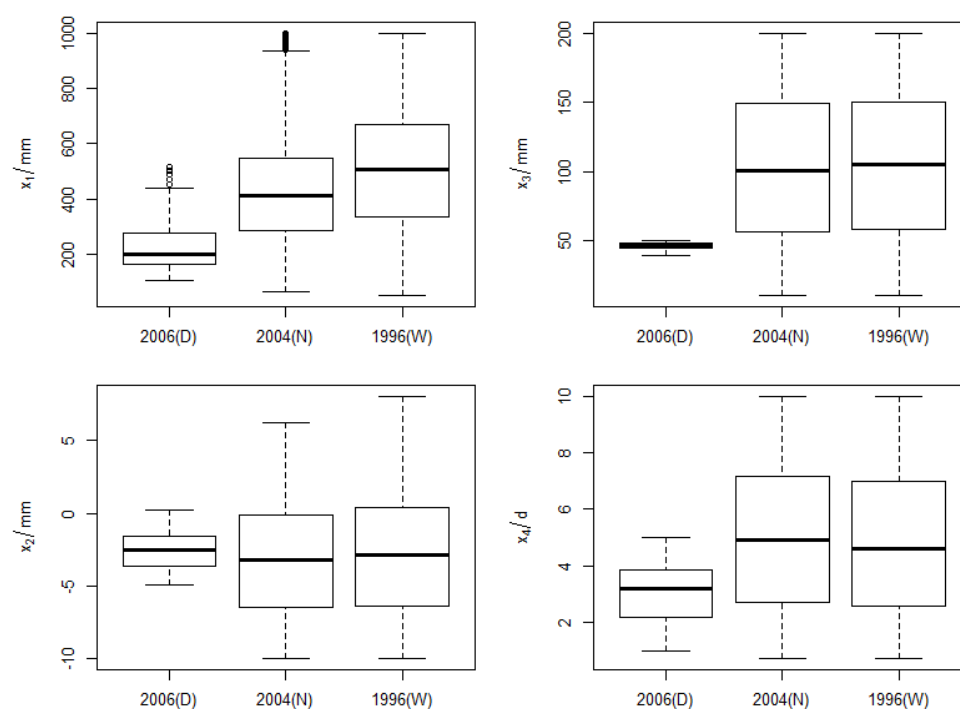


Figure 7. Feasible range of model parameters under different meteorological conditions (catchment ID 405264).

4.3. Model Performance

The traditional method for rainfall-runoff model is to divide the data into training period and testing periods without selecting, namely, the first 2/3 series as the training period while the other 1/3 series is the testing period. Taking catchment ID 405219 as an example, in order to test the prediction performance of the basin in the wettest year (1996), the traditional method takes the data from 1975 to 1993 as the training period, the data from 1994 to 1995 as the warm-up period and the data from 1996 to 2006 as the testing period. Then, the obtained performance is compared with that which is calculated by the selected training period (1993) of the meteorological classification, and the results are shown in Table 5 and Figure 8.

Table 5. Comparison of NSE values between the meteorological classification method (C-M) and the traditional method (T-M).

Category	Period	ID: 405264			ID: 405219			ID: 225219		
		T-M	C-M	$\Delta/\%$	T-M	C-M	$\Delta/\%$	T-M	C-M	$\Delta/\%$
Wet	Training	0.816	0.847	+3.80	0.771	0.916	+18.81	0.553	0.673	+21.70
	Testing	0.902	0.903	+0.11	0.787	0.861	+9.40	0.203	0.541	+166.50
Normal	Training	0.816	0.839	+2.82	0.771	0.917	+18.94	0.553	0.847	+53.16
	Testing	0.576	0.671	+16.49	0.856	0.742	−13.32	0.42	0.472	+12.38
Dry	Training	0.816	0.533	−34.68	0.771	0.518	−32.81	0.553	0.268	−51.54
	Testing	−7.72	0.541	+107.01	−10.9	0.448	+104.11	0.284	0.442	+55.63

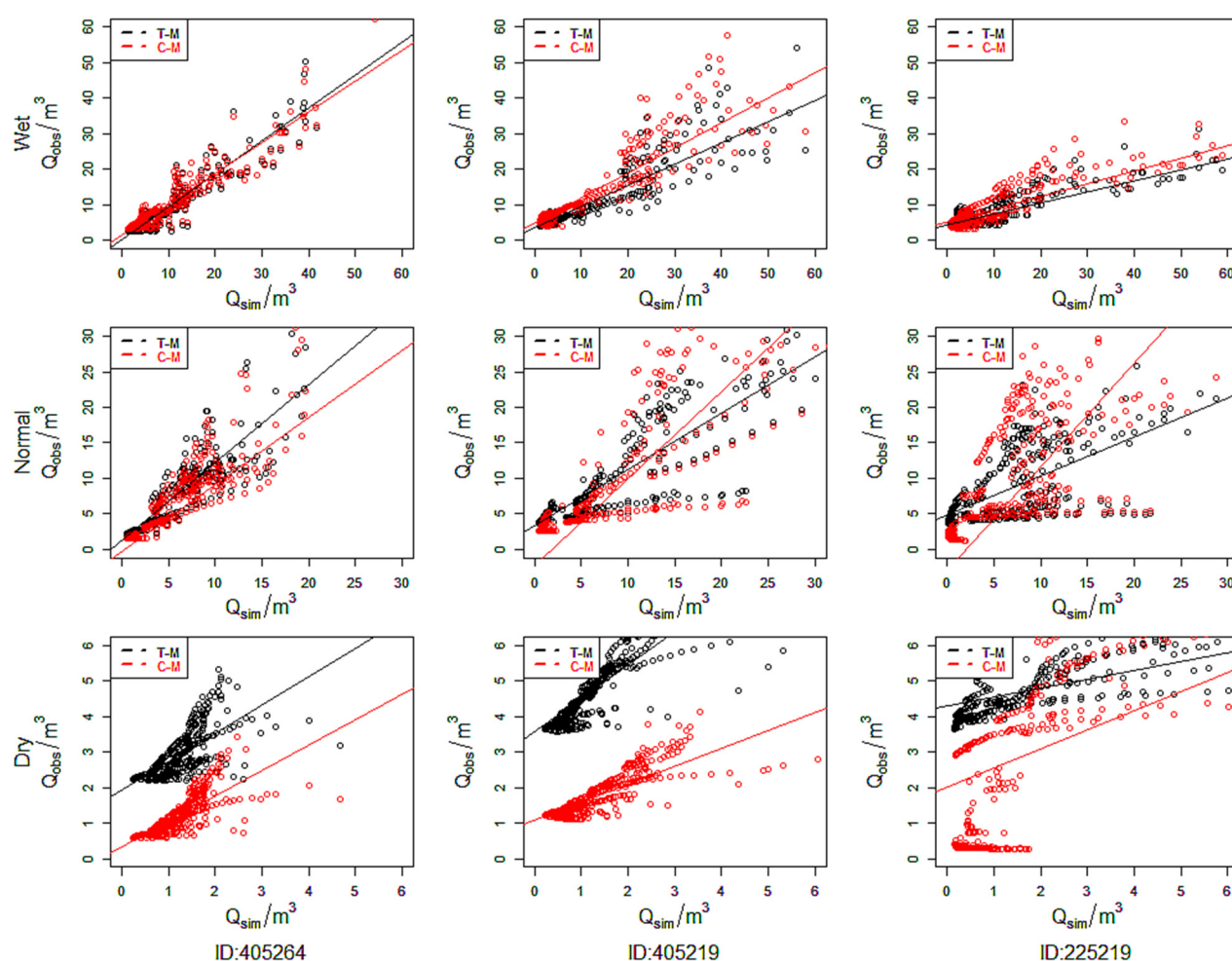


Figure 8. Comparison of runoff simulation results between the T-M and C-M methods.

It can be seen from Figure 8, compared with the traditional method (T-M), the efficiency of hydrological prediction method based on meteorological classification in the testing period of various meteorological conditions has been improved in varying degrees.

Under extreme meteorological (extremely dry/extremely wet) conditions, prediction efficiency is significantly improved. This is because the longer the selected training period is, the closer the runoff characteristics of the basin are to the long-term average level of the basin. Under extreme meteorological conditions (extremely dry/extremely wet), the runoff characteristics change abruptly, and the meteorological conditions and runoff characteristics are significantly different from the long-term runoff process over the years. Under this condition, the hydrological parameters obtained by long-term data calibration are no longer suitable. Especially in the drought period, the traditional rainfall-runoff model cannot obtain good performance. As shown in Figure 8, the traditional prediction of the three basins in the dry period in the figure shows obvious skewness. Selecting the data under the same extreme dry meteorological conditions as the training periodic data is closer to the runoff characteristics of the basin in the extreme dry period in the testing period, so as to correct this skewness. The C-M method proposed in this paper can find the year closest to the meteorological conditions for parameter optimization by calculating the SRI value in the testing period, which is suitable for rainfall-runoff simulation under any meteorological conditions.

It is worth mentioning that, in the dry condition, T-M outperforms C-M in the training period, while being worse in the testing period. As mentioned above, it is a phenomenon of “over fitting” that T-M performs better in training periods. Previous studies have shown that the performance of various hydrological models is poor in the dry period. When there

is prediction of runoff under specific meteorological conditions (especially extremely dry) in the basin, the training period of the T-M method is not distinguished; it includes the long-term data under dry, normal and wet meteorological conditions. Therefore, it is easier to find the parameter set that makes the performance better. While the C-M method only optimizes parameters during the extremely dry periods (it has the closest SRI value of the testing period), and the data length is very short, the NSE value in the training is therefore low. The performance in the testing period is better because the parameter group obtained by C-M method is more in line with the meteorological conditions in the testing period.

It should be noted that the prediction performance of catchment ID 225219 is poor, because of the difference of underlying surface conditions. The topographic elevation variation of the ID 225219 river basin is large, while the other two basins' elevation variation is relatively small. Since the difference of underlying surface conditions in the basin leads to the change of the rainfall-runoff relationship, it is difficult to simulate in the ID 225219 basin.

5. Conclusions

This paper compares the parameter distribution of rainfall-runoff model under different meteorological conditions and finds that the parameter distribution can be changed. In order to solve the issue of time-varying model parameters, previous research studies often added the parameter time-varying correlation function in the rainfall-runoff model. This is because the correlation between the parameters of the model is complicated. Reestablishing a set of time-varying laws not only complicates the method system, but also increases the complexity and uncertainty of the rainfall-runoff model structure. The parameter group of the model based on meteorological classification is obtained via finding the training periodic data which are closest to the testing period. The conclusions can be drawn as follows:

- (1) The distribution of hydrological parameters is varied under different meteorological conditions. However, they are similar for the two years with a proximately equal SRI value.
- (2) The rainfall-runoff model should be calibrated with a similar SRI year rather than all years. The prediction efficiency of the hydrological model based on meteorological classification is greater than that of the traditional model with all meteorological conditions. Especially in the extremely dry condition, in the test period of the three study basins, the prediction efficiency coefficients were increased 107%, 104% and 55.6%, respectively.

To evaluate the dry or wet conditions, many assessment indexes, such as surface water supply index (SWSI) and river streamflow dry index (SDI), etc., can be used. In future research, the comparison of different meteorological classification methods will be conducted to find the most scientific and reasonable meteorological classification method. A potential application is the runoff prediction under climatic change, where the precipitation is the force and the SRI can be predicted. In practical applications, methods such as the Mann–Kendall trend test and cross wavelet analysis can be used to predict the future meteorological pattern of the research basin and select the corresponding training period from the historical data.

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References

1. Sittner, W.T.; Schauss, C.E.; Monro, J.C. Continuous hydrograph synthesis with an API-type hydrological model. *Water Resour. Res.* **1969**, *5*, 1007–1022. [\[CrossRef\]](#)
2. Huang, S.; Li, P.; Huang, Q.; Leng, G.; Hou, B.; Ma, L. The propagation from meteorological to hydrological drought and its potential influence factors. *J. Hydrol.* **2017**, *547*, 184–195. [\[CrossRef\]](#)
3. Rui, X.F. *Principles of Hydrology*; Water Resources and Electric Power Press: Beijing, China, 2013. (In Chinese)
4. Zhao, R.J. *Catchment Hydrologic Modeling*; Water Resources and Electric Power Press: Beijing, China, 1984. (In Chinese)
5. Wagener, T. Can we model the hydrological impacts of environmental change? *Hydrol. Process.* **2007**, *21*, 3233–3236. [\[CrossRef\]](#)
6. Wang, D.; Hejazi, M. Quantifying the relative contribution of the climate and direct human impacts on mean annual streamflow in the contiguous United States. *Water Resour. Res.* **2011**, *47*, W00J12. [\[CrossRef\]](#)
7. Meng, S.; Xie, X.; Yu, X. Tracing temporal changes of model parameters in rainfall-runoff modeling via a real-time data assimilation. *Water* **2016**, *8*, 19. [\[CrossRef\]](#)
8. Brown, A.E.; Zhang, L.; McMahon, T.A.; Western, A.W.; Vertessy, R.A. A review of paired catchment studies for determining changes in water yield resulting from alterations in vegetation. *J. Hydrol.* **2005**, *310*, 28–61. [\[CrossRef\]](#)
9. Merz, R.; Parajka, J.; Blöschl, G. Time stability of catchment model parameters: Implications for climate impact analyses. *Water Resour. Res.* **2011**, *47*, W02531. [\[CrossRef\]](#)
10. Westra, S.; Thyer, M.; Leonard, M.; Kavetski, D.; Lambert, M. A strategy for diagnosing and interpreting hydrological model nonstationarity. *Water Resour. Res.* **2014**, *50*, 5090–5113. [\[CrossRef\]](#)
11. Chiew, F.H.S.; Vaze, J. Hydrologic nonstationarity and extrapolating models to predict the future: Overview of session and proceeding. *Proc. Int. Assoc. Hydrol. Sci.* **2015**, *371*, 17–21. [\[CrossRef\]](#)
12. Patil, S.D.; Stieglitz, M. Comparing spatial and temporal transferability of hydrological model parameters. *J. Hydrol.* **2015**, *525*, 409–417. [\[CrossRef\]](#)
13. Bastola, S.; Murphy, C.; Sweeney, J. The role of hydrological modelling uncertainties in climate change impact assessments of Irish river catchments. *Adv. Water Resour.* **2011**, *34*, 562–576. [\[CrossRef\]](#)
14. Klemes, V. Operational testing of hydrological simulation models. *Hydrol. Sci. J.* **1986**, *31*, 13–24. [\[CrossRef\]](#)
15. Deng, C.; Liu, P.; Guo, S.; Li, Z.; Wang, D. Identification of hydrological model parameter variation using ensemble Kalman filter. *Hydrol. Earth Syst. Sci.* **2016**, *20*, 4949–4961. [\[CrossRef\]](#)
16. Wang, W.; Fu, J. Global assessment of predictability of water availability: A bivariate probabilistic Budyko analysis. *J. Hydrol.* **2018**, *557*, 643–650. [\[CrossRef\]](#)
17. Sheng, Y.H.; Yi, X.J.; Huang, Y.C.; Li, J.B.; Yao, C.; Li, H. Parameter transfer based on simultaneous calibration of the HBV model. *China Rural. Water Hydropower* **2021**, *2*, 66–70.
18. Fowler, K.J.A.; Peel, M.C.; Western, A.W.; Zhang, L.; Peterson, T.J. Simulating runoff under changing climatic conditions: Revisiting an apparent deficiency of conceptual rainfall-runoff models. *Water Resour. Res.* **2016**, *52*, 1820–1846. [\[CrossRef\]](#)
19. Liu, D.; Guo, S.; Wang, Z.; Liu, P.; Yu, X.; Zhao, Q.; Zou, H. Statistics for sample splitting for the calibration and validation of hydrological models. *Stoch. Environ. Res. Risk Assess.* **2018**, *32*, 3099–3116. [\[CrossRef\]](#)
20. Shafii, M.; Tolson, B.A. Optimizing hydrological consistency by incorporating hydrological signatures into model calibration objectives. *Water Resour. Res.* **2015**, *51*, 3796–3814. [\[CrossRef\]](#)
21. Duan, Q.Y.; Gupta, V.K.; Sorooshian, S. Shuffled complex evolution approach for effective and efficient global minimization. *J. Optim. Theory Appl.* **1993**, *76*, 501–521. [\[CrossRef\]](#)
22. Singh, S.K.; Andr, S.B. Calibration of hydrological models on hydrologically unusual events. *Adv. Water Resour.* **2012**, *38*, 81–91. [\[CrossRef\]](#)
23. Broderick, C.; Matthews, T.; Wilby, R.L.; Bastola, S.; Murphy, C. Transferability of hydrological models and ensemble averaging methods between contrasting climatic periods. *Water Resour. Res.* **2016**, *52*, 8343–8373. [\[CrossRef\]](#)
24. Shukla, S.; Wood, A.W. Use of a standardized runoff index for characterizing hydrologic drought. *Geophys. Res. Lett.* **2008**, *35*, L02405. [\[CrossRef\]](#)
25. Khedun, C.P.; Chowdhary, H.; Giardino, J.R.; Mishra, A.K.; Singh, V.P. Analysis of Drought Severity and Duration Based on Runoff Derived from the Noah Land Surface Model. In Proceedings of the 2011 Symposium on Data-Driven Approaches to Droughts, West Lafayette, IN, USA, 21–22 June 2011.
26. Keskin, F.; Sorman, A.U. Assessment of the dry and wet period severity with hydrometeorological index. *Int. J. Water Resour. Environ. Eng.* **2010**, *2*, 29–39.
27. Xiang, Y.; Wang, Y.; Chen, Y.; Bai, Y.; Zhang, L.; Zhang, Q. Hydrological Drought Risk Assessment Using a Multidimensional Copula Function Approach in Arid Inland Basins, China. *Water* **2020**, *12*, 1888. [\[CrossRef\]](#)

-
28. Shao, J.; Li, Y.; Song, S.B. New computing method for standardized runoff index and its application. *J. Nat. Disasters* **2014**, *23*, 79–81.
 29. Zhang, Q.; Zou, X.K.; Xiao, F.J. *National Standard of the People's Republic of China—Meteorological Drought Level (GB/T20481-2006)*; China Standards Press: Beijing, China, 2006.
 30. Perrin, C.; Michel, C.; Andréassian, V. Improvement of a parsimonious model for streamflow simulation. *J. Hydrol.* **2003**, *279*, 275–289. [[CrossRef](#)]
 31. Nash, J.E.; Sutcliffe, J.V. River flow forecasting through conceptual models part I—A discussion of principles. *J. Hydrol.* **1970**, *10*, 282–290. [[CrossRef](#)]
 32. Beven, K. A manifesto for the equifinality thesis. *J. Hydrol.* **2006**, *320*, 18–36. [[CrossRef](#)]
 33. Uhlenbrook, S.; Seibert, J.; Leibundgut, C.; Rodhe, A. Prediction uncertainty of conceptual rainfall-runoff models caused by problems in identifying model parameters and structure. *Hydrol. Sci. J.* **1999**, *44*, 779–797. [[CrossRef](#)]
 34. Beven, K.; Freer, J. Equifinality, data assimilation, and uncertainty estimation in mechanistic modeling of complex environmental systems using the GLUE methodology. *J. Hydrol.* **2001**, *249*, 11–29. [[CrossRef](#)]
 35. Yongqiang, Z.; Neil, V.; Andrew, F.; Alison, O.; Matthew, B.; Yun, C.; Nathan, C. *Collation of Australian Modeller's Streamflow Dataset for 780 Unregulated Australian Catchments*, CSIRO Water for a Healthy Country Flagship Report; CSIRO: Canberra, Australia, 2013; pp. 1–115. [[CrossRef](#)]
 36. Pan, Z.; Liu, P.; Gao, S.; Xia, J.; Chen, J.; Cheng, L. Improving hydrological projection performance under contrasting climatic conditions using spatial coherence through a hierarchical Bayesian regression framework. *Hydrol. Earth Syst. Sci.* **2019**, *23*, 3405–3421. [[CrossRef](#)]