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# Intelligent Adaptation to Runoff Generation Mechanism for Hydrological Forecasting: A Case Study of the Xun River Basin

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**Abstract.** Runoff generation is a key process of the hydrologic cycle. In studies, most hydrological models can't explain how changes in the runoff generation mechanism caused by rainfall and soil conditions. Accounting for this issue, this article proposed a runoff generation mechanism index (RGMI) to realize intelligent adaptation to runoff generation mechanism. The posteriori RGMI was constructed with runoff coefficient (C) and curve number (CN) by weighting, and the priori RGMI was calculated based on rainfall and antecedent soil moisture through nonlinear fitting. Further, Xin'anjiang model (XAJ), Green-Ampt model (GA), and Vertically Mixed Runoff Model (VMM) were adopted to compose a novel adaptive runoff generation module. In the Xun River basin, the performances of the proposed runoff generation method and three fixed runoff generation methods were compared. The forecasting results of flood events were evaluated using relative peak error ($Q_p$), error between simulated and observed peak times ($T_p$), Nash-Sutcliffe efficiency ($E_{\mathrm{NS}}$), and relative flood volume error ($W_p$). The results showed that the adaptive runoff generation module can simulate the flood peak flow and peak time with higher accuracy than fixed runoff generation module. In addition, the dominant runoff generation processes in the Xun River basin mostly are saturation-excess and hybrid runoff generation processes.

**Keywords:** Runoff Generation Mechanism, Index Construction, Hydrological Modelling.

## 1 Introduction

The high accuracy of hydrological forecasting plays a pivotal part in water disaster prevention and control, scientific management and rational scheduling of water

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resources. And the performance of hydrological models can be improved by selecting the suitable runoff generation mechanism.

In general, there exit three mechanisms of runoff generation processes, which including runoff from saturation excess, runoff from infiltration excess, and a combination of these two, known as hybrid runoff mechanism [1]. Traditionally, flood forecasting mostly adopts a singular hydrological model with a specific runoff generation mechanism. Examples of such models include variable infiltration capacity land surface model (VIC), and Xin'anjiang model (XAJ) [2]. However, relying solely on a single runoff generation mechanism usually has shortcomings on capturing the complexity and spatiotemporal heterogeneity of runoff processes, particularly in regions with semi-arid to semi-humid climates [1]. Because in fact, different flood events likely experience different mechanisms with the variation of rainfall and soil conditions.

To address this issue, some studies proposed the solution that components of hydrological model could be adaptive to accommodate the varying dominant runoff processes across distinct watersheds [1][3]. But the variations of runoff generation mechanism between flood events still have been less considered. Therefore, the purpose of this research was to implement the intelligent adaptation strategy for runoff mechanisms within the flood events.

Firstly, a runoff generation mechanism index (RGMI) was proposed and it was composed with runoff coefficient (C) and curve number (CN) through weighting. Then the nonlinear relationships between RGMI and the condition of rainfall and soil were derived, in order to establish the runoff mechanism discrimination model. Considering the RGMI value, the research selected the XAJ model for saturation-excess runoff generation, the Green-Ampt model (GA) [4] for infiltration-excess runoff generation, and the Vertically Mixed Runoff Model (VMM) [5] for hybrid runoff generation. At last, the parameters of the runoff mechanism discrimination model and hydrological models were calibrated, and then verified and evaluated the accuracy and effectiveness of the proposed hydrological forecasting model.

# 2 Methods

## 2.1 Runoff Generation Mechanism Discrimination model

Meteorological and surface factors are important determinants of runoff generation mechanism, such as rainfall characteristics and antecedent soil moisture. The CN is the most important parameter of the Soil Conservation Service Curve Number (SCS-CN) model and characterizes infiltration capacity. The C is defined as the ratio of runoff to precipitation and is influenced by soil condition, climate and so on. Hence, the CN-C method [6] have been proposed to discriminate the dominant runoff generation process. It is carried out with two steps: tentatively, two thresholds were set to determine the flood events' dominant runoff generation mechanism by C; Then, other two thresholds of CN were set to selected the conditions that the discrimination results were different by CN and C, and these flood events were redesignated as a flow event dominated by hybrid runoff process. But the discrimination method is unable to be used for flood forecasting. Moreover, there is still a lack of a simple discriminant of the dominant runoff generation process.

The lager value of C represents the larger possibility of saturation-excess, but the lager value of CN represents the larger possibility of infiltration-excess. In addition, the value of C varies from zero to one, but the value of CN varies from zero to one hundred. Consequently, in order to maintain consistency with the discrimination mechanism of C and CN, the CN value is transformed. The runoff generation mechanism index, named as RGMI, therefore was constructed. The posteriori RGMI is expressed by:

$$\text{The posteriori } RGMI = \lambda_1 C + \lambda_2 (1 - CN / 100) \tag{3}$$

where $\lambda_1$ and $\lambda_2$ are the weights, and the sum of $\lambda_1$ and $\lambda_2$ is equal to 1; the value of RGMI varies from zero to one.

To use this index for priori runoff mechanism discrimination, pre-existing soil moisture content and rainfall were selected as forecasting factors. The runoff mechanism discrimination model is as follows:

$$\text{The priori } RGMI = w_0 + w_1 / P + w_2 P + w_3 e^{w_4 P_a^{w_5}} \tag{4}$$

where $P_a$ is antecedent soil moisture; $P$ is the total rainfall of a flood event; $w_0, w_1, w_2$ and $w_3$ are coefficients and calibrated through the posteriori RGMI.

According to the thresholds of C and CN [1][3][6], in this work, a flood event was considered to be dominated by infiltration-excess runoff when the RGMI value was below 0.35; conversely, a flow event was considered to be dominated by saturation-excess runoff if the RGMI value exceeded 0.4; the rest were regarded as hybrid-excess dominant flow events.

## 2.2 The adaptive runoff generation model

XAJ, GA, and VMM models are classical hydrological model designed for capturing the runoff generation process. Therefore, they were selected to describe different runoff generation conditions and compose the adaptive runoff generation model as shown in Fig. 1.


**Fig. 1.** Flowchart of the adaptive runoff generation model.

### 2.3 Model calibration and evaluation Method

Due to its widespread use in hydrological field, the Shuffled Complex Evolution Algorithm (SCE-UA) was adopted to optimize the parameters of model. It is a global optimization algorithm developed by the Department of Hydrology and Water Resources at the University of Arizona [7]. It integrates the simplex algorithm with directed random search, competitive evolution, and complex shuffling concept. Particularly, the Nash-Sutcliffe efficiency ($E_{\rm NS}$) was selected as the target function for optimization.

$$E_{\rm NS}=1-\frac{\sum_{t=1}^{T}\left|Q_t^s-Q_t^o\right|}{\sum_{t=1}^{T}\left|Q_t^o-\overline{Q^o}\right|} \tag{5}$$

where $Q_t^s$ is the simulated discharge at time $t$; $Q_t^o$ is the observed discharge at time $t$; $\overline{Q^o}$ is the average of observed discharge.

For model performance evaluation, four criteria were calculated, which included the, the relative flood peak error ($Q_p$), the error between simulated and observed times to peak ($T_p$), $E_{\rm NS}$ and the relative flood volume error ($W_p$).

## 3 Study area and Data

The Xun River basin, which located in the upper reaches of the Han River Basin, is 218 km long with a catchment area of 6703 km$^2$. In this basin, there are 1 flow station (the Xiangjiaping Station) and 6 rain-gauge stations (see Fig. 2).

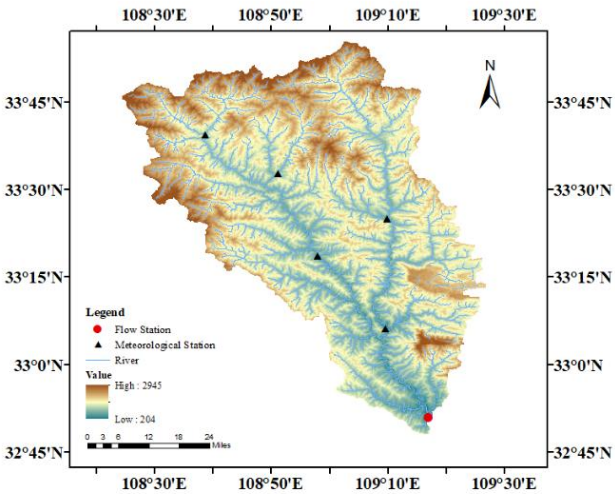


**Fig. 2.** The locations of hydrological stations in study area.

The daily runoff, rainfall and evaporation data were collected at the above 7 hydrological stations, spanning from 2000 to 2020. The 32 major flood events from 2000 to 2013 were used to calibrate the model parameters, and the 13 major flood events between the rest years were used to verify the model performances. Further, total precipitation and antecedent soil moisture of the flood event were calculated.

# 4 Results and discussion

## 4.1 Calibrated parameters

The optimized parameters of the four runoff generation modules and the runoff mechanism discrimination model are shown in the Table 1 and the Table 2 below. It must be stressed that the weights ( $\lambda_1$ and $\lambda_2$ ) in the Eq. (3) and the parameters of three runoff generation models were simultaneously calibrated. By this way, the performances of runoff generation mechanism discrimination can be improved and the constructed RGMI was suitable for the study area.

**Table 1.** Calibrated parameters of hydrologic models.

| Parameters | Physical meaning | Single runoff generation mechanism | | | Adaptation to runoff generation mechanism | | |
|---|---|---|---|---|---|---|---|
| | | XAJ | GA | VMM | XAJ | GA | VMM |
| WM | Averaged soil moisture storage capacity | 127.0 | 148.3 | 97.0 | 102.2 | 126.4 | 132.1 |
| B | Exponential of distribution of tension water capacity | 0.4 | / | 0.4 | 0.4 | / | 0.2 |
| fc | Watershed stable infiltration rate | / | 1.5 | 9.4 | / | 3.6 | 19.6 |
| KF | Conductivity at soil saturation | / | 27.4 | 30.0 | / | 6.1 | 28.0 |
| BF | Exponential of distribution of infiltration capacity | / | 2.00 | 0.86 | / | 1.05 | 0.52 |

**Table 2.** Calibrated parameters of the runoff mechanism discrimination model.

| Parameters | $\lambda_1$ | $\lambda_2$ | $w_0$ | $w_1$ | $w_2$ | $w_3$ | $w_4$ | $w_5$ |
|---|---|---|---|---|---|---|---|---|
| The posteriori RGMI | 0.08 | 0.92 | / | / | / | / | / | / |
| The priori RGMI | / | / | 0.15 | 0.0002 | 11.86 | 0.95 | 1.86 | -0.21 |

### 4.2 Results of runoff generation discrimination

Through the posteriori RGMI, the amounts of infiltration-excess, hybrid-excess and saturation-excess dominant flood events were 27, 9 and 9, respectively. Through the prior RGMI, the amounts were 32, 10 and 3. Most of the relative errors between the posteriori RGMI and prior RGMI were within 15% (see Fig. 3).

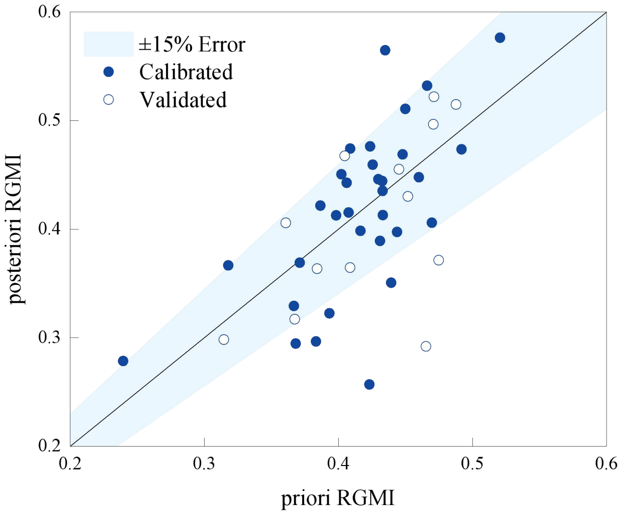


**Fig. 2.** The comparison between posteriori RGMI and priori RGMI.

### 4.3 Performances of the different runoff generation methods

In the assessment of model performance for the 45 flood events, four evaluation indexes were used, which included the $Q_p$, $T_p$, $E_{NS}$ and $W_p$. Method M1 to M3 represent XAJ, GA, and VVM models, respectively. Method M4 represents adopting one of above three models by adaptation to runoff generation mechanism.

As shown in Fig. 3, method M4 showed the best performances among the four methods. In calibration period, the performances of method M1 was better than method M2 and M3. In validation period, the performances of method M3 was better than method M1 and M2. Therefore, it can be concluded that the dominant runoff generation processes in the Xun River basin mostly are saturation-excess and hybrid runoff generation processes.

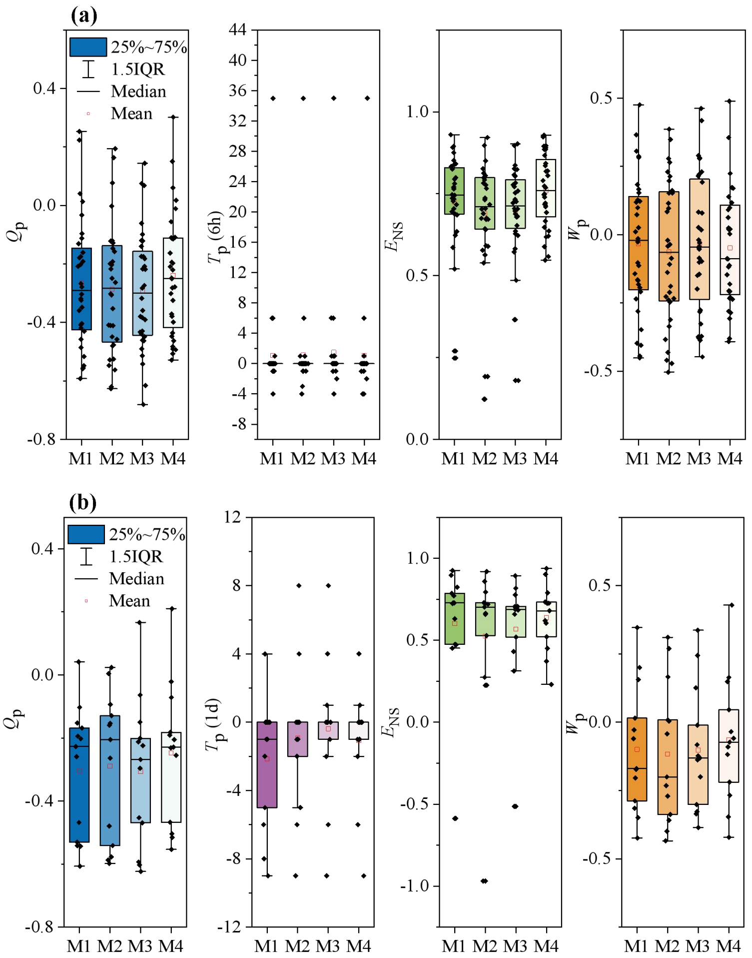


**Fig. 3.** The performances of four different runoff generation models (a) calibration period (b) validation period.

## 5 Conclusion

The posteriori and priori RGMI were constructed to discriminate runoff generation mechanism. In addition, XAJ, GA, and VMM models were employed to simulate saturation-excess, infiltration-excess and hybrid-excess mechanisms. Taking the Xun River basin as the study area, the performances of adaptive runoff generation model and single runoff generation models for flood events were evaluated. The conclusions of the research are as follows:

(1) The runoff generation mechanism for flood events were varied with rainfall and antecedent soil moisture.

(2) For flood events forecasting, the adaptive runoff generation model

outperformed single flow generation methods.

(3) In Xun River basin, the majority of the flood events between 2000-2020 were dominated by saturation-excess, hybrid-excess is second, and infiltration-excess is least.

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## References

1. Liu, Y., Zhang, K., Li, Z., et al.: A hybrid runoff generation modelling framework based on spatial combination of three runoff generation schemes for semi-humid and semi-arid watersheds. Journal of Hydrology, 590, 125440 (2020).
2. Zhao, R.J., Zhang, Y.L., Fang, L.R.: The Xinanjiang model, Hydrological Forecasting Proceedings Oxford Symposium. IASH, 129, 351–356 (1980).
3. Huang, P., Li, Z., Yao, C., Li, Q., Yan, M.: Spatial Combination Modeling Framework of Saturation-Excess and Infiltration-Excess Runoff for Semi-humid Watersheds. Advances in Meteorology, 2016, 1-15 (2016).
4. Green, W. H., and G. A. A.: Studies on soil physics, The Journal of Agricultural Science, 4(1), 1–24 (1911).
5. Bao, W. M. and Wang, C. L.: Application of a vertically-mixed runoff model. Hydrology, 3, 18-21 (1997). (in Chinese)
6. Yi, B., Chen, L., Liu, Y.Z., et al.: Hydrological modelling with an improved flexible hybrid runoff generation strategy[J]. Journal of Hydrology, 620, 129457 (2023).
7. Duan, Q. Y., Sorooshian, S. and Gupta, V.: Effective and efficient global optimization for conceptual rainfall-runoff models. Water Resources Research. 28(4): 1015-1031 (1992).

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