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Multi-Model Comparison in the Attribution of Runoff Variation across a Humid Region of Southern China

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Abstract: The natural hydrological cycle of basins has been significantly altered by climate change and human activities, leading to considerable uncertainties in attributing runoff. In this study, the impact of climate change and human activities on runoff of the Ganjiang River Basin was analyzed, and a variety of models with different spatio-temporal scales and complexities were used to evaluate the influence of model choice on runoff attribution and to reduce the uncertainties. The results show the following: (1) The potential evapotranspiration in the Ganjiang River Basin showed a significant downward trend, precipitation showed a significant upward trend, runoff showed a nonsignificant upward trend, and an abrupt change was detected in 1968; (2) The three hydrological models used with different temporal scales and complexity, GR1A, ABCD, DTVGM, can simulate the natural distribution of water resources in the Ganjiang River Basin; and (3) The impact of climate change on runoff change ranges from 60.07% to 82.88%, while human activities account for approximately 17.12% to 39.93%. The results show that climate change is the main driving factor leading to runoff variation in the Ganjiang River Basin.

Keywords: runoff response; climate change; human activities; hydrological model; elasticity coefficient; Ganjiang River Basin



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1. Introduction

Climate change and human activities have changed the natural characteristics of the hydrological processes, the spatio-temporal distribution of precipitation and surface water resources, and the basin is now facing a series of increasing extreme hydro-climatic issues such as floods and droughts [1–3]. The variability of water resources under a changing environment presents pressing challenges for the planning and management of water resources, which is also a prominent research topic. As the most important indicator of water resources, runoff is not only distributed by human activities, but is also very sensitive to climate change. It is a comprehensive result of climate and human activities [4]. Therefore, in order to further understand the process of hydrological cycle, it is important to distinguish the impacts of climate change and human actions on runoff.

Currently, almost all processes in the water cycle are directly or indirectly affected by climate change and human activities to varying degrees. Temperature and precipitation are the most critical meteorological elements affecting the water cycle. Runoff is mainly replenished by precipitation and consumed by evapotranspiration, which is highly affected

by temperature. As reported by the IPCC [1], global surface temperature in the first two decades of the 21st century was 0.99 °C higher than 1850–1900, and global precipitation had a faster speed of increase since the 1980s. On the one hand, rising temperature will accelerate the melting of glaciers and snowpack, increasing runoff. On the other hand, rising temperature will change evapotranspiration and reduce runoff [5]. The influence of human activities on runoff can be classified into two aspects: one involving the manipulation of reservoirs and gates to store and redirect runoff, thereby altering its seasonal distribution; and the other entailing the modification of underlying surface conditions to influence the processes of runoff generation and concentration. Recently, the increasing frequency and intensity of human activities had a significant impact on hydrological processes. Gao and Ruan [6] pointed out that human activities were the dominate factor, accounting for 87.20% of the relative contribution rate, while climate change only contributed 12.80% in the middle reaches of Huaihe River Basin, China. Ni et al. [7] considered the influence of the underlying surface on runoff, and estimated that the contributions of the underlying surface, precipitation and potential evaporation were 64.22%, 20.09% and 15.69% in the Yellow River source areas of China, respectively. Similarly, Hu et al. [8] analyzed the relative contribution of human activities that exceeded 100%, while that of climate change was between −14.25% and −5.43% in the Amu Darya River Basin.

There exist three primary approaches for runoff attribution analysis: empirical statistics, paired catchment comparisons, and hydrological modelling methods [9]. The empirical statistics method, is mostly employed in establishing a relationship between runoff and meteorological variables, which can be linear or nonlinear [10,11]. Although this method is simple to implement and only requires runoff and meteorological data, it lacks adequate physical mechanisms and is highly sensitive to input values. The paired catchment method involves the comparison of hydrological processes in a minimum of two neighboring catchments that share similar climatic and geographical attributes (area, topography, vegetation, soil, etc.) [12,13]. However, it is hard to find a catchment with similar hydroclimatic characteristics for a unique catchment, especially for medium and large-sized catchments, which limits the widespread application of this method [14]. The third approach involves the utilization of hydrological models to distinguish the influence of climate change and human actions on runoff. The hydrological model is usually composed of a series of functions with various parameters, which can describe a variety of hydrological processes in detail [15]. Among these three methods, the hydrological modelling method is more comprehensive than the others, and a series of hydrological models have been applied in a large number of studies, such as the SWAT (Soil and Water Assessment Tool) [16,17], VIC (Variable infiltration Capacity) [18], XAJ (Xin'anjiang model) [19], TOPMODEL (topography-based hydrological model), DTVGM (Distributed Time Variant Gain Model) [20,21], SWIM (Soil and Water integrated Model) [6], and Budyko coupled hydrothermal equilibrium equation [7,8,11].

Due to the variations in model structures, complexities, process representations, and parameters among different hydrological models, there is a consistent presence of significant uncertainties in the results obtained from hydrological modeling [22]. A large number of efficient numerical techniques have been employed in evaluating the impact of parameter uncertainties, while the uncertainties arising from model structures resulting from the simplification of hydrological processes have received comparatively less attention [23]. Consequently, the selection of a hydrological model can exert a significant influence on the analysis of runoff attribution, thereby introducing substantial uncertainties into the obtained results. At present, the quantitative assessment of the response of runoff to climate change and human activities mostly adopts a single attribution method, which fails to consider the uncertainties of the assessment results brought by model or method choice, and the attribution analysis using multiple attribution methods to verify each other still needs to be further strengthened. This study focuses on quantitatively evaluating and separating the influence of meteorological elements and human activities on runoff changes in a humid area of southern China, Ganjiang River Basin (GRB). The primary

purposes of this study are to (1) analyze the trends and mutations of meteorological and hydrological series in the GRB, (2) quantify the contributions of climate change and human activities to the runoff changes, and (3) analyze the influence of model choice on the runoff attribution analysis. This study serves as a reference for local authorities, decision-makers, and researchers in understanding the driving mechanisms of hydrological processes in a changing environment. The findings will significantly contribute to establishing a scientific foundation for practical water resource management and future planning in the GRB.

2. Study Area and Data

2.1. Study Area

The Ganjiang River, spanning a main river length of 823 km, is the largest river in Jiangxi province of China and also one of the eight major tributaries of the Yangtze River. The Ganjiang River Basin (GRB), located between 113°30' and 116°40' E and 24°29' and 29°21' N, encompasses a total area of 80,948 km² above the Waizhou hydrological station, accounting for approximately 48.5% of the area of Jiangxi province (Figure 1). The topography exhibits diversity, ranging from hills in the southern region to alluvial plains in the northeastern region; mountains constitute around 50%, hills account for about 30%, and plains make up roughly 20%. Elevation varies between −105 and 2128 m above sea level. Annual precipitation in this basin amounts to an average of 1626.8 mm with an annual average evaporation rate of approximately 1550 mm. The average temperature is about 18 °C. Summer is the warmest season, accompanied by heavy rainfall, the plum rain precipitation is the most concentrated from April to June, and typhoon-type heavy rainfall occurs from July to September, resulting in significant seasonal variations in streamflow.

2.2. Data

The daily precipitation data of 36 rainfall gauges in and around the GRB from 1956 to 2018 were collected, along with the daily meteorological elements (precipitation, temperature, relative humidity, etc.) of 9 meteorological gauges for the same period. The gauge distribution was relatively uniform, providing a rough representation of temporal and spatial changes in meteorological and hydrological variables within the basin. Some missing data were interpolated by establishing a regression relationship with the corresponding meteorological variable sequences of adjacent gauges. Daily and monthly streamflow data at the Waizhou hydrological station were obtained from the Hydrology Bureau of Jiangxi province for calibration and validation in hydrological models. Due to the limited availability of measured evapotranspiration over long periods, potential evapotranspiration was estimated using the Penman–Monteith method recommended by the Food and Agriculture Organization of the United Nations (FAO). Basic geographic datasets, including digital elevation model (DEM), land cover, and soil type data, were collected from the Resource and Environmental Science Data Center of the Chinese Academy of Sciences. Previous studies have confirmed that all the data used in this study are reliable and suitable for driving hydrological models [24–26]. The location and gauge distribution of the GRB are shown in Figure 1.

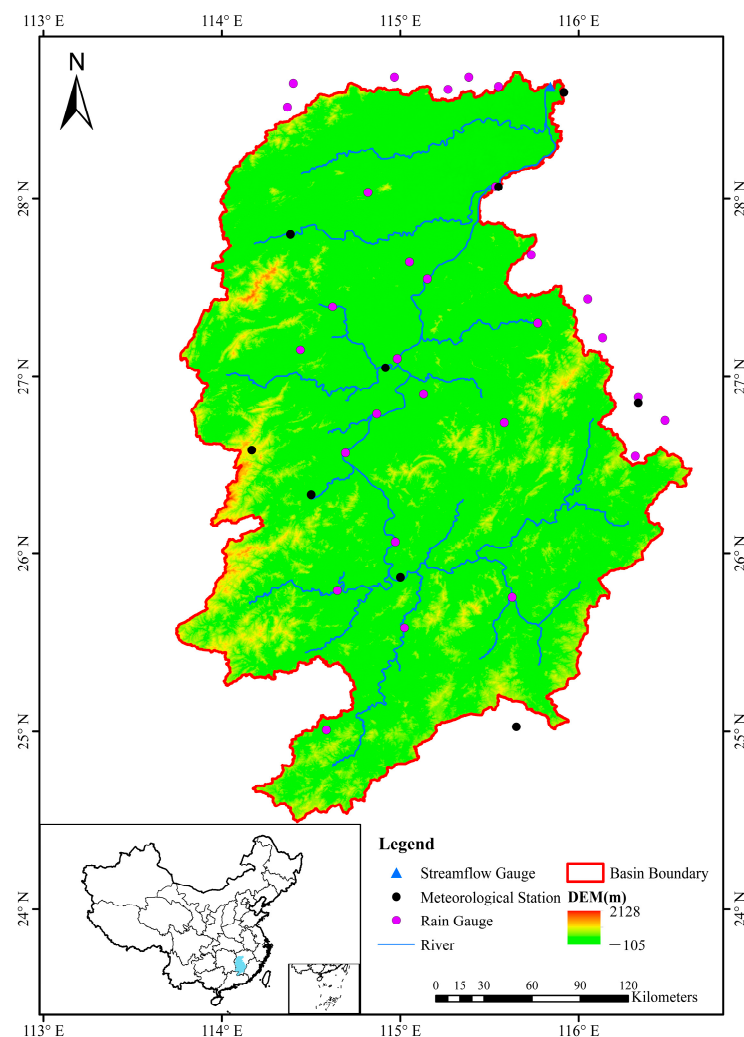


Figure 1. The location of the Ganjiang River Basin (GRB) and corresponding rain gauges, meteorological stations and streamflow gauge.

3. Methodology

3.1. Trend and Mutation Analysis

In this study, the Mann–Kendall (M-K) method was employed to detect trends and abrupt changes in precipitation, evapotranspiration, and runoff time series. The M-K method is a nonparametric statistical test that serves as a robust and reliable approach for trend detection. Consequently, it has been recommended by the World Meteorological Organization (WMO) for examining time series trends in meteorology, hydrology, and environmental science fields. The calculated statistic index Z from the M-K method is utilized to indicate the magnitude of the trend: $Z > 0$ represents an increasing trend; $Z < 0$ signifies a decreasing trend; and $Z = 0$ indicates no discernible trend detected. While the M-K method can only identify statistically significant trends but not their slopes, this study assumes linearity in trends as a quantification of temporal change. To determine the slope of time series unaffected by outliers or data errors, Sen's slope method was employed. Additionally, an abrupt change test is conducted using a critical value at the 95% significance level.

3.2. Hydrological Model

In order to analyze the influence of model choice on runoff attribution analysis, three hydrological models with different complexities and temporal scales, are selected to simulate streamflow. The GR1A model is an annual-scale hydrological model with a simple

structure, the ABCD model is a monthly scale hydrological model with a more complex structure, while the DTVGM model is a daily scale hydrological model with the most complex structure. Additionally, the first two models are lumped hydrological models, while the DTVGM is a distributed hydrological model. A detailed description of these three models is given as follows.

3.2.1. GR1A Model

The GR1A model, developed at Cemagref at the end of 1980s, is an annual runoff simulation model [27,28]. The GR1A model adopts a simplified and aggregated framework, taking into account the influence of dynamic storage and preceding precipitation conditions. This model is characterized by a concise mathematical equation featuring only one parameter, as shown in Equation (1).

$$Q_k = P_k \left\{ 1 - \frac{1}{\left[1 + \left(\frac{0.7P_k + 0.3P_{k-1}}{X \cdot PET_k} \right)^2 \right]^{0.5}} \right\}, \quad (1)$$

where Q_k and PET_k are simulated streamflow and average potential evapotranspiration of the year k ; P_k and P_{k-1} are the basin average precipitation of the year k and $k - 1$; X is the only parameter of this model to be optimized. The GR1A model indirectly characterizes the impact of initial soil water storage on runoff through the antecedent precipitation P_{k-1} . The optimized model parameter X exhibits a median value of 0.7, with a 90% probability confidence interval ranging from 0.13 to 3.5.

3.2.2. ABCD Model

The ABCD model, originally proposed by Thomas [29], is a physics-based, lumped, and nonlinear watershed model. The monthly streamflow in this model is determined by the inputs of monthly precipitation and potential evapotranspiration. In this model, the catchment storage is divided into soil water and groundwater compartments (Figure 2). Precipitation is partitioned into actual evapotranspiration, surface runoff, and soil water recharge processes. The total runoff consists of both surface runoff and baseflow released from groundwater. The physical interpretation and range of parameters are listed in Table 1.

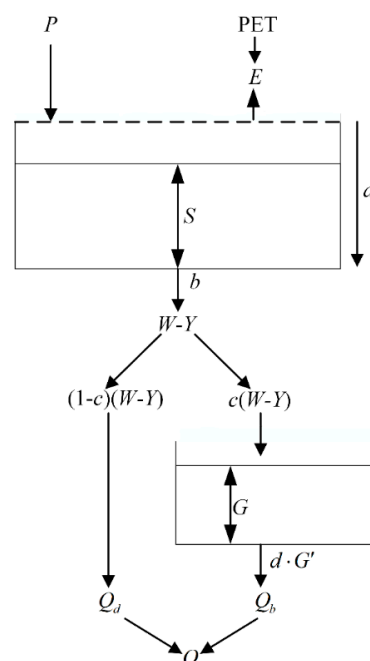


Figure 2. Model structure of the ABCD model.

Table 1. Physical interpretation and range of ABCD model parameters.

Parameter	Physical Interpretation	Range
<i>a</i>	The propensity of runoff occurs before the soil is fully saturated	[0, 1]
<i>b</i>	Upper soil water storage capacity(mm)	[100, 1000]
<i>c</i>	Groundwater recharge coefficient	[0, 1]
<i>d</i>	Groundwater runoff recession constant	[0, 1]

3.2.3. DTVGM Model

The Distributed Time Variant Gain Model (DTVGM), developed by Xia et al. [30], is a physics-based, distributed and nonlinear watershed hydrological model. The distinguishing feature of the DTVGM model lies in its incorporation of soil moisture as a crucial link between runoff generation and flow routing processes. Moreover, this model has a relatively parsimonious model structure and limited free parameters to describe the rainfall–runoff processes. Consequently, the DTVGM model has demonstrated successful applications in many basins in China with satisfactory results [31–34]. Therefore, this model was selected to simulate streamflow process of the GRB.

3.2.4. Model Calibration

The hydrological model contains many parameters that will affect hydrological simulation results. The optimized model has better potential to characterize the conditions and processes of hydrological systems [35]. In this study, the Shuffled Complex Evolution-University of Arizona (SCE-UA) optimization algorithm, developed by Duan et al. [36], is used for the parameter calibration of these three hydrological models. Three different indices were selected to evaluate model performance in this study, including the Nash–Sutcliffe efficiency (NSE) [37], regression coefficient of determination (R^2), and relative error (Bias) [38]. The detailed calculation formulas of NSE, R^2 and Bias are shown as follows.

$$NSE = 1 - \frac{\sum_{i=1}^n (Q_{i,obs} - Q_{i,sim})^2}{\sum_{i=1}^n (Q_{i,obs} - \overline{Q_{obs}})^2}, \quad (2)$$

$$R^2 = \frac{\sum_{i=1}^n (Q_{i,obs} - \overline{Q_{obs}})(Q_{i,sim} - \overline{Q_{sim}})}{\sqrt{\sum_{i=1}^n (Q_{i,obs} - \overline{Q_{obs}})^2 \sum_{i=1}^n (Q_{i,sim} - \overline{Q_{sim}})^2}}, \quad (3)$$

$$Bias = \frac{\sum_{i=1}^n (Q_{i,sim} - Q_{i,obs})}{\sum_{i=1}^n Q_{i,obs}} \times 100\%, \quad (4)$$

where n is the number of samples, $Q_{i,sim}$ and $Q_{i,obs}$ are the simulated and observed streamflow values, respectively, $\overline{Q_{obs}}$ and $\overline{Q_{sim}}$ are their mean values, respectively. The model performance criteria were provided by Moriasi et al. [38] and Krause et al. [39].

3.3. Attribution of Runoff Changes

3.3.1. Hydrological Model Method

The quantitative separation of climate change and human activities can be mathematically formulated as follows.

$$\Delta Q = Q_L - Q_N, \quad (5)$$

$$\Delta Q_C = Q_M - Q_N, \quad (6)$$

$$\Delta Q_H = \Delta Q - \Delta Q_C, \quad (7)$$

$$F_C = \frac{\Delta Q_C}{\Delta Q} \times 100\%, \quad (8)$$

$$F_H = \frac{\Delta Q_H}{\Delta Q} \times 100\%, \quad (9)$$

where ΔQ represents the disparity between average streamflow during reference period (Q_N) and average streamflow during changed period (Q_L); Q_M is the simulated natural streamflow under changed period; ΔQ_C and ΔQ_H indicate the changes in streamflow attributed to climate change and human activities, respectively; and F_C and F_H represent the relative contribution rates of climate change and human activities on runoff variation, correspondingly.

3.3.2. Climatic Elastic Coefficient Method

In recent years, the Budyko framework has gained significant popularity in runoff attribution analysis due to its concise physical mechanism. Within this framework, it is assumed that the long-term hydro-meteorological characteristics of a basin adhere to the balance of water and energy. Actual evapotranspiration (E) primarily depends on both the atmospheric water supply (P) and the land surface's evapotranspiration capacity (PET). As a result, actual evapotranspiration can be expressed as a function of aridity index ϕ .

$$E = f\left(\frac{PET}{P}\right) \cdot P = f(\phi) \cdot P, \quad (10)$$

where ϕ is the aridity index, $\phi = \frac{PET}{P}$; $f(\cdot)$ is the Budyko function. On the year or multi-year scale, the alteration in water storage within a watershed may be insignificant, therefore the water balance between runoff (Q) and climate variables (P and E) can be expressed as:

$$Q = P - E, \quad (11)$$

As pointed by Donohue et al. [40], the runoff change caused by climate change could be described as:

$$\frac{\Delta Q_C}{Q} = \varepsilon_P \frac{\Delta P}{P} + \varepsilon_{PET} \frac{\Delta PET}{PET}, \quad (12)$$

where ε_P and ε_{PET} are the climate elasticity coefficient to express the sensitivity of Q to P and PET . ε_P and ε_{PET} are defined as:

$$\varepsilon_P = \lim_{\frac{\Delta P}{P} \rightarrow 0} \frac{\Delta Q/Q}{\Delta P/P} = \frac{\partial Q}{\partial P} \times \frac{P}{Q} = 1 + \frac{\phi f'(\phi)}{1 - f(\phi)}, \quad (13)$$

$$\varepsilon_{PET} = \lim_{\frac{\Delta PET}{PET} \rightarrow 0} \frac{\Delta Q/Q}{\Delta PET/PET} = \frac{\partial Q}{\partial PET} \times \frac{PET}{Q} = -\frac{\phi f'(\phi)}{1 - f(\phi)}, \quad (14)$$

$$\varepsilon_P + \varepsilon_{PET} = 1, \quad (15)$$

As shown in Equations (13) and (14), different forms of the Budyko function would obtain different elasticity coefficients. With the advancement of the Budyko framework, numerous Budyko functions have been employed in describing the relationship between water and energy. Therefore, four frequently utilized Budyko functions are used in this study, as listed in Table 2.

Table 2. Four frequently utilized forms of $f(\phi)$ and $f'(\phi)$ functions based on the Budyko hypothesis.

Reference	$f(\phi)$	$f'(\phi)$
Schreiber [41]	$1 - e^{-\phi}$	$e^{-\phi}$
Ol'Dekop [42]	$\phi \tanh\left(\frac{1}{\phi}\right)$	$\tanh\left(\frac{1}{\phi}\right) - \frac{4}{\left[\phi \left(e^{-\frac{1}{\phi}} + e^{\frac{1}{\phi}}\right)\right]^2}$
Budyko [43]	$\left[\phi \tanh\left(\frac{1}{\phi}\right) (1 - e^{-\phi})\right]^{0.5}$	$0.5 \left[\phi \tanh\left(\frac{1}{\phi}\right) (1 - e^{-\phi})\right]^{-0.5} \left[\left(\tanh\left(\frac{1}{\phi}\right) - \frac{\text{sech}^2\left(\frac{1}{\phi}\right)}{\phi} \right) (1 - e^{-\phi}) + \phi \tanh\left(\frac{1}{\phi}\right) e^{-\phi} \right]$
Turc-Pike [44]	$(1 + \phi^{-2})^{-0.5}$	$\frac{1}{\left[\phi^3 \left(1 + \left(\frac{1}{\phi}\right)^2\right)^{1.5}\right]}$

4. Results and Discussion

4.1. Trends of Hydro-Meteorological Variables

Figure 3 provides the series of annual potential evapotranspiration, precipitation and runoff in the GRB. The M-K method and Sen's slope method were utilized to analyze the trend of annual precipitation, potential evapotranspiration, and runoff series, with the results presented in Table 3. The annual potential evapotranspiration series of the GRB generally showed a downward trend, with a decreasing rate of 0.91 mm/year. The Z value of potential evapotranspiration estimated by the M-K method was -2.16 , which shows that the potential evapotranspiration series presented a downward trend, and the trend was significant (0.05 significance level). The precipitation and runoff series in the GRB showed an overall upward trend, with a rising rate of 3.21 mm/year and 1.75 mm/year, respectively. The precipitation had a slightly significant upward trend with 0.10 significance level, while the upward trend of runoff was not significant.

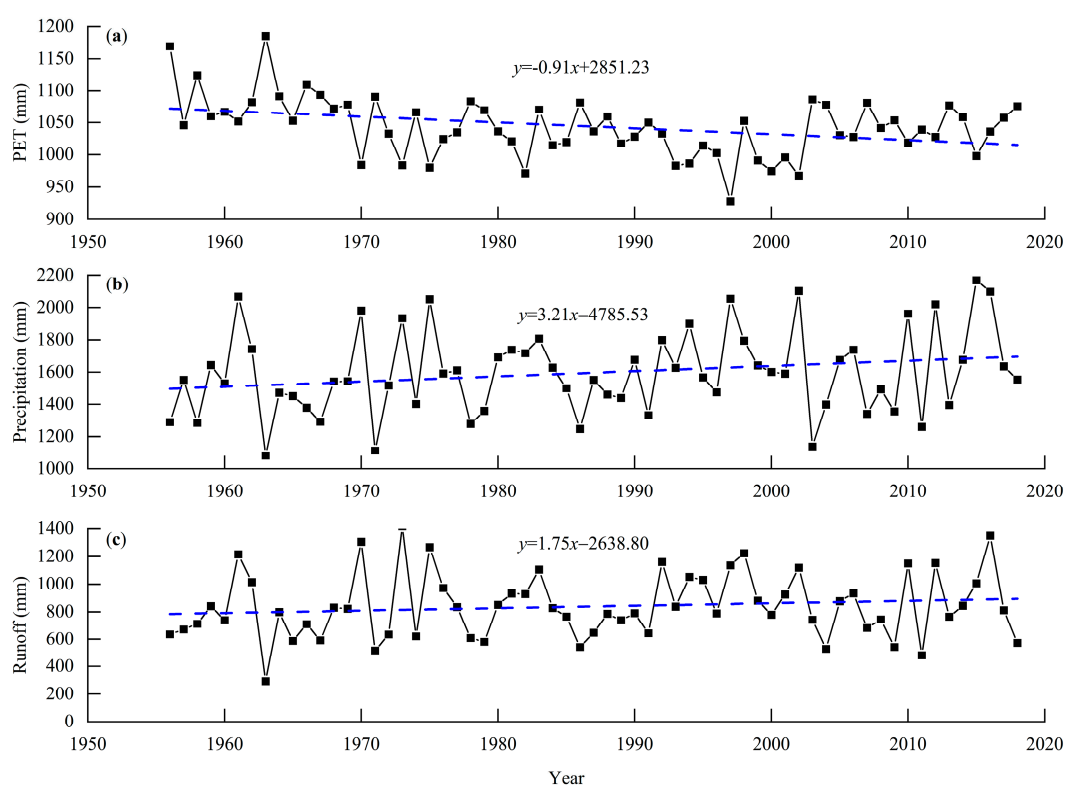


Figure 3. The time series of hydro-climatic variables in Ganjiang River Basin ((a) potential evapotranspiration; (b) precipitation; (c) runoff). The black square lines are observed values, and the best-fit lines estimated by the OLS (ordinary least square) method are the blue dotted lines.

Table 3. Variations of hydro-climatic series before and after the abrupt change point in the GRB.

Variable	Z	Significance	Sen's Slope	Average Value/mm		Change Rate/%
				1956–1968	1969–2018	
PET	-2.61	**	-0.89	1092.64	1031.01	-5.64
P	1.67	*	2.96	1487.12	1624.58	9.24
Q	1.15	ns	1.98	742.09	865.71	16.66

Note: ** Significant at $p < 0.05$; * significant at $p < 0.1$; ns indicates there is no significant trend.

As shown in Figure 4, the M-K mutation test exhibited more than one mutation point, and the moving-T test was used to divide the reference period and the changed period. Consequently, the GRB changed abruptly in the year of 1968; a similar result was obtained by using the standard normal homogeneity test (SNHT) and other studies by Lei et al. [45],

Fan et al. [46] and Zhang et al. [47]. Taking 1968 as the critical time point, the whole sequence is divided into the reference period (1956–1968) and the changed period (1969–2018), and the influence of climate change and human activities on runoff is quantitatively analyzed (Table 3). Compared with the reference period, the annual potential evapotranspiration in the changed period decreased by 5.64%, while the annual precipitation and annual runoff increased by 9.24% and 16.66%, respectively.

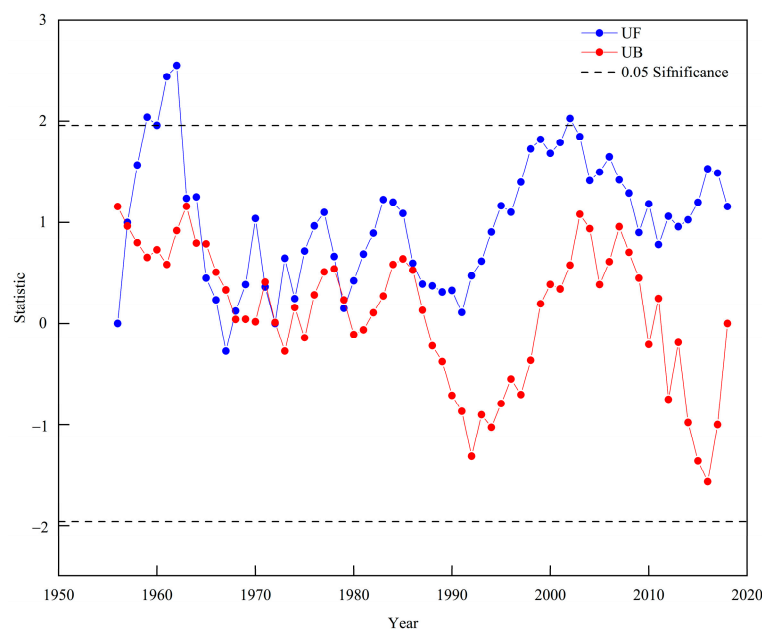


Figure 4. The mutation point detection of runoff series at Waizhou station.

4.2. The Calibration and Validation of Hydrological Models

This study employed three hydrological models, each characterized by distinct temporal scales and complexities. Due to the limited duration of the annual precipitation, potential evapotranspiration, and runoff series in the reference period (1956–1968), the entire hydro-meteorological datasets for that period were employed for parameter calibration in the GR1A model. Utilizing the SCE-UA optimization algorithm [48], the parameter of the GR1A model was calibrated, resulting in an optimized parameter X of 0.79. Figure 5 shows the simulated and observed annual runoff processes for the reference period (1956–1968), demonstrating a general agreement. The NSE and R^2 values of the GR1A model were both 0.83, and the Bias was 1.76%. The simulation results demonstrated the applicability of the GR1A model for simulating runoff variations in the GRB.

When using ABCD and DTVGM models for runoff simulations, the reference period was divided into two periods: calibration (1956–1962) and validation (1963–1968) periods. The SCE-UA algorithm was used to calibrate the ABCD model with NSE and R^2 as the objective functions, and the optimized parameter values were $a = 0.94$, $b = 548.42$, $c = 0.16$ and $d = 0.34$. Table 4 lists the simulation accuracy evaluation of the ABCD model in the calibration and validation periods, and Figure 6 shows the monthly runoff simulated by the ABCD model. The ABCD model obtained NSE of 0.86 and 0.92, R^2 of 0.87 and 0.92, and Bias of -1.96% and 3.44% in the calibration and validation periods, respectively. The strong agreement between the simulated and observed monthly runoff during both calibration and validation periods, as shown in Figure 6, indicates that the ABCD model was highly effective in simulating monthly runoff in the GRB.

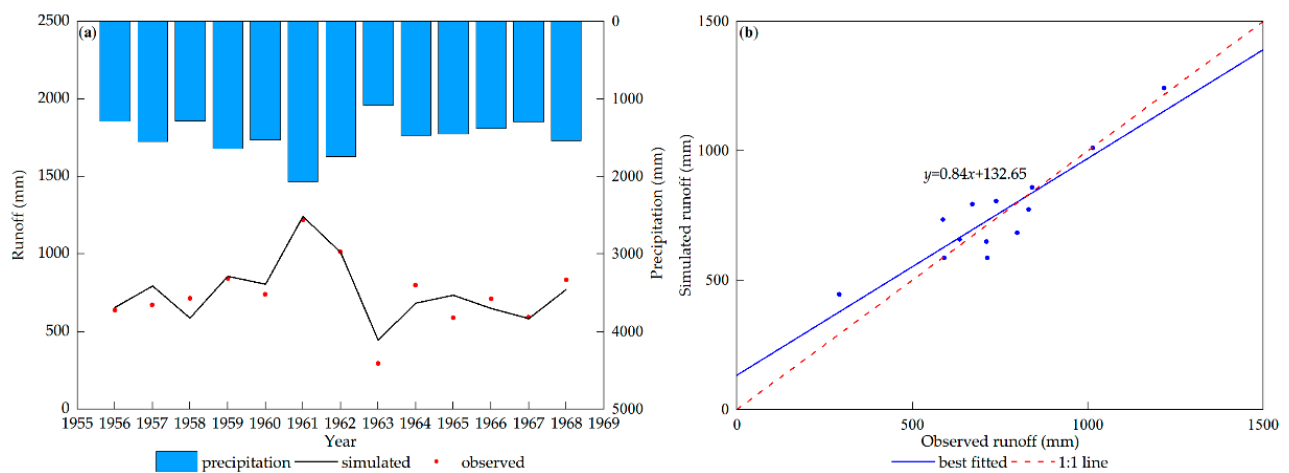


Figure 5. Comparison between simulated runoff and observed runoff at Waizhou station during 1955–1968 by using GR1A model, for (a) runoff processes and (b) scatter curve chart.

Table 4. Model performance evaluation of ABCD model.

Period	Statistical Metrics		
	NSE	R^2	Bias
Calibration period (1956–1962)	0.86	0.87	−1.96%
Validation period (1963–1968)	0.92	0.92	3.44%

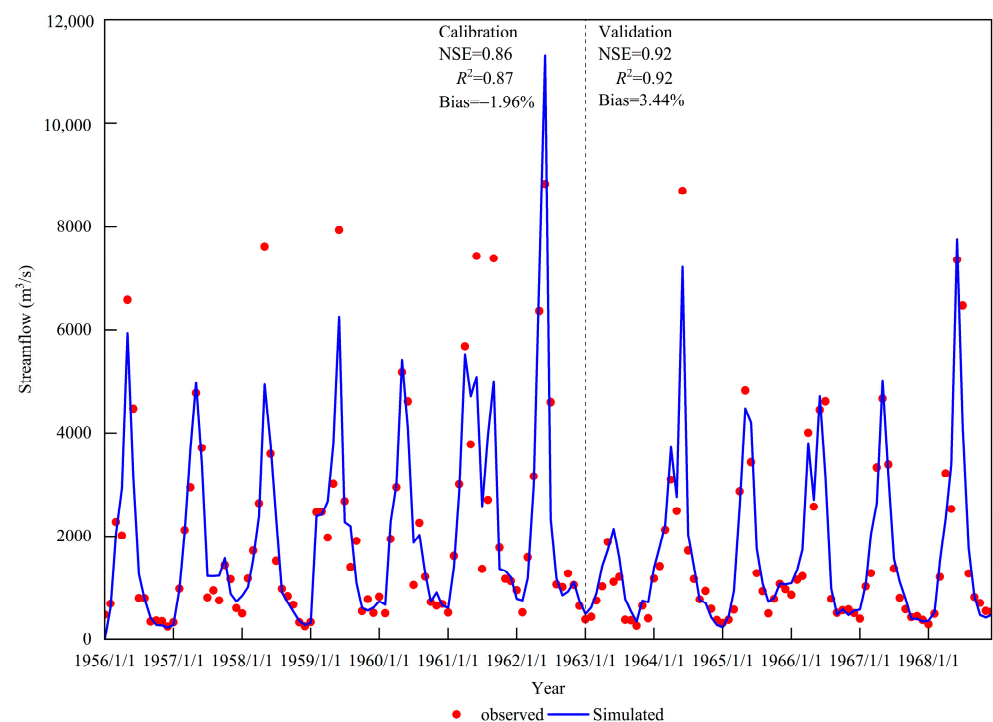


Figure 6. Comparison between simulated runoff and observed runoff and curve chart at Waizhou station during 1955–1968 by using ABCD model.

The optimized parameters of the DTVGM model are presented in Table 5, while Table 6 demonstrates the evaluation of simulation accuracy for this model. Both the calibration and validation periods exhibit NSE and R^2 values exceeding 0.95, accompanied by Bias values of −1.25% and 3.85%, respectively. Figure 7 illustrates a strong agreement between

simulated and measured runoff throughout calibration and validation periods, thereby validating the effectiveness of the DTVGM model.

Table 5. The description of the parameters of the DTVGM model and the optimal values.

Parameter	Physical Interpretation	Optimal Value
g_1	Surface runoff generation parameter	0.06
g_2	Surface runoff generation parameter	0.47
g_3	Subsurface runoff generation parameter	0.22
Nashn	Unit hydrograph shape parameter	2.93
Nashk	Unit hydrograph scale parameter	1.86
kg	The recession parameter of groundwater storage	0.80

Table 6. Model performance evaluation of the DTVGM model.

Period	Statistical Metrics		
	NSE	R^2	Bias
Calibration period (1956–1962)	0.95	0.95	−1.25%
Validation period (1963–1968)	0.95	0.96	3.85%

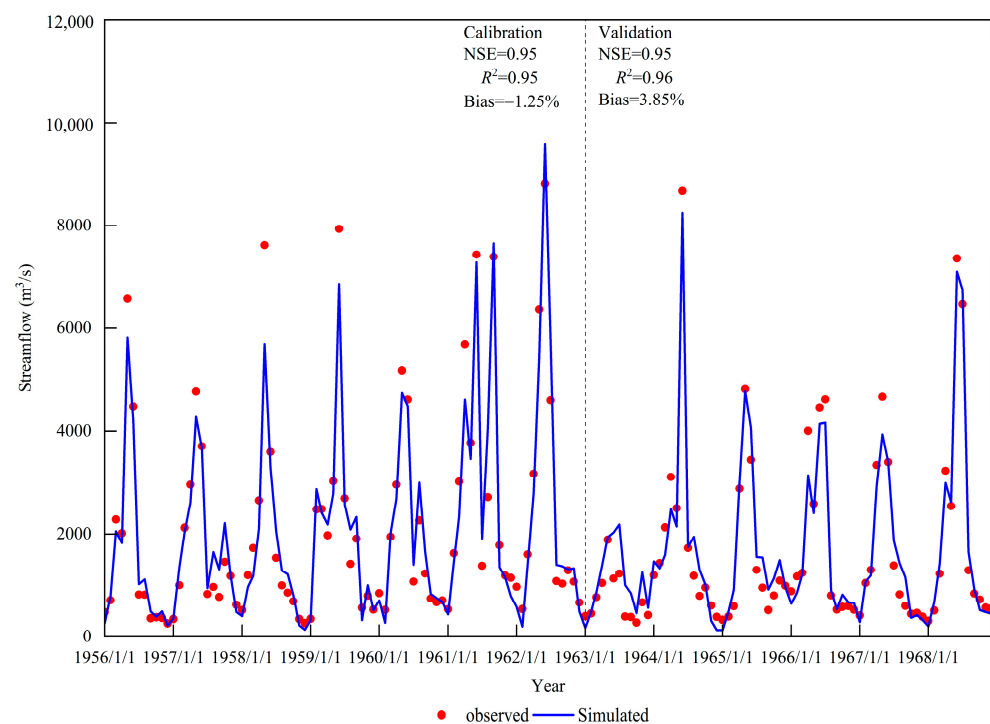


Figure 7. Comparison between simulated runoff and observed runoff and curve chart at Waizhou station during 1955–1968 by using the DTVGM model.

4.3. Contributions of Climate Change and Human Activities to Runoff Change

4.3.1. Climate Elasticity Coefficient Analysis

The climate elastic coefficient method to quantitatively separate the influence of climate change and human activities is mainly carried out on a multi-year scale. As the most important input variable of the Budyko formulas, the aridity index of the GRB is 0.65. The elastic coefficient of runoff to precipitation was calculated as listed in Table 7. The elastic coefficients of runoff to precipitation were 1.63, 1.57, 1.61, and 1.59 for four different Budyko functions, which meant that the runoff would increase 1.63 mm, 1.57 mm, 1.61 mm, and 1.59 mm with a unit increase in precipitation. Similarly, the runoff would change −0.63 mm, −0.57 mm, −0.61 mm, and −0.59 mm with a unit increase in potential evapotranspiration.

In addition, although different forms of the Budyko function were applied in this study, the elastic coefficients obtained by different formulas were very close. The average elastic coefficients of runoff to precipitation and potential evapotranspiration were 1.60 and -0.60 , respectively. The choice of the Budyko function had a relatively small impact on the runoff attribution analysis results, while the aridity index was more sensitive to the results.

Table 7. Separating the effects of climate change and human activities by climate elasticity method.

Period	Variable	Budyko Equation				Mean
		Schreiber	Ol'dekop	Budyko	Turc-Pike	
	ε_P	1.63	1.57	1.61	1.59	1.60
	ε_{PET}	-0.63	-0.57	-0.61	-0.59	-0.60
1969–1979	$\Delta Q_C/\text{mm}$	107.50	102.00	104.89	103.30	104.42
	$\Delta Q_H/\text{mm}$	21.94	27.44	24.55	26.14	25.02
	$F_C/\%$	83.05	78.80	81.03	79.81	80.67
	$F_H/\%$	16.95	21.20	18.97	20.19	19.33
1980–1989	$\Delta Q_C/\text{mm}$	108.78	103.05	106.06	104.40	105.57
	$\Delta Q_H/\text{mm}$	-37.83	-32.10	-35.11	-33.46	-34.62
	$F_C/\%$	74.20	76.25	75.13	75.73	75.30
	$F_H/\%$	25.80	23.75	24.87	24.27	24.70
1990–1999	$\Delta Q_C/\text{mm}$	215.16	204.79	210.23	207.24	209.35
	$\Delta Q_H/\text{mm}$	-2.07	8.30	2.86	5.85	3.74
	$F_C/\%$	99.05	96.10	98.66	97.25	98.25
	$F_H/\%$	0.95	3.90	1.34	2.75	1.75
2000–2009	$\Delta Q_C/\text{mm}$	78.38	73.78	76.20	74.87	75.81
	$\Delta Q_H/\text{mm}$	-32.64	-28.05	-30.46	-29.14	-30.07
	$F_C/\%$	70.60	72.46	71.44	71.99	71.60
	$F_H/\%$	29.40	27.54	28.56	28.01	28.40
2010–2018	$\Delta Q_C/\text{mm}$	253.10	242.41	248.02	244.94	247.12
	$\Delta Q_H/\text{mm}$	-90.94	-80.24	-85.86	-82.77	-84.95
	$F_C/\%$	73.57	75.13	74.29	74.74	74.42
	$F_H/\%$	26.43	24.87	25.71	25.26	25.58
1969–2018	$F_C/\%$	80.28	79.82	80.24	80.01	80.17
	$F_H/\%$	19.72	20.18	19.76	19.99	19.83

Then, the changed period was divided into five decades, including 1969–1979, 1980–1989, 1990–1999, 2000–2009, 2010–2018, and the contribution rates of climate change and human activities in each decade were estimated in Table 7 and Figure 8. For the whole changed period, the contribution rates estimated by four different Budyko formulas were almost the same, with the average contribution rate of climate change and human activities 80.17% and 19.83%, respectively. Among the five decades, the contribution rate of climate change during 1990–1999 was the highest, with a value of 98.25%, while the values of other decades were around 70–80%. Based on the climate elastic coefficient method, climate change was the main factor affecting runoff change in the GRB.

4.3.2. Hydrological Simulation Analysis

The runoff process of the changed period was simulated by using the calibrated GR1A, ABCD and DTVGM models, as shown in Figure 9. The three model evaluation indices for assessing the applicability of three hydrological models are shown in Table 8. Compared with the reference period, GR1A and DTVGM models had a relatively worse performance with a lower NSE and R^2 , while ABCD models showed the same performance with an NSE of 0.91 and R^2 of 0.92. These values of the three hydrological models were all within a reasonable range and reached a satisfactory level based on Moriasi et al. [38].

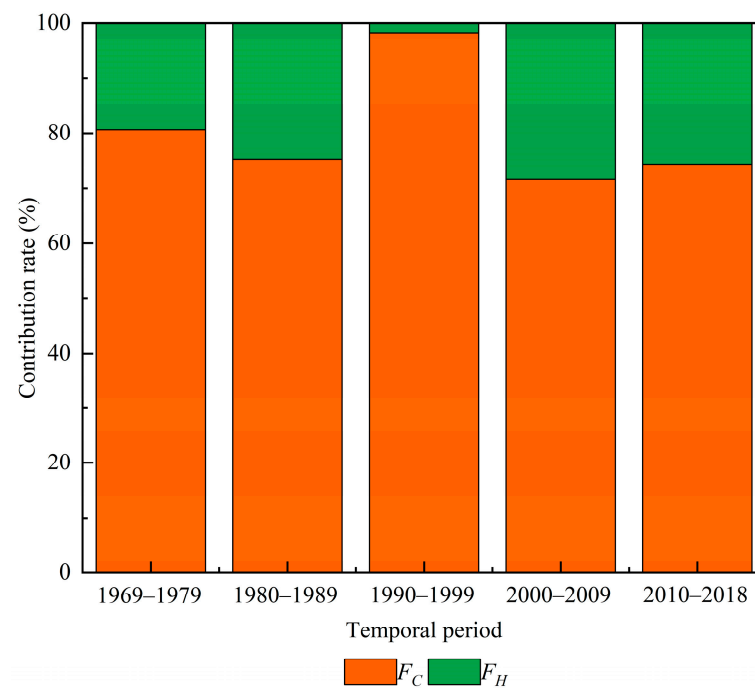


Figure 8. Relative contribution rate of runoff to climate change and human activities estimated by climate elasticity coefficient analysis.

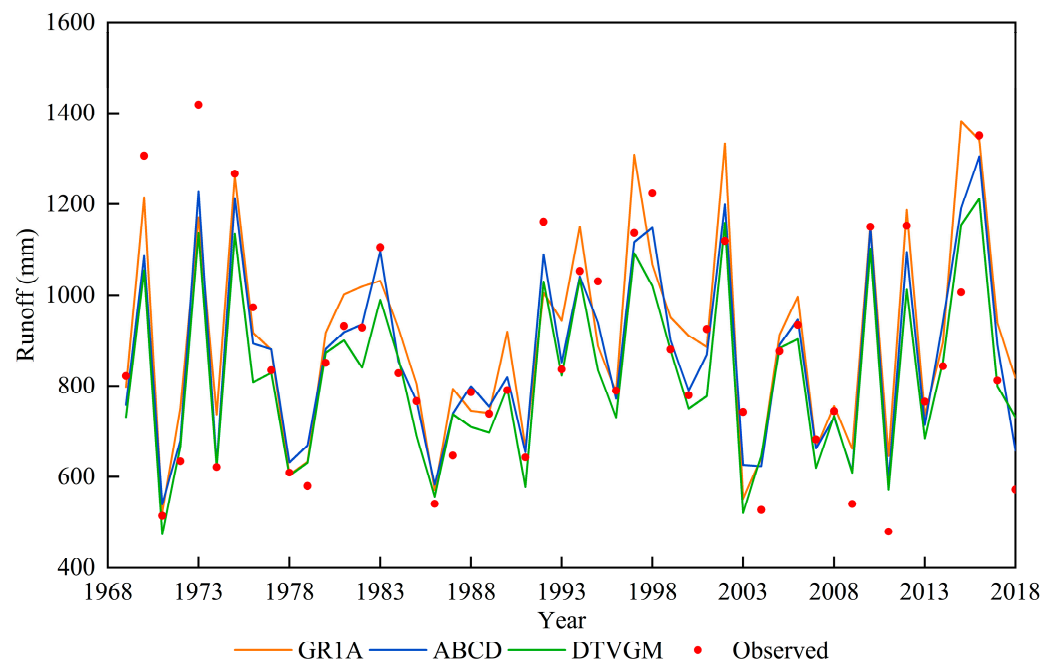


Figure 9. Comparison of annual streamflow with simulated streamflow obtained by different hydrological models during the changed period.

Based on the hydrological simulation method, the influence of climate change and human activities on the runoff change were quantitatively distinguished, as shown in Table 9. There were significant variations in the detected contribution rates among different hydrological models. Within the three models, the impact of climate change on runoff varied from 60.07% to 82.88%, whereas human activities accounted for a range of 17.12% to 39.93%. The respective average values were 74.40% and 25.60%, respectively. The contribution rate results indicated that the impact of climate change on runoff change is

higher than that of human activities, which is consistent with the results of the climatic elastic coefficient method. However, the ranges of the contribution rate estimated by hydrological models were wider than those estimated by Budyko formulas, indicating greater uncertainties.

Table 8. The statistical metrics of three hydrological models for the annual runoff simulation of changed period.

Model	Statistical Metrics		
	NSE	R ²	Bias
GR1A	0.75	0.78	4.36%
ABCD	0.91	0.92	0.24%
DTVGM	0.80	0.85	−4.99%

Table 9. Separating the effects of climate change and human activities by hydrological simulating method.

Period	Variable	Hydrological Model			Mean
		GR1A	ABCD	DTVGM	
1969–1979	$\Delta Q_C/\text{mm}$	121.15	95.69	48.69	88.51
	$\Delta Q_H/\text{mm}$	8.29	33.74	80.74	40.93
	$F_C/\%$	93.60	73.93	37.62	68.38
	$F_H/\%$	6.40	26.07	62.38	31.62
1980–1989	$\Delta Q_C/\text{mm}$	113.79	91.43	44.52	83.24
	$\Delta Q_H/\text{mm}$	−42.84	−20.48	26.43	−12.30
	$F_C/\%$	72.65	81.70	62.75	72.37
	$F_H/\%$	27.35	18.30	37.25	27.63
1990–1999	$\Delta Q_C/\text{mm}$	227.14	191.98	140.77	186.63
	$\Delta Q_H/\text{mm}$	−14.05	21.11	72.32	26.46
	$F_C/\%$	94.17	90.09	66.06	83.44
	$F_H/\%$	5.83	9.91	33.94	16.56
2000–2009	$\Delta Q_C/\text{mm}$	90.08	53.51	18.70	54.10
	$\Delta Q_H/\text{mm}$	−44.34	−7.78	27.04	−8.36
	$F_C/\%$	67.01	87.31	40.89	65.07
	$F_H/\%$	32.99	12.69	59.11	34.93
2010–2018	$\Delta Q_C/\text{mm}$	269.39	206.95	160.85	212.40
	$\Delta Q_H/\text{mm}$	−107.22	−44.79	1.32	−50.23
	$F_C/\%$	71.53	82.21	99.19	84.31
	$F_H/\%$	28.47	17.79	0.81	15.69
1969–2018	$F_C/\%$	80.23	82.88	60.07	74.40
	$F_H/\%$	19.77	17.12	39.93	25.60

The average relative contribution rates of climate change and human activities over five decades are given in Figure 10. Among these five decades, the contribution rates of climate change during 1990–1999 and 2010–2018 were the highest, with values of 84.44% and 84.31%, while the values of other decades ranged between 65% and 73%. Contribution rates of climate change estimated by climate elasticity coefficient and hydrological model analysis were 80.17% and 74.40%, respectively. Both methods identified climate change as the main factor influencing runoff changes. However, the contribution rate of human activities detected by the hydrological simulation method was higher than that detected by the elastic coefficient method, and the two methods identified different periods as the most sensitive to climate change.

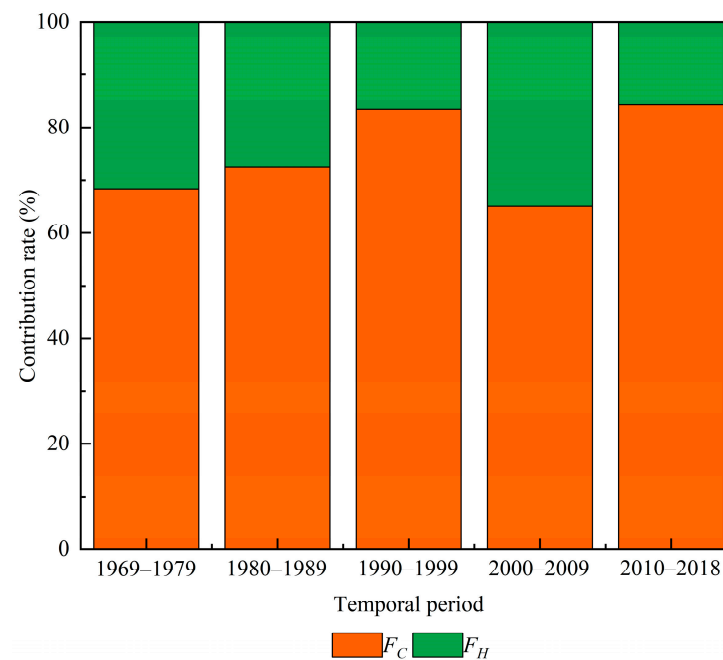


Figure 10. The average relative contribution rates of runoff to climate change and human activities are estimated by hydrological simulation analysis.

The contribution rates of climate change and human activities estimated by different hydrological models are shown in Figure 11. The contribution rate of each factor estimated by the three hydrological models was significantly different. Among three hydrological models, the GR1A model identified 1969–1979 and 1990–1999 as the most sensitive periods to climate change, with contribution rates larger than 90%, while the ABCD model determined that 1990–1999 and 2000–2009 were more sensitive to climate change, with contribution rates of 90.09% and 87.31%. In contrast, the DTVGM model tended to overestimate the contribution rate of human activities. The influence of human activities was more prominent in the periods of 1969–1979 and 2000–2009, with contribution rates of 62.38% and 59.11%, while climate change was most significant in 2010–2018, with a contribution rate as high as 99.19%.

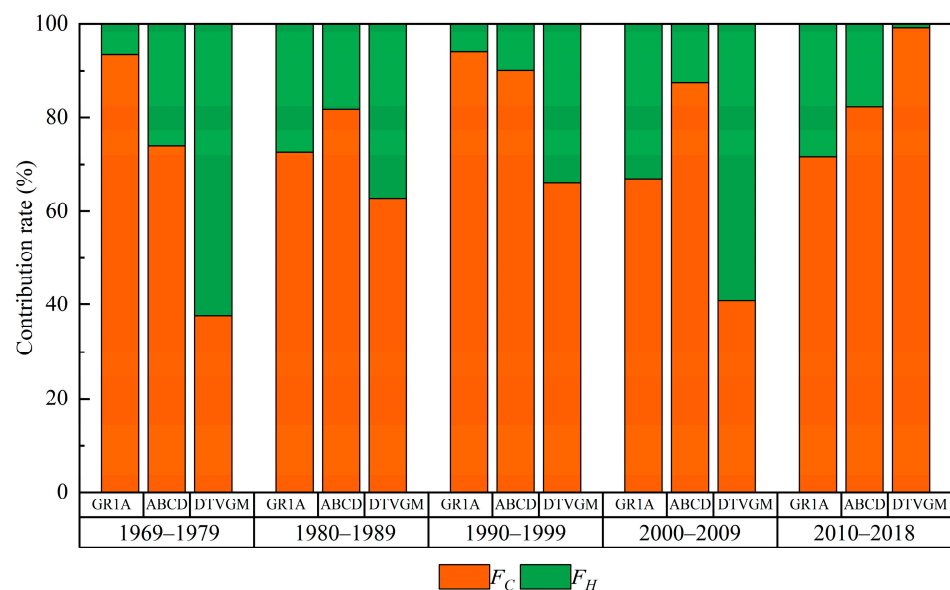


Figure 11. The contribution rates of climate change and human activities are estimated by different hydrological models.

4.4. Discussion

Climate change and human activities play important roles in runoff variation, especially in tropical and subtropical areas. However, these two factors would cause different impacts on hydrological processes in different study areas. For example, Ni et al. [7] highlighted that human activities predominantly influence runoff in the source area of the Yellow River, while Wang et al. [49] concluded that climate change was the main factor for runoff change in the delta area of the Yangtze River. This difference could be attributed to the basin characteristics of study areas (size, soil types, slope, etc.) and the spatio-temporal heterogeneity of climate change and human activities.

For the GRB, climate change, especially in the form of precipitation and temperature changes, was the main factor causing runoff change according to previous results in Section 4.3, which is consistent with the conclusion of Guo et al. [50], Lei et al. [45], Ye et al. [51] and Fan et al. [46], while Liu et al. [52] found the influence of reservoir construction on the runoff change was more significant. Runoff attribution results for the GRB obtained by different studies are listed in Table 10, and the contribution rates of climate change and human activities vary significantly among different studies. Currently, water reservoir construction and land use/cover change are the two primary ways to alter runoff. Based on the reservoir construction report from Jiangxi Province, a large number of medium and small-sized reservoirs were constructed from the 1950s to the 1970s with agricultural irrigation the primary purpose. Subsequently, several large and medium-sized reservoirs primarily for power generation were built after the 1980s. Today, there are 13 large reservoirs, 120 medium-sized reservoirs, and 3678 small reservoirs in the GRB. These reservoirs predominantly influence the annual runoff distribution process by storing excess water during the wet season and releasing it during the dry seasons. Consequently, these reservoirs have a significant influence on the annual runoff distribution but have little influence on the inter-annual variability of runoff. Furthermore, there have been substantial land use/cover changes in the GRB. From the 1950s to the 1980s, forest coverage dropped from 40.1% to 31.5%. However, since the 1980s, the implementation of afforestation and forest restoration projects has led to a remarkable increase in forest coverage, surpassing 60%. This considerable increase in vegetation can reduce runoff during the flood seasons and enhance it during dry seasons. Additionally, following the initiation of the Reform and Opening Policy, China's urbanization has developed rapidly, with significant changes taking place in the underlying surface of cities. Rapid urbanization has contributed to an increase in surface runoff and a reduction in evapotranspiration, consequently decreasing river streamflow. As pointed out by Zhang et al. [47], the increase in streamflow caused by urbanization would offset the decrease caused by afforestation. Therefore, despite extensive human activities over nearly six decades within the GRB, the overall impact of human activities on runoff is still less significant than that of climate change.

Table 10. Comparison of runoff attribution results of the GRB estimated by different studies.

Model	Period		Contribution Rate		Reference
	Reference Period	Changed Period	$F_C/\%$	$F_H/\%$	
Budyko framework	1956–1968	1969–2018	80.17	19.83	Section 4.3.1
ABCD	1956–1968	1969–2018	80.23	19.77	Section 4.3.2
GR1A	1956–1968	1969–2018	82.88	17.12	Section 4.3.2
DTVGM	1956–1968	1969–2018	60.07	39.93	Section 4.3.2
Linear regression	1960–1987	1988–2015	90.71	9.29	[45]
Budyko framework	1960–1969	1970–2007	73.91	26.09	[51]
AWBM	1955–1969	1970–2009	61.00	39.00	[47]
Linear regression	1970–1993	1994–2015	82.72	17.28	[53]
Budyko framework	1955–1991	1992–2017	95.54	4.46	[54]

Various uncertainties affect the model performance and the runoff attribution results, including data sources, methods and temporal periods. In this study, the choice of the

hydrological model is a significant source of uncertainty in separating impacts. As shown in Table 7, different formulas yielded almost the same results, indicating that the choice of the Budyko formula is not sensitive to the runoff attribution results. However, selecting an appropriate hydrological model can greatly affect the results, as shown in Table 10. The Budyko framework constructs a relatively simple relationship between precipitation, actual evapotranspiration and potential evapotranspiration. Although a series of Budyko formulas have been proposed, these formulas are relatively simple, with only one or two key parameters. Therefore, the input is more sensitive to the results when using Budyko formulas. In contrast, the simulation results of the hydrological model are mainly dominated by inputs, model structure and model parameters. The runoff attribution results obtained by different hydrological models would vary obviously. The choice of hydrological model plays an important role in the separation of climate change and human activities on runoff. It is worth noting that higher complexity in a hydrological model does not necessarily translate to more reliable and accurate simulation. More complex models typically involve numerous parameters and require additional inputs, leading to challenges such as parameter identification difficulties and uncertainties [55]. A recommended approach to account for these uncertainties is to run different models, compare results using different methods, and subsequently obtain a more accurate and acceptable runoff attribution analysis.

5. Conclusions

In this study, the impacts of climate change and human activities on runoff variations are quantitatively evaluated based on hydrological simulation and the Budyko framework. Their individual contributions are separated by multiple attribution methods in different periods. Results show that annual potential evapotranspiration has significantly decreased, annual precipitation has slightly increased, and annual runoff has no significant change. The reference period and changed period are detected and the abrupt year is 1968. Three hydrological models simulate the daily runoff well in the GRB, with NSE and R^2 being larger than 0.8. The average contributions of climate change and human activities are 80.17% and 19.83%, by using the climate elasticity method. Similar results are obtained through hydrological simulation analysis, with the average contributions of climate change and human activities being 74.40% and 25.60%, respectively. Therefore, climate change plays a dominant role in runoff variations. The different Budyko formulas have a small impact on the runoff attribution analysis, while different hydrological models might cause dramatic deviation. In order to reduce the uncertainties caused by different data sources, model structures and model parameters, the more accurate way is to assemble multiple models and compare their results for runoff attribution analysis.

The impact of climate change and human activities on runoff process and basin hydrological characteristics are complex owing to it is associated with multiple factors and processes. Furthermore, the impact of human activities on runoff can be divided into fast impact(reservoirs, water diversion projects) and slow impact(land use and land cover changes), while the impacts of these two changes were not clearly distinguished in this study. Therefore, how to quantitatively distinguish the impact of different types of human activities and meteorological elements on the runoff process and understand the impact mechanism of climate change and human activities on basin hydrological processes are important areas for further research.

This study highlights the influence of model choice on the runoff attribution analysis. The outcomes will help provide a scientific basis for practical water resource management and planning of the GRB in the future and will be beneficial to decision-makers in improving the evolutionary characteristics and understanding the driving mechanisms of hydrological processes in a changing environment.

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