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Separating climate change and human contributions to variations in streamflow and its components using eight time-trend methods

Ling Zhang[1] | Zhuotong Nan[2,3] | Weizhen Wang[1] | Dong Ren[4] | Yanbo Zhao[1] | Xiaobo Wu[5]

[1] Key Laboratory of Remote Sensing of Gansu Province, Northwest Institute of Eco-Environment and Resources, Chinese Academy of Sciences, Lanzhou, China

[2] Ministry of Education, Key Laboratory of Virtual Geographic Environment, Nanjing Normal University, Nanjing, China

[3] Jiangsu Center for Collaborative Innovation in Geographical Information Resource Development and Application

[4] Hydrology Water Resources Bureau of Gansu Province, Lanzhou, China

[5] College of Resources, Sichuan Agricultural University, Chengdu, China

Correspondence
Ling Zhang, Key Laboratory of Remote Sensing of Gansu Province, Northwest Institute of Eco-Environment and Resources, Chinese Academy of Sciences, Lanzhou 730000, China.
Email: zhanglingky@lzb.ac.cn

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Abstract

Separating impacts of human activities and climate change on hydrology is essential for watershed and ecosystem management. Many previous studies have focused on the impacts on total streamflow, however, with little attentions paid to its components (i.e., baseflow and surface run-off). This study distinguished the contributions of climate change and human activities to the variations in streamflow, baseflow, and surface run-off in the upstream area of the Heihe River Basin, a typical inland river basin in northwest China, by using eight different forms of time-trend methods. The isolated contributions to streamflow variation were also compared with those obtained by two Budyko-based approaches. Our results showed that the time-trend methods consistently estimated positive contributions of climate variability and human activities to the increases in streamflow and its components but with obviously varying magnitudes. With regard to streamflow, the time-trend method double-mass-curve–Wei, with a physical basis, produced a reasonable smaller contribution of human activities than climate changes, inconsistent with the Budyko-based approaches. However, all the other time-trend methods led to contrary results. The contributions to baseflow variation diverged more significantly than those to streamflow and surface run-off, ranging from 24% to 92% for human activities and from 8% to 76% for climate variability. In terms of surface run-off, most of the time-trend approaches produced smaller contributions of human activities (ranging from 21% to 49%) than climate change. The uncertainties associated with the various time-trend approaches and the baseflow separation algorithm were revealed and discussed, along with some recommendations for future work.

KEYWORDS

baseflow, Budyko framework, climate change, Heihe River Basin, human activities, streamflow, surface run-off, time-trend method

1 | INTRODUCTION

Climate change and human activity are two main factors that influence watershed hydrology (Dey & Mishra, 2017). Climate change, particularly rising temperatures and changing precipitation regimes, can exert profound impacts on hydrological processes and spatial-temporal patterns of water resources (Joo, Zhang, Li, & Zheng, 2017; Lee et al., 2018; Sunde, He, Hubbart, & Urban, 2017). On the other hand, human activities such as deforestation, urbanization, and overgrazing, which have increasingly become more intensified in recent decades due to the rapidly growing economy and population, could strongly interfere the natural hydrological processes such as evapotranspiration (ET) and surface run-off, adding further pressure to the earth's water resources (da Silva, Silva, Singh, de Souza, & Braga, 2018; Rogger et al., 2017; Wada et al., 2017; Zhou et al., 2013). Under such background, the hydrological impacts of climate change and human activities become a hot and foreland topic in the fields of water and environmental sciences.

Climate changes interact with human activities and impact the hydrological regimes jointly, leading to multiple challenges for water resource management (Li, Liu, Zhang, & Zheng, 2009; Natkhin, Dietrich, Schäfer, & Lischeid, 2015). Many previous studies, however, have only investigated the hydrological variations induce solely by climate change or human activities (e.g., Faramarzi et al., 2013; Kundu, Khare, & Mondal, 2017; Rogger et al., 2017; Sorribas et al., 2016). In recent years, there are increasingly more studies have been carried out to separate hydrological impacts of climate change and human activities (Marhaento, Booij, & Hoekstra, 2017; Wang, 2014). Overall, four major categories of methods that have been frequently used, that is, (a) the Budyko-based approach (Budyko, 1974; Wu, Miao, Wang, Duan, & Zhang, 2017), (b) the time-trend method (Gao, Mu, Wang, & Li, 2011; Wei & Zhang, 2010; Zhao, Zhang, Xu, & Scott, 2010), (c) the modelling-based approach (Feng et al., 2017; Qiu et al., 2017), and (d) the Tomer–Schilling framework (Tomer & Schilling, 2009; Ye, Zhang, Liu, Li, & Xu, 2013). Among them, the former two are perhaps the most widely used techniques due to the simplicity and the few data requirements. Both the Budyko-based and time-trend methods have different forms depending on diversified hypotheses. Recently, Wu et al. (2017) assessed the impacts of climate change and human activities on run-off on the Loess Plateau in China by using eight kinds of Budyko-based methods; and they found the results could diverge significantly, particularly in the low-flow season. To our best knowledge, however, very few studies have compared the consistency and uncertainty of different forms of time-trend methods in hydrological impact separations. Most importantly, many previous studies have mainly focused on the contributions of climate change and human activities to streamflow variations, with little attentions paid to its components, that is, baseflow and surface run-off (Li, Wei, et al., 2018). They might not be able to provide a holistic picture of the hydrological impacts because streamflow and its components may respond very differently to climate change and human activities.

The Heihe River Basin (HRB) is the second largest inland river basin in northwest China and serves as an important test bed for watershed science, because of the distinct landscape patterns, special eco-hydrological processes, and serious water problems (Cheng et al., 2014; Li, Cheng, et al., 2018; Zhang, Nan, Xu, & Li, 2016). The upstream area of the HRB is the main headwater region of the Heihe River and plays an essential role in the agricultural development and ecological system in the midstream and downstream areas. In recent years, a number of studies have been carried out to assess and project the impacts of land-use change and climate variability on the hydrological regimes in the upper HRB (e.g., Wu, Zhan, Chen, He, & Zhang, 2015; Yang et al., 2017; Yin et al., 2017; Zhang, Liu, Yin, Fu, & Zheng, 2016; Zhang, Nan, Yu, & Ge, 2015; Zhang, Nan, Yu, & Ge, 2016). However, few have quantitatively distinguished the impacts of climate change and human activities on both streamflow and its components over a relatively long time period. This necessitates further investigations for a deep knowledge of the hydrological variations and better management of water resources in the HRB.

The main objective of this study is to separate impacts of climate change and human activities on streamflow and its components in the upper HRB over the period 1960–2014 by using eight different forms of time-trend methods. The isolated contributions to streamflow variation were also compared with those obtained by two Budyko-based approaches. We specifically aim to (a) quantify the contributions of climate change and human activities to the changes in streamflow, baseflow, and surface run-off, (b) compare different forms of time-trend methods in separating hydrological impacts, and (c) reveal the uncertainties associated with the various time-trend methods and the baseflow separation algorithm, along with some useful recommendations.

2 | STUDY AREA AND DATA

The HRB is a typical inland river basin in the arid region of northwest China. It is located on the northeastern Tibetan Plateau lying between 98.0°E–101.3°E and 38.0°N–42.0°N. The HRB has a drainage area of approximately 143 × 10^3 km^2, with the mainstream (i.e., the Heihe River) that is about 821 km long. The basin can be naturally divided into the upstream, midstream, and downstream areas from the southern Qilian Mountain to the northern Inner Mongolia. As shown in Figure 1, the upstream area, which was focused in this research, is characterized by steep mountainous terrains. The structural fractures are extensively developed in this region, with widely distributed bedrock fissure water (Ye, 2005). A thrust fault distributes along the foot of the Qilian Mountains in a north-west and south-east (NW–SE) direction, which makes the mountainous groundwater can hardly flow out laterally (Yang et al., 2011). The elevation ranges from 1,679 m above sea level (ASL) in the mountain valley to 5,013 m ASL at the mountain peak. The upper HRB has a continental alpine semihumid climate with an average precipitation of about 450 mm/year and a mean annual temperature less than 1°C from 1960 to 2014. Snowfall is an important component of the precipitation; and snowmelt contributes a dominant fraction of the spring streamflow (Wang, Yang, Lei, & Yang, 2015). The land-use/cover map of the year 2011, which was derived from the 30-m Landsat Thematic Mapper(TM)/Enhanced Thematic Mapper Plus (ETM+) images, shows that the upper HRB is mainly covered by grassland (69.2%) and barren land (24.2%; Wang, Zhao, Hu, & Ge, 2014). The dominant soil types include the alpine meadow soil, alpine chestnut soil, subalpine shrub meadow soil, and alpine frost desert soil; and the main soil textures are the loam, silt loam, and sandy loam (Zhang, Nan, Xu, & Li, 2016).

Daily meteorological data measured at four national weather stations for the period 1960–2014, including maximum and minimum temperature, precipitation, relative humidity, and wind speed, were

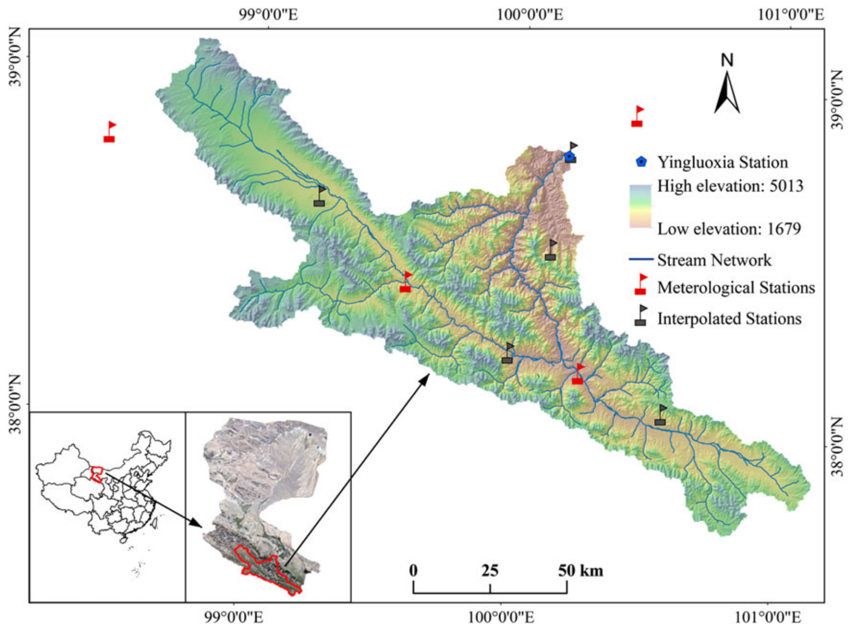

FIGURE 1 Location of the study area

obtained from the China Meteorological Data Sharing Service System (http://cdc.nmic.cn/). The time-series precipitation of five fictitious stations (Figure 1) was interpolated through the MicroMet, an intermediate-complexity, quasiphysically-based meteorological model (Liston & Elder, 2006), in order to better capture the strong spatial heterogeneity of precipitation over the upper HRB. The potential ET (PET) was calculated by the Penman–Monteith method. The Thiessen-polygon scheme was used to generate spatially averaged precipitation and PET over the whole study area. Monthly streamflow data from 1960 to 2014, observed at the outlet of the upper HRB (i.e., the Yingluoxia hydrological station), were obtained from the Water Resources Bulletin of Gansu Province (http://www.gssl.gov.cn/).

3 | METHODOLOGY

3.1 | Overview

The workflow of the study is illustrated in Figure 2. The methodology mainly consists of three parts: baseflow separation, break-point identification, and hydrological impact separation. Baseflow and surface run-off were first separated from the streamflow observations using a digital filter-based algorithm. The break point of the annual streamflow and its components was then comprehensively determined through three statistical techniques, that is, the accumulated anomaly approach, the Pettitt's test, and the heuristic segmentation algorithm. Finally, eight different forms of time-trend approaches were adopted to separate impacts of climate variability and human activities on streamflow and its components based on the detected break points and the estimated watershed average precipitation and PET. The quantified contributions to streamflow variation were compared with those obtained via two Budyko-based approaches.

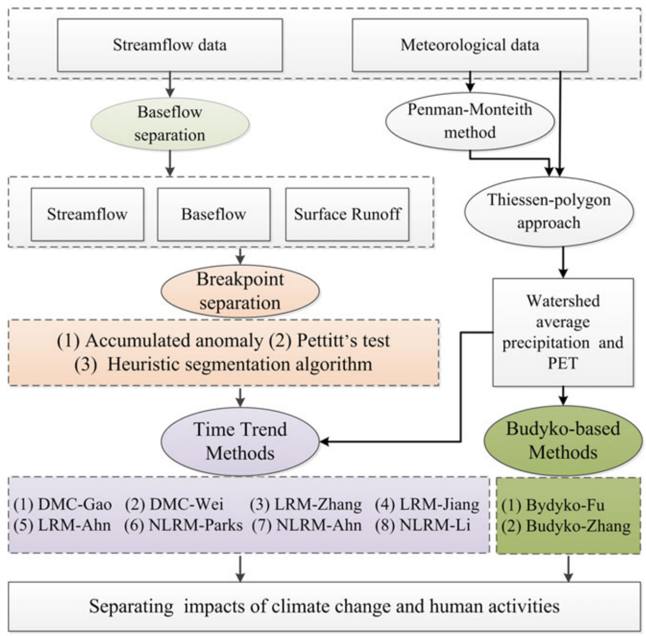

FIGURE 2 Workflow of this study

3.2 | Baseflow separation method

The digital filter-based scheme was used in this study to separate baseflow from streamflow. This technique, which was originally used in signal analysis and processing, is widely applied to estimate baseflow and has proved to be able to produce reasonable estimates of baseflow in the arid regions of northwest China (Lyne & Hollick, 1979; Yao et al., 2017). Despite the lack of a true physical basis, it is objective and reproducible (Arnold & Allen, 2007). The equations of the filter are expressed as follows:

$$SF_t = \beta SF_{t-1} + \frac{(1+\beta)}{2}(Q_t - Q_{t-1}), \tag{1}$$

$$BF_t = Q_t - SF_t, \tag{2}$$

where *BF* and *SF* are baseflow and surface run-off, respectively, *Q* is streamflow, and β is the filter parameter, which was determined through a trial-and-error procedure. The filter can pass streamflow observations three times (forward, backward, and forward), and each of which will generally result in less proportion of baseflow from the total streamflow (Arnold, Muttiah, Srinivasan, & Allen, 2000). Only one filter pass was implemented by referring to the study of Zhang, Zhang, and Zhao (2011).

3.3 | Break-point identification

The accumulated anomaly algorithm was used to detect the break points of streamflow and its components (Ran, Wang, & Fan, 2010). For a discrete series x_i, the accumulated anomaly (X) for the time step t is expressed as follows:

$$X_t = \sum_{i=1}^{t} (x_i - x_{\text{ave}}) \quad t = 1, \ 2, \ldots, n, \tag{3}$$

where x_{ave} is the mean value of the time series x_i and n is the number of data points. The accumulated anomaly is mainly used to signify the fluctuations of the analysed data. The increase in accumulated anomaly indicates that the current data value is larger than the average and vice versa. The point before and after which the accumulated anomaly exhibits inverse trends could be determined as the break point. The non-parametric approach, that is, the Pettitt's test (Pettitt, 1979), has been widely used to detect the break points of hydroclimatic variables (Wang et al., 2013). It was also employed in this research. Because of the complexity and high variability of hydrological processes, the streamflow and its components are nonlinear and nonstationary, which may bring about uncertainties to the break-point analyses when using the accumulated anomaly approach and the Pettitt's test (Feng, Gong, Dong, & Li, 2005). Hence, the Borowsky–Gafni (BG) algorithm, an effective heuristic segmentation algorithm proposed by Bernaola-Galván, Ivanov, Nunes Amaral, and Stanley (2001), was additionally applied to identify the break points of streamflow and its components, as a reconfirmation of the results obtained through the other two approaches.

3.4 | Methods used for separating impacts of climate change and human activities

3.4.1 | General framework

Streamflow variations are the combined effects of human activities and climate changes (Qiu et al., 2017). Streamflow can therefore be modelled as follows:

$$Q = f(C, \ H), \tag{4}$$

where Q is streamflow and C and H represent climatic factors and human activities, respectively. Using a first-order approximation, the changes in streamflow can be expressed as follows:

$$\Delta Q = \Delta Q_C + \Delta Q_H, \tag{5}$$

where ΔQ_C and ΔQ_H mean the changes in streamflow due to climate change and human activities, respectively. In order to estimate ΔQ_C and ΔQ_H, the study period needs to be divided into two parts by the cutting point before which human activities are slight and negligible (Wang, 2014). The cutting point is typically detected through the break-point analysis of the streamflow observations. The time periods before and after the break point refer to the baseline period and the altered period, respectively. Without considering the interactions between climate change and human activity, the variables in Equation (5) including ΔQ, ΔQ_C, and ΔQ_H can be estimated as follows.

$$\Delta Q = Q_{\text{altered}} - Q_{\text{baseline}}, \tag{6}$$

$$\Delta Q_C = Q^C_{\text{altered}} - Q_{\text{baseline}} \quad \text{or} \quad \Delta Q_H = \Delta Q - Q^C_{\text{altered}}, \tag{7}$$

$$\Delta Q_H = \Delta Q - \Delta Q_C \quad \text{or} \quad \Delta Q_C = \Delta Q - \Delta Q_H, \tag{8}$$

where Q_{altered} and Q_{baseline} are the mean annual streamflow observations for the altered and baseline periods, respectively, and Q^C_{altered} is the mean annual streamflow under the climatic condition of the altered period. The relative contributions of climate change (R_C) and human activities (R_H) to streamflow variations can be calculated using Equations (9) and (10).

$$R_C = \frac{\Delta Q_C}{\Delta} Q \times 100\% \tag{9}$$

$$R_H = \frac{\Delta Q_H}{\Delta} Q \times 100\% \tag{10}$$

3.4.2 | Time-trend methods

The procedure of the time-trend method for distinguishing impacts of climate change and human activities on hydrology, expressed by Lee (1980), is given as follows. The relationship between streamflow and the climatic factors such as precipitation and PET, as in Equation (11), is first established for the baseline period. This relationship is then employed to estimate streamflow under the climatic condition of the altered period without considering human activities, as in Equation (12). The absolute and relative contributions of climate change and human activities to streamflow variations could finally be estimated by using Equations (7)–(10).

$$Q_{\text{baseline}} = f(C_{\text{baseline}}) \tag{11}$$

$$Q^C_{\text{altered}} = f(C_{\text{altered}}) \tag{12}$$

To date, various methods have been proposed to establish the relationship in Equation (11) (Ahn & Merwade, 2014; Gao et al., 2011; Jiang et al., 2011; Wei & Zhang, 2010; Zhao et al., 2010), resulting in various forms of time-trend methods. By reviewing the literatures, eight different approaches were collected and used in this study, as listed in Table 1. They describe the relationships between streamflow and climatic factors mainly by using the double mass curves (DMCs), the linear regression model (LRM), and the nonlinear regression model (NLRM). Thus, we classified them into three categories, that is, the DMC-based, LRM-based, and NLRM-based approaches. Typically, these methods were used to separate impacts on streamflow. In this research, we also applied them to distinguish impacts on surface run-off and baseflow, as did by Li et al. (2018). The parameter values for each time-trend method were estimated using the linear or nonlinear least square regression methods.

3.4.3 | Budyko-based methods

The contributions of climate variability and human activities to streamflow variation were also estimated using the two Budyko-based approaches, as a comparison for the time-trend methods. The water balance in a watershed can be described as follows:

$$P = Q + E + \Delta S, \tag{13}$$

where P is precipitation, E is evapotranspiration, Q is streamflow, and ΔS is the changes in water storage, which is typically assumed to be 0 over a long time period.

Budyko (1974) considered that the available energy and water are the primary factors determining the rate of ET and suggested that the ratio of evaporation to precipitation is controlled by the ratio of PET to precipitation. According to Budyko, the actual ET can be expressed as a function of dryness index $\varnothing = PET/P$, as in Equation (14), known as the Budyko hypothesis.

$$ET = P \cdot F(\phi) \tag{14}$$

Following a similar assumption made by Budyko (1974), Fu (1981) and Zhang, Dawes, and Walker (2001) proposed to express the above relationship as Equations (15) and (16), respectively.

$$\frac{ET}{P} = 1 + \frac{PET}{P} - \left(1 + \left(\frac{PET}{P}\right)^{w}\right)^{1/w}, \tag{15}$$

TABLE 1 Eight time-trend methods used to separate impacts of climate change and human activities on streamflow and its components

Time-trend methods	$Q_{baseline} = f(C_{baseline})$	References
DMC–Gao	$\sum_{i=1}^{t} Q_i = a + b\sum_{i=1}^{t} P_i$	Gao et al. (2011)
DMC–Wei	$\sum_{i=1}^{t} Q_i = a + b\sum_{i=1}^{t} (P_i - ET_i)$	Wei and Zhang (2010)
LRM–Zhang	$Q_t = a + b \cdot P_t$	Zhao et al. (2010)
LRM–Jiang	$Q_t = a + b \cdot P_t + c \cdot PET_t$	Jiang et al. (2011)
LRM–Ahn	$Q_t = a + b \cdot P_t + c \cdot P_{t-1} + d \cdot PET_t$	Ahn and Merwade (2014)
NLRM–Parks	$Q = a \cdot P_t^b$	Parks and Madison (1985)
NLRM–Ahn	$Q = a \cdot P_t^b \cdot PET_t^c$	Ahn and Merwade (2014)
NLRM–Li	$Q = a + b \cdot P_t \cdot \rho^c$	Li et al. (2007)

Note. DMC: double mass curve; LRM: linear regression model; NLRM: nonlinear regression model.

$$\frac{ET}{P} = \frac{1 + w(PET/P)}{1 + w(PET/P) + (PET/P)^{-1}}, \tag{16}$$

where the parameter w reflects the watershed characteristics and is a function of vegetation type, soil properties, and topographical characteristics.

Because precipitation and PET are the dominant factors influencing the mean annual water balance, the changes in streamflow caused by climate change can be expressed as follows:

$$\Delta Q_C = \frac{\partial Q}{\partial P}\Delta P + \frac{\partial Q}{\partial PET}\Delta PET = \varepsilon_P \Delta P + \varepsilon_{PET}\Delta PET, \tag{17}$$

where $\varepsilon_P = \frac{\partial Q}{\partial P}$ and $\varepsilon_{PET} = \frac{\partial Q}{\partial PET}$ represent the change rate of streamflow with precipitation and PET, respectively. If the solution of Fu (1981) was used, the change rates can be derived as follows by combining Equations (13) and (15).

$$\varepsilon_P = P^{w-1}\left(PET^w + P^w\right)^{1/w-1} \tag{18}$$

$$\varepsilon_{PET} = PET^{w-1}\left(PET^w + P^w\right)^{1/w-1} - 1 \tag{19}$$

If the solution of Zhang et al. (2001) was used, the change rates can be deduced as follows by combining Equations (13) and (16). The two Budyko-based approaches referred as Budyko–Fu and Budyko–Zhang, respectively, in this study.

$$\varepsilon_P = \frac{1 + 2\phi + 3w\phi}{\left(1 + \phi + w\phi^2\right)^2} \tag{20}$$

$$\varepsilon_P = -\frac{1 + 2w\phi}{\left(1 + \phi + w\phi^2\right)^2} \tag{21}$$

4 | RESULTS

4.1 | Baseflow separation

Figure 3 presents the average monthly baseflow and surface run-off in the upper HRB over the period 1960–2014. Baseflow exhibits temporal variations, with the largest value in September whereas the

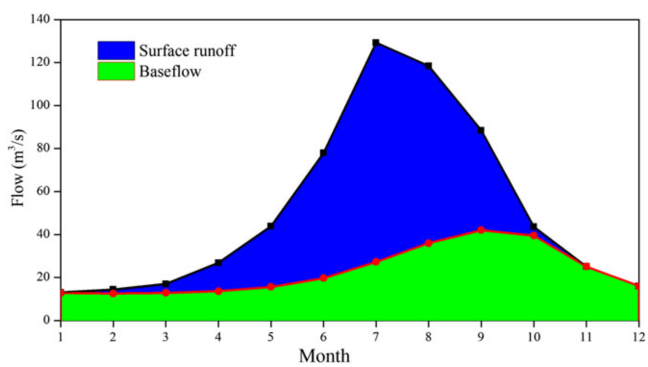

FIGURE 3 Monthly baseflow and surface run-off in the upper Heihe River Basin

smallest value in January. Surface run-off approaches the largest value in July but with tiny magnitudes in the months from October to March. The mean baseflow index (BFI), that is, the ratio of baseflow to streamflow, is about 0.44, indicating that baseflow is an important component of streamflow in the upper HRB. The higher BFI can be explained by the good vegetation cover, the greatly undulate terrain, the deep river valleys, and the extensively developed structure fractures (Ye, 2005; Zhang et al., 2011); all of which are favourable for baseflow generation. The higher BFI agrees well with many previous studies, in which the BFI was estimated to range from 0.35 to 0.55 via other baseflow separation methods (Dang, Wang, & Liu, 2011) and hydrological modelling (e.g., Wu, Li, Tian, & Zhao, 2013; Zhang, Nan, Xu, & Li, 2016). In particular, Yao et al. (2017) recently conducted a groundwater modelling over the upper HRB; and they estimated the mean baseflow of the upper HRB, which is 21.1 m^3/s over the period 1951–2010, and is very close to our result (i.e., 22.74 m^3/s).

4.2 | Break-point analysis

Figure 4 shows the cumulative anomaly of streamflow, baseflow, and surface run-off in the upper HRB over the period 1960–2014. They all first exhibit a downward trend and then an upward trend. The break points of streamflow, baseflow, and surface run-off are the years of 1980, 1979, and 2001, respectively. The break points detected by the Pettitt's test and the BG algorithm are presented in Table 2. The results of the Pettitt's test agree well with the cumulative anomaly method. In terms of streamflow and baseflow, the BG algorithm identified two change points, of which the first one is inconsistent with those determined by the other two approaches. In terms of surface run-off, only one break point (i.e., the year 2005) was detected by the BG algorithm, which is close to that was determined via the other two methods.

Zhang et al. (2011) detected the break point of baseflow over the period 1944–2004, which is the year 1979, by using the Mann–Kendall test. Using the same method, Cong, Shahid, Zhang, Lei, and Yang (2017) detected the break point of streamflow over the period 1960–2010, which is the year 1980. These previous studies

TABLE 2 Break points of streamflow and its components detected by the Pettitt's test and the Borowsky–Gafni (BG) algorithm

Flow components	Break point	
	Pettitt's test (year)	BG algorithm (year)
Streamflow	1979	1980 and 2005
Baseflow	1980	1980 and 2005
Surface run-off	2001	2005

Note. The significance level of a possible cutting point was set to 0.50 for the BG algorithm, and the imposed minimum length of the segment is 25 years.

reconfirmed our results. Hence, we determined the time periods 1960–1979, 1960–1978, and 1960–2000 as the baseline periods for streamflow, baseflow, and surface run-off, respectively, whereas the remaining study periods as the altered periods, through comprehensive break-point analyses. The break point of the year 2005 identified by the BG algorithm was not used in this study considering that it will lead to a very short altered periods, which is insufficient in representing an average climatic condition, and might bring biases to the separated hydrological impacts (Zhang, Nan, Yu, Zhao, & Xu, 2018).

4.3 | Separated contributions of climate change and human activities to hydrological variations

Table 3 lists the parameter values of different time-trend methods for streamflow, baseflow, and surface run-off. Figure 5a shows the relative contributions of climate change and human activities to the increases in streamflow estimated by the time-trend and Budyko-based approaches. The methods including DMC–Wei, Budyko–Zhang, and Budyko–Fu generated smaller contributions of human activities than climate variability to the increases in streamflow, ranging from 22% to 35%. However, the other methods led to contrary results; the contributions of human activities range from 51% to 74%. Streamflow, baseflow, and surface run-off increased by about 29.60, 13.78, and 18.38 mm, respectively, from the baseline to the altered periods. The relative contributions to the increases in baseflow and surface run-off estimated by the time-trend methods are shown in

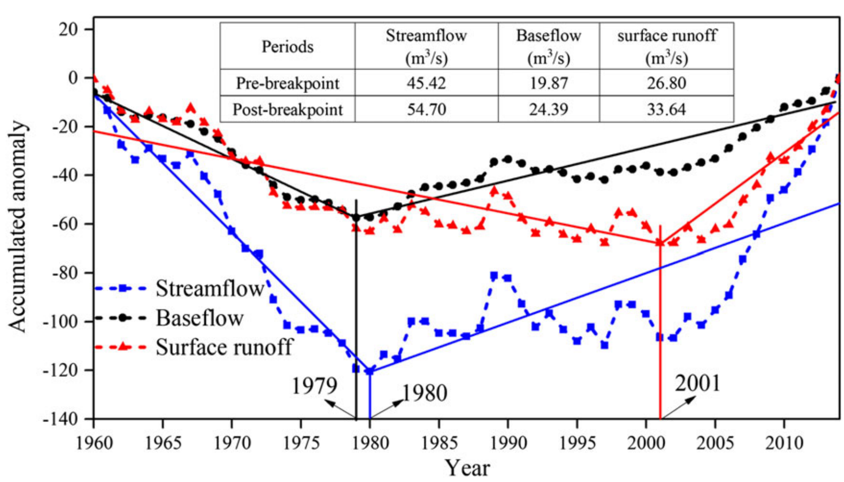

FIGURE 4 Variations of the cumulative anomaly of streamflow, baseflow, and surface run-off in the upper Heihe River Basin over the period 1960–2014. The table included in the figure shows the mean annual values of streamflow, baseflow, and surface run-off for the prebreak-point and postbreak-point periods

TABLE 3 The parameter values of different time-trend methods for streamflow, baseflow, and surface run-off

Methods	$Q_{baseline} = f(C_{baseline})$	Streamflow	Baseflow	Surface run-off
DMC–Gao	$\sum_{i=1}^{t} Q_i = a + b \sum_{i=1}^{t} P_i$	a = 23.81; b = 0.33	a = 3.37; b = 0.15	a = −5.68; b = 0.19
DMC–Wei	$\sum_{i=1}^{t} Q_i = a + b \sum_{i=1}^{t} (P_i - ET_i)$	a = 26.86; b = 1.00	a = 4.03; b = 0.44	a = 22.31; b = 0.56
LRM–Zhang	$Q_t = a + b \cdot P_t$	a = −13.71; b = 0.36	a = 17.98; b = 0.10	a = −34.83; b = 0.27
LRM–Jiang	$Q_t = a + b \cdot P_t + c \cdot PET_t$	a = 191.64; b = 0.31; c = −0.25	a = 93.55; b = 0.08; c = −0.09	a = 67.47; b = 0.25; c = −0.12
LRM–Ahn	$Q_t = a + b \cdot P_t + c \cdot P_{t-1} + d \cdot PET_t$	a = 181.82; b = 0.31; c = 0.02; d = −0.25	a = 71.01; b = 0.09; c = 0.04; d = −0.09	a = 47.28; b = 0.25; c = 0.03; d = −0.12
NLRM–Parks	$Q = a \cdot P_t^b$	a = −1.61; b = 1.08	a = −0.01; b = 0.69	a = −4.07; b = 1.40
NLRM–Ahn	$Q = a \cdot P_t^b \cdot PET_t^c$	a = 7.47; b = 0.93; c = −1.24	a = 7.66; b = 0.53; c = −1.02	a = 3.37; b = 1.25; c = −0.99
NLRM–Li	$Q = a + b \cdot P_t \cdot \rho^c$	a = −88.57; b = 1.60; c = −0.29	a = 3.49; b = 0.34; c = −0.24	a = −51.03; b = 0.48; c = −0.12

Note. DMC: double mass curve; LRM: linear regression model; NLRM: nonlinear regression model.

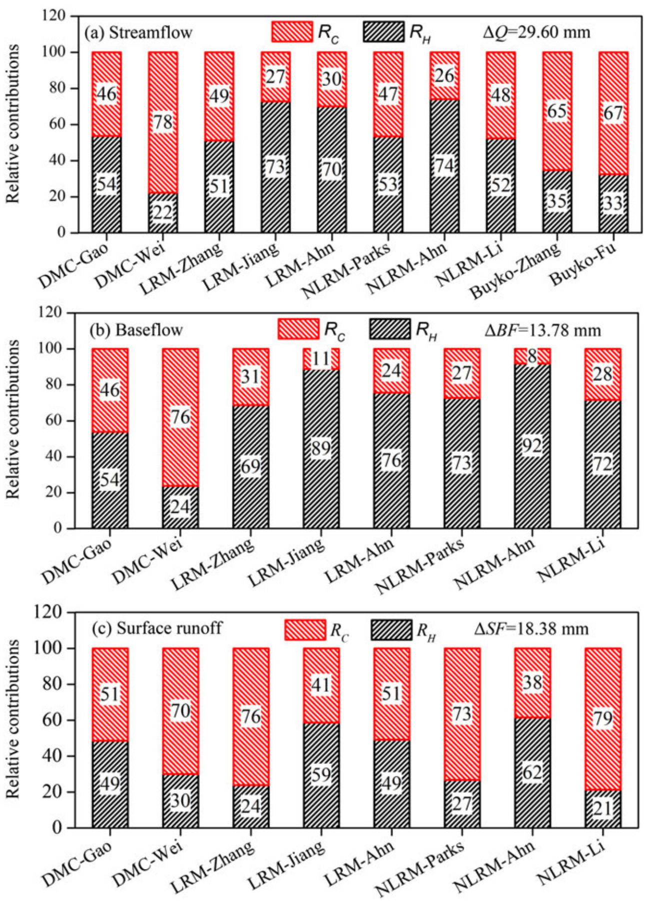

FIGURE 5 Relative contributions of climate change (RC) and human activities (RH) to the changes in (a) streamflow, (b) baseflow, and (c) surface run-off in the upper Heihe River Basin estimated by different methods

Figure 5b,c. With regard to baseflow, all the methods excepted for DMC–Wei induced greater contributions of human activities (ranging from 54% to 9ss2%) than climate change. In terms of surface run-off, most of the time-trend approaches produced smaller contributions of human activities (ranging from 21% to 49%) than climate change. In contrast, the two methods LRM–Jiang and NLRM–Ahn estimated the contributions of human activities that are of greater magnitudes than those of climate change.

5 | DISCUSSION

5.1 | Comparisons of different time-trend methods

The two Budyko-based approaches produced very consistent results; that is, about 33–35% increase in streamflow was due to human activities whereas the remaining was due to climate variability. The higher contribution of climate change than human activities is reasonable considering that the vast area of the upper HRB is located in the mountainous regions with a very low population density, whereas climate change is significant and manifests in the form of rapid increases in air temperature and precipitation and substantial variations of the cryospheric processes (Cheng et al., 2014; Li, Wei, et al., 2018; Zhang, Zheng, Wang, & Yao, 2015). Moreover, the finding is in line with the previous studies. He, Zhang, Sun, and Jin (2012) distinguished the contributions of climate change and human activities to streamflow variations, which is 40.29% and 59.71%, respectively, by using the method of change rate of accumulation slope. Meanwhile, Cong et al. (2017) distinguished them to be about 12% and 57%, respectively, by using the water-balance model and the Budyko framework. However, we found that all the time-trend methods except for DMC–Wei obtained greater contributions of human activities than climate variability to streamflow changes. The DMC–Wei method includes a physical basis; that is, the cumulative difference between precipitation and ET is equal to the cumulative streamflow over a long time period for which the changes in water storage can be neglected (Wei & Zhang, 2010). Hence, the separated hydrological impacts by this approach, which agrees well with those obtained by the Budyko-based approaches and the previous studies, may be more convincing than the other time-trend methods.

All of the time-trend methods except for DMC–Wei are based on the assumptions of linear or nonlinear statistical relationships between climatic factors and streamflow or its components, as represented by Equation (11), which, however, lack a physical basis. Figure 6 shows the coefficients of determination (R^2) for those relationships assumed by different time-trend methods. All the methods except for DMC–Gao and DMC–Wei have small to medium R^2 values, ranged 0.54–0.79, 0.36–0.65, and 0.71–0.80, respectively, for streamflow, baseflow, and surface run-off. Lower values of the R^2 indicate a relatively small proportion of the variations in streamflow or its components, which could be explained by the hypothesized rainfall–run-off relationships of those time-trend methods. The upper HRB is an alpine watershed where the melting water of glaciers and snow contributes substantially to streamflow; and, meanwhile, they are very sensitive to climate variability (Wang, Li, & Hao, 2010; Zhang, Zheng, et al., 2015). The simple linear or nonlinear equations assumed by some time-trend methods might not be able to represent the rainfall–run-off relationship appropriately, which is potentially to bring about biased or even erroneous results. Although the method DMC–Gao achieved a high value of R^2 (i.e., 0.99), it also induced inconsistent results in comparison with the Budyko-based approaches, which may be due to that only precipitation was considered. This also implies that the time-trend methods could have large uncertainties even they are able to describe the rainfall–run-off relationships very well for the baseline period. In order to get more convincing and robust results, we highly recommend to use the time-trend method, which has a physical basis such as DMC–Wei to separate hydrological impacts, or to adopt the time-trend method together with some other physically-based approaches such as the Budyko-based framework and the hydrological modelling.

In spite of obviously varying magnitudes, all the time-trend methods estimated positive contributions of climate variability and human activities to the increases in streamflow and its components. Over the last few decades, both temperature and precipitation exhibit an increasing trend in the upper HRB, indicating a warmer and wetter climate (Zhang, Nan, Xu, & Li, 2016). This contributed to explain the increase in streamflow, baseflow, and surface run-off. At the same time, the area of grassland and forest shows a decreasing trend, due to the human activities such as deforestation, overgrazing, and grassland reclamation. For example, An et al. (2013) found that the percentage of forest and grassland dropped by 5.1% and 4%, respectively, whereas barren land and farmland increased by 6.9% and 2.5%, respectively, from 1980s to 2000s by using the Landsat images. The shrinkage of forest and grassland could lead to decreases in ET and canopy interception, as a result of reductions in leaf areas and root depths, which could induce increases in streamflow and its components. Moreover, the other human activities such as the large-scale mine exploration and the constructions of reservoirs and hydropower stations could also contribute to explain the hydrological variations. The effects of climate variability and human activities intensified each other on streamflow and its components in the upper HRB, which have also been observed in some other basins such as the Samin catchment in Indonesia (Marhaento et al., 2017), the catchment of Ursern Valley in Swiss (Alaoui et al., 2014), and the Qingyi River watershed in China (Liu, Zhang, Xia, & You, 2013).

5.2 | Influences of baseflow separation

The baseflow was isolated from streamflow through the digital filter-based algorithm in this research. Considering the filter parameter β could be an important source of uncertainty, we have further compared the separated impacts of human activities and climate variability on baseflow and surface run-off when the filter parameter β varied from 0.86 to 0.92. The span of the parameter was determined so that the mean BFI could lie in the range of 0.35–0.55 estimated by the previous studies (e.g., Dang et al., 2011; Wu et al., 2013; Yao et al., 2017; Zhang, Nan, Xu, & Li, 2016). Figure 7 shows the results obtained using the method DMC–Wei, along with the Pettitt's test employed for break-point detection. The relative contributions of human activities to baseflow show a downward trend, whereas those to surface run-off exhibit an upward trend over the range of the filter parameter. Moreover, it is seen that there are small oscillations in the quantified contributions to baseflow variation, which is caused by the inconsistent break points resulting from various filter parameter values. Despite the varying magnitudes, the relative contribution of climate variability is greater than human activities for all the filter parameter values. The uncertainties associated with the various time-trend methods seem to be greater than those related to the parameter of the digital filter-based baseflow separation algorithm.

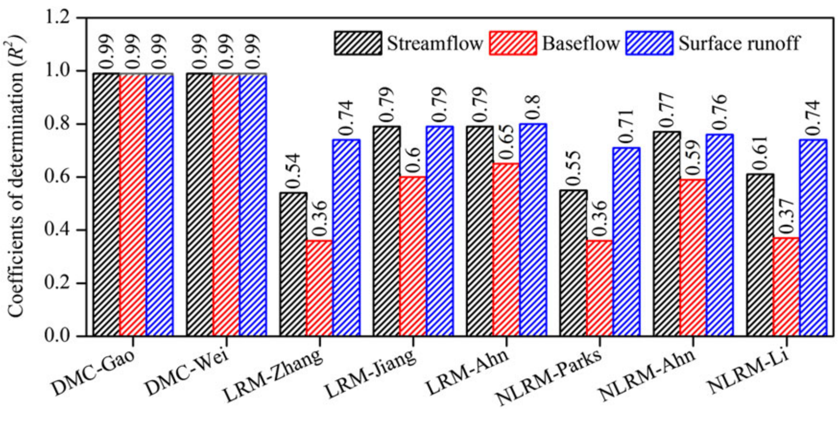

FIGURE 6 Coefficients of determination (R^2) for the relationships between climatic factors and streamflow and its components assumed by different time-trend methods

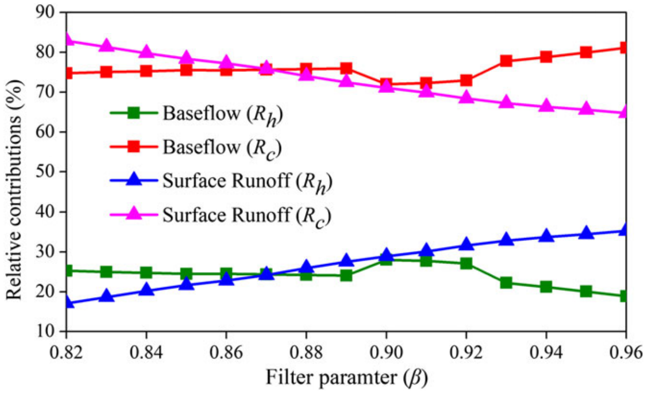

FIGURE 7 Relative contributions of human activities (RH) and climate variability (RC) to baseflow and surface run-off for varying filter parameter values of the digital filter-based baseflow separation algorithm

5.3 | Temporal variation of the contributions of human activities

The altered periods were determined to be relatively long for streamflow and baseflow, which were 1980–2014 and 1979–2014, respectively. Taken the year 2000 as the dividing point, we further divided them into two subperiods and estimated the temporal variation of the relative contribution of human activities. The varying BFI was considered, which ranges from 0.35 to 0.55, as a result of adopting different filter parameter values, in line with the above Subsection 5.2. As shown in Figure 8, the contribution of human activities to streamflow becomes smaller in recent years (i.e., 2000–2014), compared with the old period before the year 2000. Similarly, the contribution to baseflow variation also exhibits a decreasing trend but with varying magnitudes resulting from different BFI. This again reveals the uncertainty of baseflow separation and implies the importance of isolating baseflow form streamflow accurately before quantifying the hydrological impacts. The reduced contribution of human activities is intimately related with the ecosystem rehabilitation projects, particularly the Grain for Green Project, which was initiated by the Chinese government in 1999 and was designed to convert sloping farmland and wasteland back to forest and grassland in order to halt soil erosion. The ecosystem rehabilitation project led to increase in the area of grassland and forest in recent years, which resulted in increased ET and decreased streamflow and baseflow, and therefore offset the hydrological impacts of climate variability. This has been confirmed by the studies of Zhang, Nan, Xu, and Li (2016) and Yang et al. (2017).

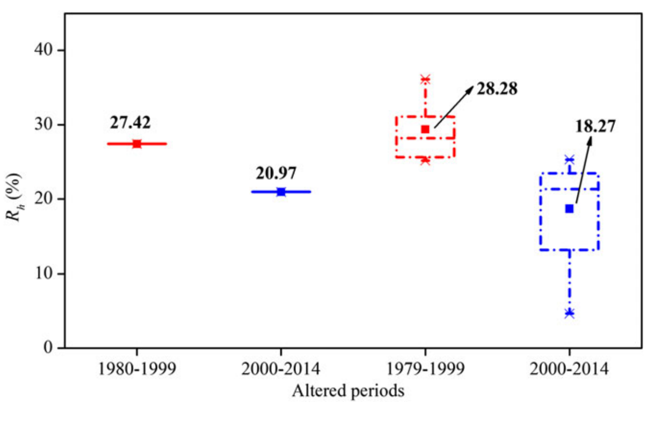

FIGURE 8 Temporal variation of the relative contributions of human activities (RH) estimated by the DMC–Wei method. The box plot shows the range of RH for the BFI varied from 0.35 to 0.55

5.4 | Limitations of the study

The upper HRB is an alpine catchment located on the northeastern Tibetan Plateau. The cryospheric processes such as snow accumulation, snowmelt, glacier ablation, and frozen ground degradation play an essential role in the hydrological cycles of the upper HRB (Chen et al., 2018; Zhang et al., 2018). However, none of the eight time-trend methods and the two Budyko-based approaches have considered the hydrological impacts of the changes in cryospheric processes resulting from climate variability, which may lead to underestimations or overestimations of the contributions of climate changes. In recent years, some researchers have developed decomposition approaches within the Budyko framework to analyse the streamflow response to frozen ground degradation and snowmelt (e.g., Wang, Yang, Yang, Qin, & Wang, 2018; Wu, Liang, Wang, Feng, & McKenzie, 2018; Zhang, Cong, Ni, Yang, & Hu, 2015), which may help to better quantify the contributions of climate change and human activities.

In this study, we have explored the uncertainties associated with the parameter of the digital filter-based baseflow separation algorithm. However, the varying baseflow separation methods could be another important source of uncertainty. It will be interesting to comprehensively investigate the uncertainties associated with different baseflow separation approaches, which, however, is out the scope of this study. Moreover, accurate baseflow separation is vital to the results of this study; however, we have only compared the mean annual BFI, calculated by the digital filter-based algorithm, with those estimated by other baseflow separation methods and hydrological modelling. This is acceptable to some extent considering that the contributions of climate change and human activities were separated based on the time series of annual baseflow instead of monthly or seasonal values. Nevertheless, it will become more convincing if the monthly or seasonal BFI can be further compared with those obtained through hydrological simulations, which have considered the cryospheric processes.

6 | CONCLUSIONS

This study separated the contributions of climate variability and human activities to the changes in streamflow and its components in the upper HRB, a typical inland river basin in northwest China, over the period 1960–2014 by using eight different forms of time-trend methods. In terms of streamflow variation, the quantified contributions were also compared with those obtained by two Budyko-based approaches. Baseflow was separated from streamflow using the digital filter-based algorithm. The break point of the annual streamflow and its components was comprehensively determined through three statistical techniques, that is, the accumulated anomaly approach, the Pettitt's test, and the heuristic segmentation algorithm. We found that the time-trend methods consistently estimated positive contributions of climate variability and human activities to the increases in streamflow and its components but with obviously varying magnitudes. With regard to streamflow, the time-trend method DMC–Wei and the Budyko-based approaches produced a reasonable smaller contribution of human activities than climate changes, ranging from 22% to 35%, which is inconsistent with the previous studies. The other time-trend methods, however, estimated greater or comparable contributions of human activities, ranging from 51% to 74%. The contributions to baseflow variation diverged more significantly than streamflow and surface run-off, ranged 24–92% for human activities and 8–76% for climate variability. As to surface run-off, most of the time-trend approaches produced smaller contributions of human activities (ranging from 21% to 49%) than climate change.

The high degree of uncertainties associated with the various time-trend approaches is mainly due to that most of them lack a physical basis. The simple linear or nonlinear equations presumed by some time-trend methods might not be able to represent the rainfall–run-off relationship appropriately, which is potentially to bring about biased or even erroneous results. We highly recommend to use the time-trend method with a physical basis such as DMC–Wei to separate hydrological impacts or to adopt the time-trend method together with some other physically-based approaches such as the Budyko-based framework and the hydrological modelling so as to get more convincing and robust results.

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ORCID

Ling Zhang https://orcid.org/0000-0003-3112-8552
Zhuotong Nan https://orcid.org/0000-0002-7930-3850

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