Journal of Hydrology 549 (2017) 547–557

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Research papers

Hydrological effects of cropland and climatic changes in arid and semi-arid river basins: A case study from the Yellow River basin, China

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ARTICLE INFO

Article history:
Received 23 November 2016
Received in revised form 19 March 2017
Accepted 11 April 2017
Available online 19 April 2017

Keywords:
Hydrological processes
Trends
Abrupt changes
Cropland changes
Precipitation
Temperature
GAMLSS model

ABSTRACT

The Yellow River basin is a typical semi-arid river basin in northern China. Serious water shortages have negative impacts on regional socioeconomic development. Recent years have witnessed changes in streamflow processes due to increasing human activities, such as agricultural activities and construction of dams and water reservoirs, and climatic changes, e.g. precipitation and temperature. This study attempts to investigate factors potentially driving changes in different streamflow components defined by different quantiles. The data used were daily streamflow data for the 1959–2005 period from 5 hydrological stations, daily precipitation and temperature data from 77 meteorological stations and data pertaining to cropland and large reservoirs. Results indicate a general decrease in streamflow across the Yellow River basin. Moreover significant decreasing streamflow has been observed in the middle and lower Yellow River basin with change points during the mid-1980s till the mid-1990s. The changes of cropland affect the streamflow components and also the cumulative effects on streamflow variations. Recent years have witnessed moderate cropland variations which result in moderate streamflow changes. Further, precipitation also plays a critical role in changes of streamflow components and human activities, i.e. cropland changes, temperature changes and building of water reservoirs, tend to have increasing impacts on hydrological processes across the Yellow River basin. This study provides a theoretical framework for the study of the hydrological effects of human activities and climatic changes on basins over the globe.

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1. Introduction

Variability and availability of instream flow are critical for the conservation of ecological conditions and for the management of water resources at the river basin scale. Investigation of hydrological processes and related underlying causes is needed to assess the influences of climatic changes and human activities on the hydrological cycle at regional and global scales (Zhang et al., 2009a; Xia et al., 2012; Zhou et al., 2014). Precipitation was widely accepted as a key factor that drives changes in streamflow (e.g. Novotny and Stefan, 2007; Zhang et al., 2013a,b). Ryberg et al. (2013) and Frans et al. (2013) also indicated that climate change is the major factor in explaining streamflow changes over the U.S. Midwest. However, streamflow changes are also the result of diverse other factors, such as temperature, and basin attributes (Tran and O'Neill, 2013; Gosling, 2014). In addition, impacts of human activities on streamflow changes have focused attention on population growth and increasing human activities, such as irrigation, dam/reservoir construction, land use and land cover changes (Barnett et al., 2008; Zhan et al., 2013; Ahn and Merwade, 2014). When analyzing the relationship between precipitation and streamflow across China, Zhang et al. (2015) indicated that the influence of human activities coupled with changes in precipitation on streamflow were different for different river basins. Zhang and Schilling (2006) indicated that most of the increases in streamflow in the Mississippi River Basin since the 1940s are largely related to changes in land use and land cover. These results are similar to the findings by Raymond et al. (2008) and Schilling et al. (2010). Damming-induced fragmentation of river basins is a major driver

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http://dx.doi.org/10.1016/j.jhydrol.2017.04.024
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for homogenization of flow regimes. Thus, through the construction of dams and reservoirs, the disturbance of human to the hydrological process has greatly changed the rainfall-runoff transformation.

The differentiation between climate change and other human influences on streamflow has attracted increasing attention in recent years. Using a macroscale hydrology model, Frans et al. (2013) assessed the hydrologic implications of climate and LUCC (Land Use and Cover Changes) changes between 1918 and 2007 in the Upper Mississippi River Basin and showed that at local scales, modelled annual runoff decreased (increased) by up to 9% (5%) where grasslands (forests) were replaced by croplands. Artificial field drainage amplified annual runoff by as much as 13%. Wang and Hejazi (2011) used the Budyko hypothesis to quantify the climate impact and direct human impact on mean annual streamflow (MAS) for 413 watersheds in the contiguous United States. They found that climate changes caused increasing MAS in most watersheds, while the direct human-induced change was spatially heterogeneous in the contiguous United States with strong regional patterns. Also, Wang and Hejazi (2011) showed that the climate- and human-induced changes were found to be more severe in arid regions. Related research has been carried out for river basins or regions in the USA (Barnett et al., 2008; Wang and Hejazi, 2011), Australia (Potter and Zhang, 2009), Canada (Tan and Gan, 2015) and other countries. Rivers in China are heavily regulated and fragmented by reservoirs and other hydraulic structures (Zhang et al., 2015). There are 98,002 reservoirs or hydraulic structures each having a storage capacity of >0.1 million m^3, and the total storage capacity of the reservoirs is about 932.3 billion m^3, accounting for 34.5% of total streamflow of the rivers in China (Sun et al., 2013). There have been numerous studies on individual impacts of climatic change (mainly changes in precipitation and temperature) and human activities (mainly building of dams or water reservoirs) to streamflow. These have included studies done in the Poyang Lake basin (S. Zhang et al., 2016; Q. Zhang et al., 2016), and Haihe basin (Xu et al., 2014), Huaihe basin (S. Zhang et al., 2016; Q. Zhang et al., 2016) and in the Yellow River basins (e.g. Wang et al., 2012; Tang et al., 2013), to name but a few.

The Yellow River is the second largest river in China and is the paramount water source in northwestern and northern China. However, it is also an area of water shortages (Zhang et al., 2009b). Due to climatic changes and intensifying human activities, particularly increasing human withdrawal of water for agriculture irrigation, streamflow in the lower Yellow River has significantly decreased since 1986 (Zhang et al., 2009b). Although there are many researches addressing individual contributions of climatic changes and human activities to streamflow changes (e.g. Wang et al., 2012; Tang et al., 2013), most researches have focused on either the influence of human activities, such as building of water reservoirs (e.g. Yang et al., 2008), or the influence of climatic changes, e.g. precipitation and temperature, on streamflow variation (Tang et al., 2013). However, no reports are available so far that concern impacts of cropland changes on streamflow changes.

This study therefore attempts to address: (1) the quantification of fractional contributions from climatic changes, e.g. precipitation and temperature, on streamflow changes; (2) impacts of cropland changes, such as maize, soybean and corns, on streamflow variations; and (3) impacts of changes in precipitation, temperature and cropland on spatial and temporal measurements of specific streamflow components. Results of this study can shed light on the impacts of agricultural activities on instream flow changes and hence would be important for management of agricultural irrigation in a changing environment.

The paper is organised as follows: Section 2 describes the study area and the data analyzed in this study; methods are introduced with considerable details in Section 3; the results are presented and discussed in Section 4; and the conclusions are obtained and summarized in Section 5.

2. Study area and data

The Yellow River has a drainage area of $7.95 \times 10^5\ km^2$ (Fig. 1), and its topography is highest in the west and the lowest in the eastern parts of the Yellow River basin. The basin is located at mid-latitudes with a different climate prevailing in the southeastern part (higher precipitation) as compared to the northwestern part (lower precipitation). In addition, 91.93% of the total land has been utilized for vegetative cover in the basin, and the unused land being mainly sandy land, bare rock gravel land and saline alkali land. Agricultural land accounted for 90.58% of land use. Grassland, cultivated land, and forest land accounted for 48.48% and 28.84%, and 13.26% respectively of that total (Yan et al., 2006). This shows that agricultural land use is dominant in the basin and thus it is necessary to quantify the contribution of cropland changes to streamflow changes across the basin.

The data used in this study were daily precipitation and temperature data for 1960–2013 from 77 meteorological stations, information pertaining to water storage for 24 large water reservoirs for the 1950–2013 period, cropland area (mainly maize, corn and soybean) for the 1950–2013 period, and daily streamflow data from 5 hydrological stations along the mainstream of the Yellow River for the period of 1960–2005. The data were obtained from the Climatic Data Center, National Meteorological Information Center, China Meteorological Administration, and Hydrological Bureau of Yellow River Conservancy Commission of Ministry of Water Resources.

3. Methodology

3.1. Detection of trends and change points

Trends in streamflow were explored using non-parametric Mann-Kendall (MK) trend test (Mitchell et al., 1966; Alan et al., 2003; Chebana et al., 2013). Hamed and Rao (1998) proposed a modified MK (MMK) test, based on effective or Equivalent Sample Size (ESS), to eliminate the effect of autocorrelation, where they used the modified variance of the MK statistic to replace the original one if the lag-i autocorrelation coefficients were significantly different from zero at the 5% level. Threshold values were defined as follows: when the value is less than 0, indicating that the streamflow components are in a decreasing tendency; when the value is less than −1.96, showing that the streamflow components are in a significant decreasing trend.

Detection of change-point (CP) was done, based on the method by Killick and Eckley (2014) which proposed a kind of fully-integrated test method, i.e. "changpoint" R package. The package includes more than one algorithm, such as binary segmentation algorithm, segment neighborhood algorithm, and Pruned Exact Linear Time (PELT) method. It can be used to detect CPs in mean and variance. In this paper, the single change point detection method, AMOC, was used. This method is the likelihood function framework with large flexibility without assuming that the series follows the Gaussian distribution and timing of change point before test analysis. For single CP detection for a time series, $y_{1:n} = (y_1, \cdots, y_n)$, there are two hypotheses: null hypothesis H_0 is that there is no CP; and alternative hypothesis H_1 is that there is CP in the series. In the alternative hypothesis, assume that the CP occurs in $\tau_1(\tau_1 \in \{1, 2, \ldots, n-1\})$, then the likelihood function for τ_1 is (Killick and Eckley, 2014):

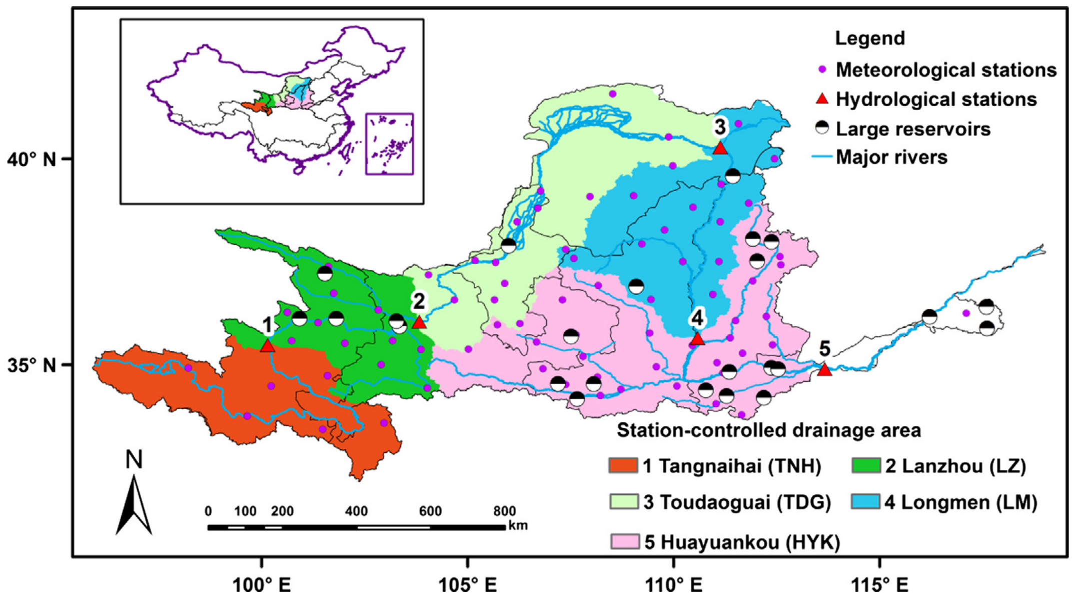

Fig. 1. Locations of water reservoirs, hydrological stations and meteorological stations.

$$ML(\tau_1) = \log p(y_{1:\tau_1}\left|\hat{\theta}_1) + \log p(y_{(\tau_1+1):n}\right|\hat{\theta}_2) \quad (1)$$

where $p(\cdot)$ denotes the probability density function of the time series, and $\hat{\theta}$ is the estimated parameters based on the likelihood function. The largest logarithm likelihood function for every time point of possible change point can be obtained from Eq. (1), and the final CP can be determined from the empirical statistical value λ (Killick and Eckley, 2014) as:

$$\lambda = 2\left[\max ML(\tau_1) - og\ p\left(y_{1:n}|\hat{\theta}\right)\right] \quad (2)$$

If statistic λ is significant at the 0.05 significance level, then it can be accepted that there is a significant CP within the time series. More information of this method can be referred to Silva and Teixeira (2008) and Eckley et al. (2011).

3.2. Generalized additive models for location, scale and shape (GAMLSS) model

A GAMLSS model is a general regression model which assumes that the response variables have a parametric distribution. All the parameters of this distribution can be modelled as functions of the available explanatory variables. So the main characteristic of GAMLSS is the ability to allow the shape of the distribution of the response variable to vary according to values of explanatory variables (Rigby and Stasinopoulos, 2005). GAMLSS is especially suited for modelling a leptokurtic or platykurtic and/or positively or negatively skewed response variable. For count type response variable it deals with over-dispersion by using proper over-dispersed discrete distributions. Heterogeneity is also dealt with by modelling the scale or shape parameters using explanatory variables (Stasinopoulos and Rigby, 2007). In this study, the predicted streamflow series (Q_i) is the output variable and annual precipitation (x_r), cropland area (x_a), water storage of large water reservoirs (x_s) and annual mean temperature (x_w) are the input variables.

Q_i is defined by quantiles from annual minimum daily streamflow of $Q_{0.00}$ to annual maximum daily streamflow of $Q_{1.00}$ with a step of 0.05. Therefore, there are 21 streamflow series defined by 21 quantiles from $Q_{0.00}$ to $Q_{1.00}$. As for specific streamflow series defined by a certain quantile, i.e. Q_i, the GAMLSS with Gamma distribution function can be developed as:

$$f_{Q_i}(q_i|\mu_i, \sigma_i) = \frac{1}{(\sigma_i^2\mu_i)^{1/\sigma_i^2}} \frac{q_i^{(1/\sigma_i^2)-1} \exp[-q_i/(\sigma_i^2\mu_i)]}{\Gamma(1/\sigma_i^2)} \quad (3)$$

where μ_i is the location parameter, and σ_i is the scale parameter; both parameters can be linear functions by log linkage function with temporally changing predictive variable of x_1, x_2, ..., x_n. In this study, four variables, i.e. annual precipitation (x_r), cropland area (x_a), water storage of large water reservoirs (x_s) and annual mean temperature (x_w) are the covariate variables for modelling the impacts of climatic changes, cropland changes and impoundment effects of large water reservoirs on instream flow changes. In this study, two interaction terms were added to quantify impacts of cropland changes on streamflow changes (Villarini and Strong, 2014). Cropland changes can reflect agricultural irrigation to a certain degree, showing the withdrawal of water and can also influence streamflow changes by its interaction with precipitation and temperature changes. This relation can be formulated as:

$$\begin{aligned} \mu_{it} &= \log(\alpha_{0i} + \alpha_{1i}x_{rt} + \alpha_{2i}x_{rt} \cdot x_{at} + \alpha_{3i}x_{st} + \alpha_{4i}x_{wt} + \alpha_{5i}x_{wt} \cdot x_{at}) \\ \sigma_{it} &= \log(\beta_{0i} + \beta_{1i}x_{rt} + \beta_{2i}x_{rt} \cdot x_{at} + \beta_{3i}x_{st} + \beta_{4i}x_{wt} + \beta_{5i}x_{wt} \cdot x_{at}) \end{aligned} \quad (4)$$

where the location parameter, μ_i, and the scale parameter, σ_i, are both positive log linkage functions; α and β are the coefficients. The expectation value of Q_i is μ_i, and variance is $\mu_i^2\sigma_i^2$. The observed values of μ_i are different quantiles of daily streamflow, and the values of σ_i can be calculated by μ_i. The corresponding coefficients of the explanatory variables and related significance test results can be obtained using GAMLSS model with flow quantile sequences and explanatory variables as independent variables.

First, the marginal effects of precipitation changes on changes in different streamflow components were defined as quantiles to evaluate the impacts of cropland changes on streamflow components in terms of quantiles and on precipitation variations. For further inspection of impacts of cropland changes on streamflow changes, different time intervals were determined to compute streamflow difference percentages with the aim to quantify marginal effects of precipitation on streamflow changes. However, the time intervals were defined by different reference years as follows (Villarini and Strong, 2014):

$$\frac{[\alpha_{1i} + \alpha_{2i}x_a(2005) + \alpha_{3i}+\alpha_{4i}+\alpha_{5i}] - [\alpha_{1i} + \alpha_{2i}x_a(t) + \alpha_{3i} + \alpha_{4i} + \alpha_{5i}]}{\alpha_{1i} + \alpha_{2i}x_a(t) + \alpha_{3i} + \alpha_{4i} + \alpha_{5i}} \quad (5)$$

where the benchmark years, t, at the Tangnaihai station were, respectively, 1966, 1986, and 1999; the benchmark years, t, at the Lanzhou station were, respectively, 1967, 1986, and 1996; the benchmark years, t, at the Toudaoguai station were, respectively, 1960, 1986, and 1999; the benchmark years, t, at the Longmen station were, respectively, 1965, 1986, and 1990; and the benchmark years, t, at the Huayuankou station were, respectively, 1950, 1956, 1982, and 1986. Selection of benchmark years was based on cropland changes. The benchmark years were the time points when cropland changes shifted from decrease to increase or the time points when the cropland areas reached the peak or trough values to reflect impacts of cropland changes on streamflow during different time points.

4. Results and discussions

4.1. Standardization for precipitation, water storage, crop land and temperature

Fig. 2 shows standardized precipitation indices, water storage, cropland and temperature indices. Fig. 1 indicates that there are no water reservoirs in the drainage areas controlled by three stations, i.e. Tangnaihai, Toudaoguai and Longmen stations, and hence effects of water reservoir-induced impoundment were neglected, but were considered for Lanzhou and Huayuankou stations (Fig. 2). Annual precipitation exhibits a large degree of variability from one year to the next, much more than for other three indexes. Annual mean temperature index showed an upward trend at all stations. Cropland was generally decreasing in drainage areas at all stations, except for the Toudaoguai station (Fig. 2c), which can be attributed to the recovery of agricultural production during 1950–1957.

4.2. Change points and trends of streamflow variations

Fig. 3 illustrates trends and change points of streamflow at the five hydrological stations considered in the study. It can be seen from Fig. 3 that all quantile-based streamflow components had a decreasing tendency. Moderately decreasing tendency of streamflow can be found at the Tangnaihai station, showing moderate streamflow changes in the upper Yellow River basin. Significant decreasing streamflow can be identified at the other four hydrological stations, i.e. in the middle and lower Yellow River basin. Therefore, water deficit becomes more serious from the upper to the lower basin. Significant change points can be detected for streamflow changes at all five hydrological stations. Fig. 3 also shows that change points of streamflow mainly occurred during the mid-1980s and the 1990s. Zhang et al. (2009b) also indicated that after 1970, the zero-flow days occurred in the lower basin, and prevailed during 1990–2000. Zhang et al. (2009b) attributed changing trends and abrupt behavior of streamflow components to hydrological regulations and precipitation changes in both space and time. Furthermore, increasingly intensified human activities, particularly increasing demand of agricultural irrigation, further complicate

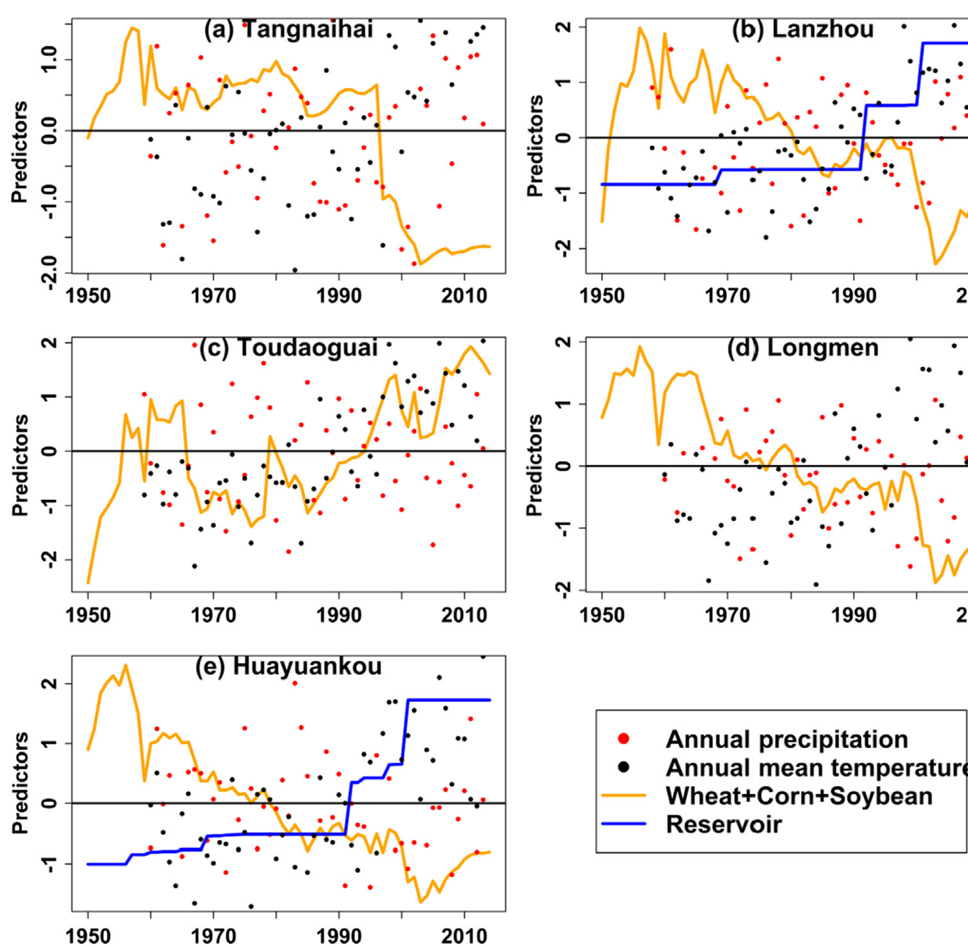

Fig. 2. Temporal changes of standardized cropland index, temperature index, water reservoir index and precipitation index.

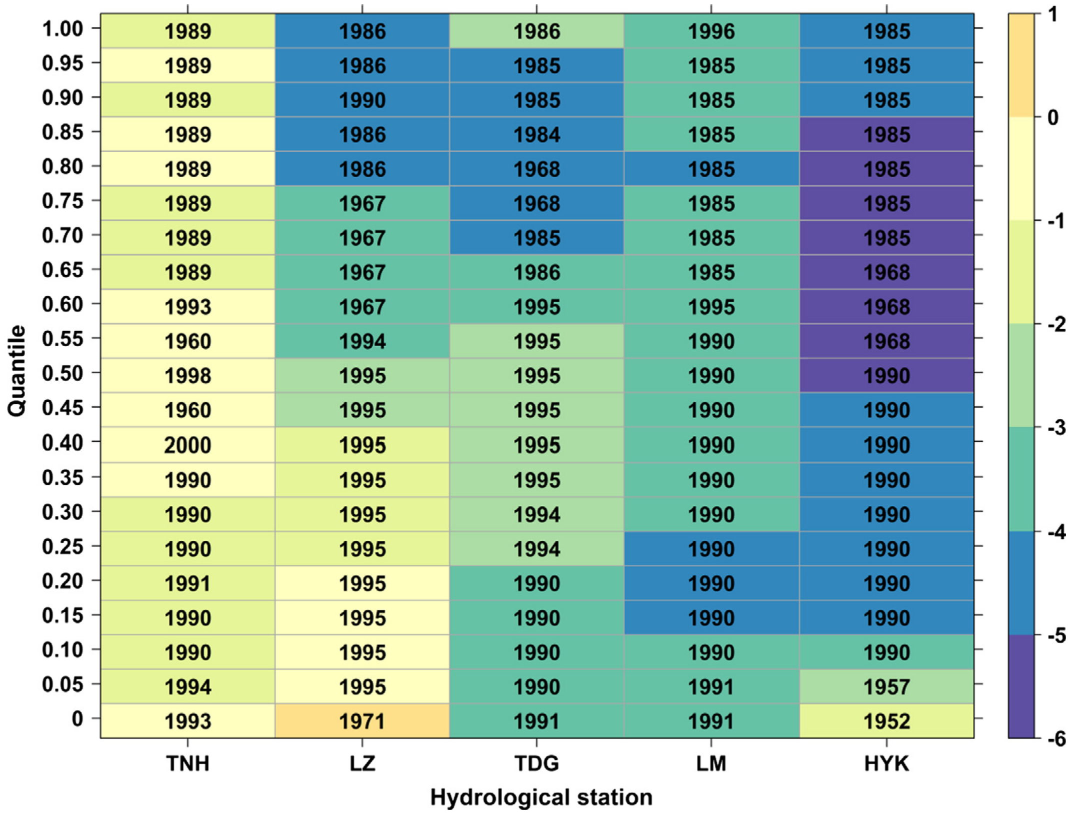

Fig. 3. Trends and timing of change points of annual streamflow series at five hydrological stations considered in this study.

the change point changes for specific hydrological regime. This is why change points of streamflow series at different parts of the Yellow River basin were different.

4.3. GAMLSS-based hydrological modelling and goodness-of-fit evaluation

Streamflow was modelled using the GAMLSS model and is shown for Huayuankou station as a case study. Fig. 4 demonstrates 6 modelled streamflow components defined by six quantiles considering influences of precipitation, temperature, cropland changes and water storages of water reservoirs. It can be inferred from Fig. 4 that GAMLSS seemed to perform better in modelling streamflow components defined by higher quantile values. However, high flow components are influenced mainly by precipitation changes, and it is particularly true for flood events. This point can be corroborated by good fitting of GAMLSS for the data points representing flood events that occurred during the early 1960s. These results further justify the idea of this study that different streamflow components should be modelled specifically and separately using GAMLSS models with potential driving factors. Moreover, it can be seen from Fig. 4 that streamflow components defined by lower quantiles are subject to moderate changes, and remarkable decreasing tendencies can be detected in the changes of streamflow components defined by higher quantiles. This result can be interpreted that the low streamflow component is mainly the result of ground water changes. In addition, hydrological regulations of water reservoirs also increase low flow and decrease high flow components, which also contribute to moderate changes of low flow components.

Furthermore, analysis of worm plot and residuals was also accomplished to evaluate the fitting performance of GAMLSS model developed in the study. The worm plot (a detrended QQ-plot, van Buuren and Fredriks (2001)), is a diagnostic tool for checking the residuals within different ranges (by default not overlapping) of the explanatory variables. The vertical axis of the worm plot portrays, for each observation, the difference between its location in the theoretical and empirical distributions. The data points in each plot form a worm-like string. The shape of the worm indicated how the data differ from the assumed underlying distribution, and when taken together, suggests useful modifications to the model (van Buuren and Fredriks, 2001). Table 1 displays the Filliben coefficients of residuals by the model. It can be found from Table 1 that the Filliben coefficients of residuals are mostly larger than 0.95, showing that the residuals follow the normal distribution. Fig. 5 presents worm plots of the GAMLSS model and shows that the standardized residuals fall within the 95% confidence intervals, corroborating statistically satisfactory modelling performance and justifying the application of the model in modelling streamflow components.

4.4. Streamflow changes and potential driving factors

Parameters of the gamma distribution (GD) changed with variations of streamflow components defined by various quantiles due to influences of different driving factors. Therefore, changes in the GD parameters can potentially identify the key driving factors exerting impacts on the magnitude and variability of streamflow variations (Fig. 6). It can be seen from Fig. 6 that the intercept coefficient of the location parameter, α_o, has a monotonically increasing tendency corresponding to increasing streamflow components defined by various quantiles, and the intercept coefficient of the scale parameter, β_o, presents a decreased tendency at first and then increased with the increase of quantiles. The results corroborate in good line with those discussed in Iowa by Villarini and Strong (2014). At the five stations, significant correlations can be

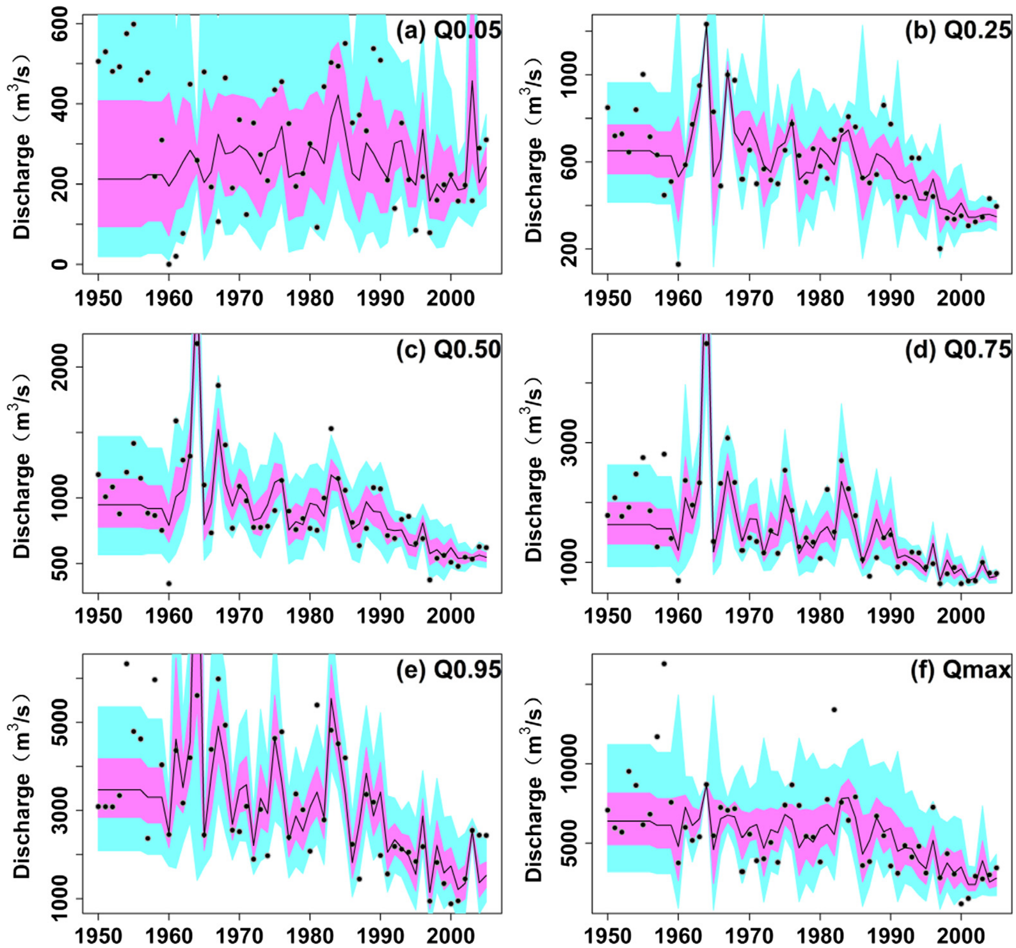

Fig. 4. GAMLSS-based modelling of streamflow processes at the Huayuankou station. Black solid curve denotes 50% percentile; Pink interval denotes fluctuation range circled by 25% and 75% percentiles; Cyan interval denotes fluctuation range circled by 5% and 95% percentiles. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Residuals of modelled percentile-based different streamflow components and related computed Filliben coefficients.

Quantile	Mean	Variance	Skewness	Kurtosis	Filliben
0.00	0.04	1.07	−1.11	4.28	0.958
0.05	0.04	1.07	−1.07	3.47	0.946
0.10	0.03	1.03	−0.27	2.34	0.991
0.15	0.00	1.01	−0.01	2.11	0.992
0.20	0.01	1.02	0.07	2.27	0.988
0.25	−0.01	1.01	0.21	2.59	0.996
0.30	−0.01	1.02	0.04	2.80	0.997
0.35	0.00	1.02	0.15	2.97	0.989
0.40	−0.01	1.02	−0.03	2.63	0.991
0.45	0.00	1.02	−0.10	2.47	0.988
0.50	0.01	1.02	−0.23	2.57	0.988
0.55	0.01	1.02	−0.29	2.32	0.987
0.60	0.01	1.02	−0.29	2.31	0.990
0.65	0.01	1.02	−0.20	2.39	0.992
0.70	0.02	1.03	−0.23	2.70	0.986
0.75	0.02	1.03	−0.39	2.53	0.980
0.80	0.02	1.03	−0.41	2.56	0.979
0.85	0.00	1.02	−0.25	2.18	0.989
0.90	0.00	1.02	−0.05	2.72	0.990
0.95	0.00	1.01	0.34	2.88	0.986
1.00	0.03	1.03	0.43	3.87	0.983

found between streamflow and location and intercept coefficient parameters at the positive 5% significance level (Fig. 6). Corresponding to location parameter, μ, coefficients α_1, α_2, α_3, α_4, and α_5, respectively, reflect the impacts of precipitation, cropland, water reservoirs and temperature on streamflow changes. Fig. 6e indicates remarkable changes of α_1 with changes of streamflow components, showing the impacts of precipitation on streamflow changes in terms of magnitude and variability of

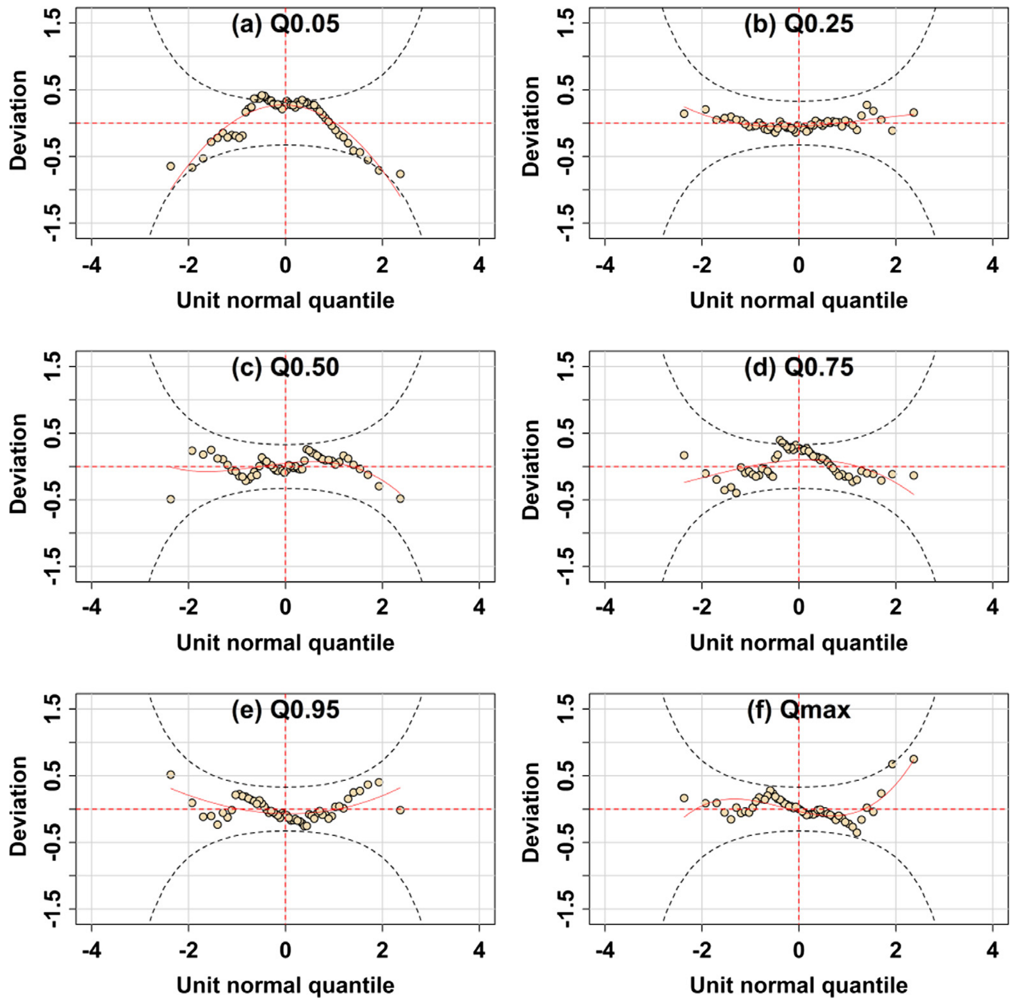

Fig. 5. Worm plots for different discharge quantiles to assess fitting performance of the developed GAMLSS model as shown in Fig. 4.

streamflow changes, and statistical analysis of this study indicates that precipitation changes have significant influences on streamflow variations at the positive 5% significance level (Fig. 6a and e). Tang et al. (2013) also indicated that the streamflow reduction in the low-flow period was mainly caused by precipitation decrease upstream to the Huayuankou station. For the lower percentiles of the discharge distribution at the Lanzhou station, α_1 is negative but not significant, indicating a reduction in mean discharge at low streamflow associated with precipitation changes. On the other hand, it changes sign as it shifts towards the upper quantiles, and the coefficient is significant (Fig. 6b).

Cropland changes have different impacts on streamflow changes at different hydrological stations, showing different degrees of impacts of agricultural irrigation on streamflow variations. At the Toudaoguai station, α_2 and α_5 corresponding to different streamflow components defined by quantiles were mostly larger than 0 but not significant at the 10% significance level (Fig. 6c), showing discernable influences of cropland changes on the increase of streamflow changes, and suggesting that cropland changes have stronger impacts on the magnitude, rather than on the variability of streamflow changes. At the Huayuankou station, α_2 was mostly larger than 0 and significant at the 5% significance level (Fig. 6e). At the Lanzhou station, for the low percentiles of the discharge distribution, α_2 is significant and negative, indicating a reduction in mean discharge at low flow associated with the changes of cropland area. On the other hand, despite the fact that the coefficient for the interaction term is not significant, it changes sign as it shifts towards the upper quantiles (Fig. 6b). However, the α_2 coefficient was significant at the 10% significance level at the Tangnaihai and Longmen stations (Fig. 6a and d), and was mostly smaller than 0 for different streamflow components, implying that cropland changes had the potential to decrease streamflow. These results are in line with those of Lorup et al. (1998), Raymond et al. (2008), Schilling et al. (2010), Xu et al. (2013) and Villarini and Strong (2014), showing similar effects of cropland changes on streamflow changes in other river basins over the globe. The α_3 coefficient reflects the effect of water storage of water reservoirs on streamflow changes. The α_3 coefficient values at the Lanzhou and Huayuankou stations were smaller than 0 related to different streamflow components, and the α_3 coefficient values was statistically significant at the 5% significance level (Fig. 6 and e), implying prominent effects of hydrological regulations of water reservoirs on streamflow variations in terms of magnitude and variability. Effects of water reservoirs on ecological streamflow and also on high and low streamflow components have also been investigated (Zhang et al., 2009b; Zhang et al., 2013a,b) and these investigations corroborated the results of the current study. The α_4 coefficient values at all stations were smaller than 0 related to different streamflow components, and the α_4 coefficient values were statistically significant at the 10% significance level (Fig. 6), implying prominent effects of temperature on streamflow variations in terms of magnitude and variability. For the low percentiles of the

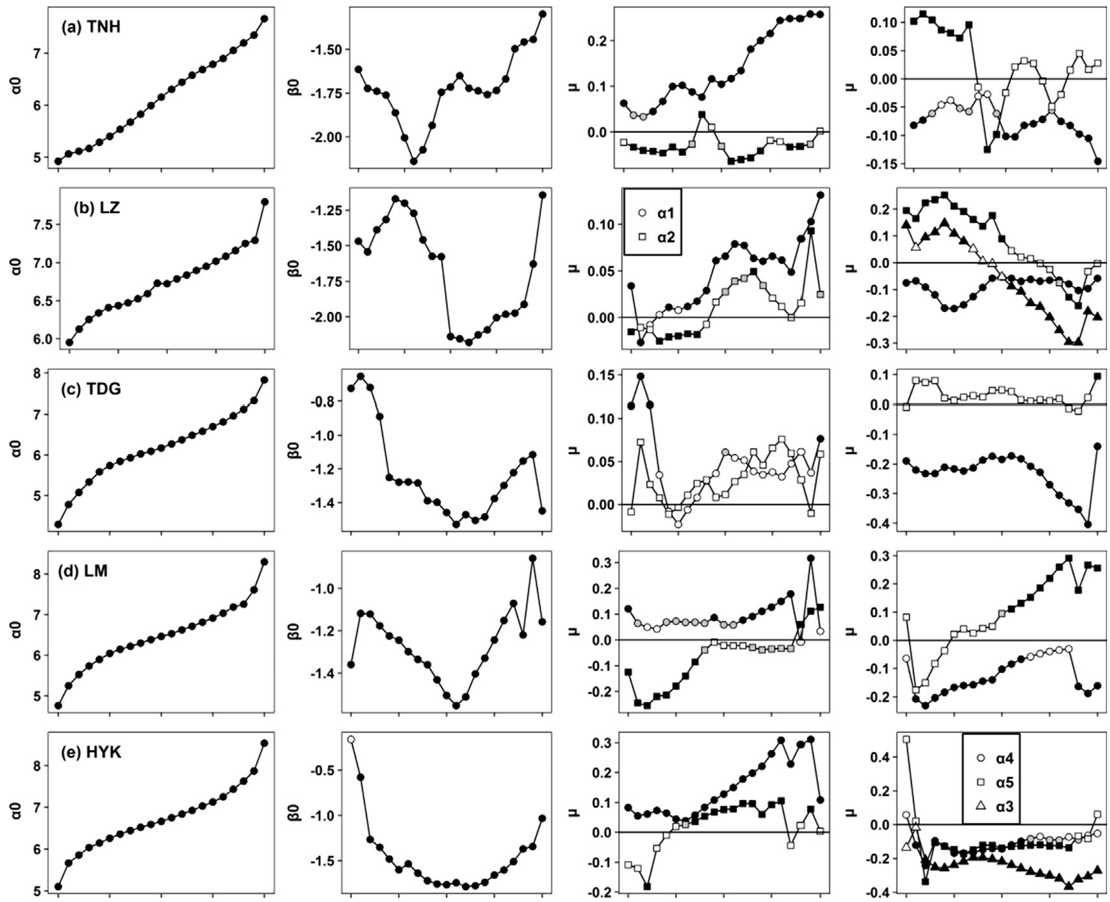

Fig. 6. Dependence of the parameters of the gamma models on the different discharge quantiles. Black/grey filled circles denote significant parameters at 5%/10% confidence level; Circles denote not significant parameters at 10% confidence level.

discharge distribution, α_5 is positive and is significant at the 5% significance level at the Tangnaihai and Lanzhou stations (Fig. 6a and b), indicating a increase in mean discharge at low flow associated with the changes of cropland area. At the Huayuankou station, α_3 and α_5 corresponding to different streamflow components defined by quantiles were mostly less than 0 and significant at the 5% significance level (Fig. 6e), showing discernable influences of cropland changes and water reservoirs on the decrease of streamflow changes. Generally, influences of precipitation, cropland, and water reservoirs on streamflow changes in terms of magnitude and variability at Huayuankou station were significant at the 10% significance level. However, impacts of these driving factors on streamflow changes were not significant at the 10% significance level, but still had considerable influence on the streamflow magnitude. These different behaviors of precipitation, cropland, water reservoirs and temperature in influencing streamflow changes at different hydrological stations should be attributed to the spatial distribution of the driving factors (Fig. 1).

Based on Eq. (5), streamflow difference percentages under the influence of cropland changes between three benchmark years as shown in Eq. (5) and 2005 were computed. It can be seen from Fig. 7a that cropland changes had evident impacts on streamflow components defined by the median quantiles, but had only slight impacts on streamflow components defined by quantiles smaller than the median. At the Lanzhou station, cropland changes had significant impacts at lower quantiles but limited impacts at higher quantiles on streamflow changes, and this result is in line with that shown in Fig. 6b. Fig. 2b indicates generally decreasing crop land and Fig. 7b indicates decreased annual maximum streamflow (related to streamflow components defined by higher quantiles). These results are in line with those by Villarini and Strong (2014). Therefore, impoundments of water reservoirs and increase of temperature contributed to decreased annual maximum streamflow (Fig. 6b). For streamflow changes at the Toudaoguai station, there are numerous irrigation areas upstream of the Toudaoguai station and remarkable impacts of agricultural irrigation on streamflow variations can be expected. It can be seen from Fig. 7c that a 40% decrease of low streamflow components (related to streamflow component by lower quantiles) can be attributed to cropland changes or to irrigation-induced water consumption. In addition, streamflow difference percentages tended to be in moderate changes in recent years, which can be due to moderate changes in cropland areas during the past ten years. This result further corroborates remarkable impacts of cropland changes on streamflow in the middle basin. Impacts of cropland changes at the Longmen and Huayuankou stations tended to be enhanced and more than 70% reduction in the effects of cropland changes on streamflow changes (see also Fig. 6d, e and Fig. 2e). Due to moderate changes in cropland areas and also temporally enhancing hydrological alterations of water reservoirs, impacts of cropland changes on streamflow changes tended to be moderate and this point should arouse concern in the management of water resources and agricultural irrigation across the Yellow River basin.

4.5. Discussion

This study mainly deals with the impacts of climate changes, cropland changes and human activities on streamflow changes in

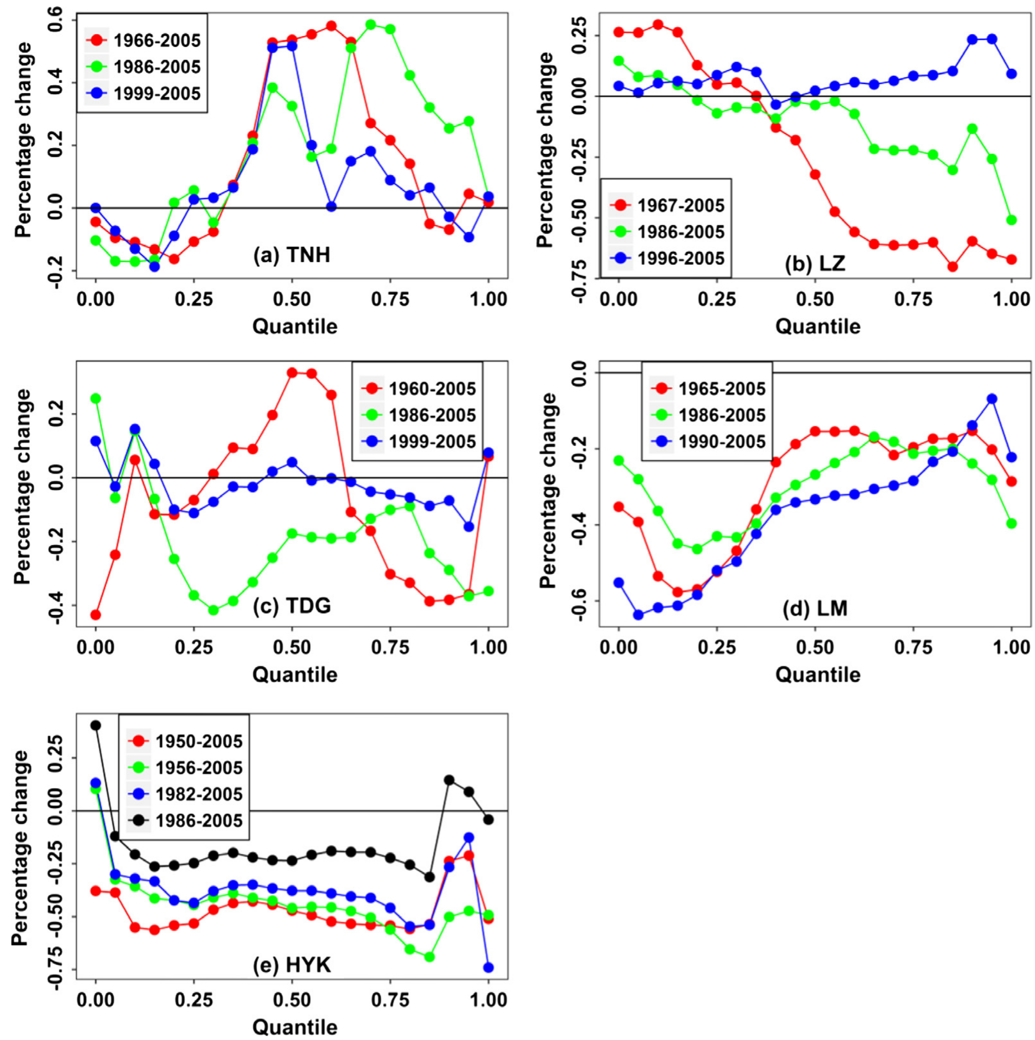

Fig. 7. Impacts of cropland areas on precipitation vs. streamflow relations during different time intervals.

the Yellow River basin, China. Fig. 3 showed that change points of streamflow mainly occurred during the mid-1980s and the 1990s. Zhang et al. (2009b) also indicated that after 1970, the zero-flow days occurred in the lower basin, and prevailed during 1990–2000. Zhang et al. (2009b) attributed changing trends and abrupt behavior of streamflow components to hydrological regulations and precipitation changes in both space and time.

It can be seen from Fig. 6 that the intercept coefficient of the location parameter, α_o, have a monotonically increasing tendency corresponding to increasing streamflow components defined by various quantiles, and the intercept coefficient of the scale parameter, β_0, presents a decreased tendency at first and then increased with the increase of quantiles. The results corroborated those discussed in Iowa by Villarini and Strong (2014). Tang et al. (2013) also indicated that the streamflow reduction in the low-flow period was mainly caused by precipitation decrease upstream to the Huayuankou station. However, the α_2 coefficient was significant at the 10% significance level at the Tangnaihai and Longmen stations (Fig. 6a and d), and was mostly smaller than 0 for different streamflow components, implying that cropland changes had the potential to decrease streamflow, and had more impacts on the streamflow magnitude than on the variability of streamflow. These results are in line with those found by Lorup (1998), Raymond et al. (2008), Schilling et al. (2010), Xu et al. (2013) and Villarini and Strong (2014), showing similar effects of cropland changes on streamflow changes in other river basins over the globe. The α_4 coefficient values at all stations, were smaller than 0 related to different streamflow components, and the α_4 coefficient values was statistically significant at the 10% significance level (Fig. 6), implying prominent effects of temperature on streamflow variations in terms of magnitude and variability. Meanwhile, Wang and Hejazi (2011) showed that the climate- and human-induced changes were found to be more severe in arid regions. Related research has been carried out for river basins or regions in the USA (Barnett et al., 2008; Wang and Hejazi, 2011), Australia (Potter and Zhang, 2009), Canada (Tan and Gan, 2015) and other countries.

5. Conclusions

In this study, potential impacts of changes in precipitation, cropland, water reservoirs and temperature on streamflow changes were thoroughly investigated within different parts of the Yellow River basin, China. The following conclusions can be drawn from this study:

(1) Almost all streamflow components defined by different quantiles exhibit a decreasing tendency and are subject to abrupt changes during the mid- and late-1980s till the mid-1990s. Decreasing streamflow is observed at the

stations in the upper Yellow River basin, such as Tangnaihai station, and streamflow components at the other four stations exhibit significantly decreasing trends.

(2) GAMLSS performs statistically well in modelling streamflow components defined by different quantiles. In addition, GAMLSS models developed in this study helped to identify different factors potentially driving changes in streamflow components in different parts of the Yellow River basin. This result can help formulate a theoretical framework for similar studies in other river basins of the globe, and can be helpful in the management of water resources and agricultural irrigation. This study also implies remarkable impacts of agricultural activities on instream hydrological processes, pertaining to precipitation, temperature and/or water reservoirs.

(3) Cropland changes tend to have increasing impacts on streamflow changes in terms of magnitude and variability. Impacts of cropland changes on streamflow changes depend on agricultural irrigation and enhancing effects of cropland changes on streamflow variations can be attributed to accumulative effects from the upper to the lower Yellow River basin. Water reservoirs and temperature changes also have remarkable impacts on streamflow and to some degrees they tend to have more remarkable influences on hydrological processes than agricultural irrigation. However, water reservoir- and cropland changes-induced impacts on streamflow changes are sometimes mixed and ambiguous. In this sense, distinct quantification of individual contributions of water reservoirs, precipitation, temperature and cropland changes is still a challenging task. This study is a significant step in this direction. The novelty of this paper lies in the fact that this study put both agricultural area and rainfall interaction under comprehensive consideration to quantify impacts of agricultural area changes on streamflow changes. This paper selected 21 different streamflow quantiles, instead of focusing on a particular streamflow quantile, so that a complete picture was provided in evaluation of whether the effects of climate and land use changes on different streamflow quantiles are different. However, this article also has some deficiencies such as the data were not updated in due time due to difficulties in data acquisition. Ongoing work can be done on seasonal variations of the spatial and temporal effects that climate and land use changes have on different streamflow quantiles.

Acknowledgments

This work is financially supported by the Fund for Creative Research Groups of National Natural Science Foundation of China (Grant No.: 41621061), the National Science Foundation for Distinguished Young Scholars of China (Grant No.: 51425903), and by National Natural Science Foundation of China (No. 41401052). Detailed information such as data can be obtained by writing to the corresponding author at zhangq68@bnu.edu.cn. The last but not the least, our cordial gratitude will be extended to the editor, Prof. Dr. Geoff Syme, for his generous kindness by kindly allowing us another opportunity to improve the quality of this paper, and also to two anonymous reviewers for their professional and pertinent comments and suggestions which are greatly helpful for further quality improvement of this paper.

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