Analysis and projection of runoff variation in three Chinese rivers

Lingqi Li, Irina Krasovskaia, Lihua Xiong and Lei Yan

ABSTRACT

Runoff variability is investigated separately for the Wei, the Bei, and the Qing Rivers in China with a focus on their respective differences in monthly flow patterns and flow duration curves (FDCs) between years with and without annual runoff deficit. The number of deficit runoff years increased in the Wei River and changed slightly in the Bei and Qing Rivers, respectively. Monthly flow variation patterns and FDCs differ between deficit and non-deficit years. The deficit years generally demonstrate earlier and more dispersed flow maxima. Deficit runoff years are contingent with the negative phase of the Polar-Eurasian Oscillation and vice versa, while generally they show contingency with the positive phase of the SST (Niño 3.4) and vice versa. The correlation between the human activity factors and the weights obtained by decomposing the runoff series into empirical orthogonal functions indicated that the human impact on the runoff variation was detectable: 22–25% in the Wei River, 28% in the Bei River, and negligible in the Qing River. We projected FDCs by weighting the distinctly different FDCs for deficit/non-deficit years according to several precipitation scenarios.

Key words | contingency, empirical orthogonal functions, flow duration curves, human impact, runoff deficit, teleconnections

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INTRODUCTION

Temporal variability in river runoff has an important impact on water use. An insight into this variability could help in counteracting negative effects of water deficit and provide valuable information for hydrological and ecological strategies (Krasovskaia 1995; Hannah *et al.* 2005; Chaves *et al.* 2010). Monthly runoff variation patterns have been discussed in many studies within a non-stationarity context (e.g., Gottschalk & Krasovskaia 1997; Bower *et al.* 2004; Dibike & Coulibaly 2005; Naik & Jay 2011).

Runoff variability caused by natural variation in climatic system as well as by human impact has long been a focus of hydrological research. Advances in the field of climatology have shown that ocean–atmosphere interactions are not necessarily chaotic or random and that patterns of low-frequency variability can be present (López & Francés 2013). These patterns are commonly characterized by different indices which can be used to investigate the influence of climate patterns on river flow (Barlow & Tippett 2008). The impact of climate on river flow in China has attracted significant interest due to water shortages experienced in many north-western provinces. Many Chinese investigations have focused on the influence of El Niño-Southern Oscillation (ENSO) characterized by sea surface temperature in the Niño 3.4 region (SST Niño 3.4) (e.g., Wu *et al.* 2010; Feng *et al.* 2011; Zhang *et al.* 2011; Zhu *et al.* 2011; Li *et al.* 2013). These studies have reported a strong connection between the flow variation and anomalies in low-frequency atmospheric circulation patterns. The impact of ENSO appears to be evolving over time and varies between different regions. In general, the large-scale climate forcing was identified as a potential modulator of the irregularities of flow regime patterns in China. The influence of other atmospheric circulation patterns has attracted less attention. In particular, the influence of the Polar-Eurasian Oscillation

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(PEO) has been indicated as relevant for northern China by the NOAA Climate Prediction Center (http://www.cpc.ncep.noaa.gov). However, to our knowledge, there are few studies in this regard in China. In addition to low-frequency climate variability, the increasing pressure from human interferences (e.g., land use change, urbanization, river regulation by dams and reservoirs) in most Chinese river basins also calls for the elucidation of the resulting impacts on river flow (e.g., Li *et al.* 2007; Zhang *et al.* 2008; Xiong *et al.* 2014; Jiang *et al.* 2015).

Qualitative and quantitative analyses of both climatic and human impact factors have attracted significant attention in the hydrological community. For example, Hundecha & Bárdossy (2004) used the HBV model to evaluate the effect of land use on the runoff in the Rhine basin. López & Francés (2013) examined the links between climate and floods by statistical regression models. Chen *et al.* (2014) investigated the impact of climate and human activity on the annual runoff of the Yangtze River via multiple regression analysis. Jiang *et al.* (2015) applied Budyko-type equations to separate the impact of climatic and human on the runoff variation in the Wei River. Dong *et al.* (2015) concluded that agricultural land use was one of the most important factors behind the observed changes of direct runoff in the Wei River.

Currently, projection of hydrological characteristics based on future climate scenarios is in the focus of hydrological research. In general, there are two main approaches: applying statistical methods to predicted climate variables (e.g., Du *et al.* 2015) and extrapolating runoff by means of hydrological models with simulated precipitation and temperature (e.g., Chen *et al.* 2012). Running a hydrological model on various climatic scenarios may help address the uncertainties induced by the scenarios, but not the uncertainty that originates from insufficient knowledge regarding the interactions of integral processes. We conjecture that projecting possible future changes in runoff characteristics based on precipitation scenarios and variation patterns discerned from long-term runoff observations can complement the results derived from hydrological models. Assessment of impacts on human and natural systems that have already occurred as a result of recent climate change is an important complement to model projections of future impacts (IPCC 2013).

Flow duration curve (FDC) is another important characteristic of runoff variation for environmental flow assessment and water management. In China, the FDCs have not been previously examined in the light of possible variation in patterns. In spite of widespread doubts and rejection of the concept of flow stationarity, the FDC is still assumed to follow the long-term stationary pattern. Innovative thinking and methods that consider possible non-stationarity in FDC patterns are obviously required given the changing environment (Li *et al.* 2007; Zhang *et al.* 2008). Possible changes in FDCs induced by climate change and future projection of these changes have not yet received due attention.

The aim of the paper is to study runoff temporal variability patterns, analyze possible mechanisms behind this variability, and apply the findings for projecting runoff variability patterns for future. To achieve these goals, we utilize the characteristics of the identified runoff variation patterns and future precipitation scenarios produced by a number of General Circulation Models (GCMs). We perform the analyses individually on the data for three Chinese rivers, i.e. the Wei (Weihe), the Bei (Beijiang), and the Qing (Qingjiang), without comparisons as the records do not cover exactly the same observation period though there is much overlap. First, we focus on temporal flow variability by examining the differences in average monthly runoff variation patterns and FDCs for the years when the mean annual runoff is at least equal ('non-deficit' years) or lower ('deficit' years) than the long-term average. We then study possible mechanisms behind this variability of flow by analyzing the effects of the PEO, SST (Niño 3.4), and human activities. We conclude the study by constructing FDCs and average monthly runoff variation patterns for future precipitation scenarios using the discerned patterns for deficit and non-deficit years.

STUDY AREA AND DATA

The Weihe, the Beijiang, and the Qingjiang basins are located in northern, southern, and central China, respectively (Figure 1). They were selected as three separate case studies due to their importance in China's regional socio-economic development (e.g., Luo *et al.* 2008; Xiong *et al.* 2014; Du *et al.* 2015).

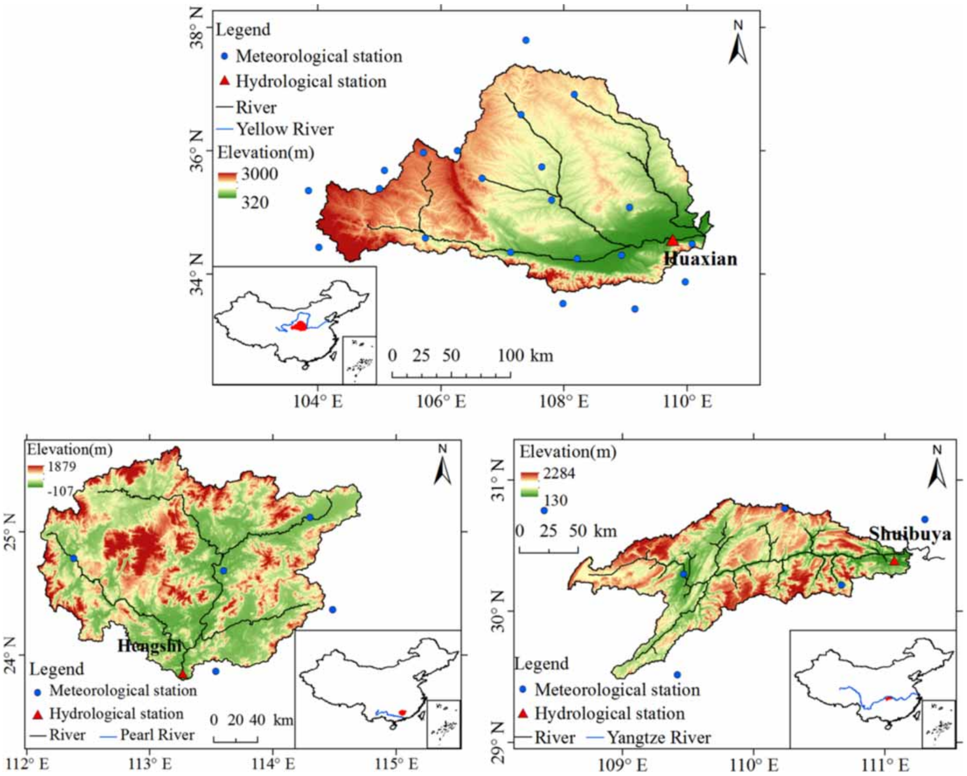

Figure 1 | Locations of the Weihe (top), the Beijiang (bottom left), and the Qingjiang (bottom right) basins and the meteorological stations. The small inset box in the right corners shows the islands in the South China Sea within the main China map.

The Weihe, the biggest tributary of the Yellow River, is known as the 'Mother River' of the Guanzhong Plain in the southern part of the Loess Plateau. The Weihe basin has a semi-arid continental climate with dry winters and warm summers (Du *et al.* 2015). The Beijiang is the second biggest tributary of the Pearl River, and it flows across Guangdong Province, one of the well developed coastal provinces of southern China. The basin is mostly located in the mountains and has a subtropical climate with high temperatures and abundant precipitation (Luo *et al.* 2008). The Qingjiang, a tributary of the middle reaches of the Yangtze River, is subject to a subtropical monsoon type climate with abundant precipitation (Chen *et al.* 2012; Yu *et al.* 2014).

Runoff, precipitation, and temperature data

The chosen basin sizes represent an appropriate regional scale at which the effect of local factors on data analyses is minor (Woods 2005). The data used are all officially supplied and were previously successfully used in both research and practical fields (e.g., Xiong *et al.* 2014; Yu *et al.* 2014; Du *et al.* 2015; Jiang *et al.* 2015). For the Weihe runoff data were provided by the Hydrology Bureau of the Yellow River Conservancy Commission; for the Beijiang – by the Administration of Feilaixia Water Conservancy Project of Guangdong Province; and for the Qingjiang – by the hydrological bulletins of the Yangtze River Water Resources Commission. Daily precipitation and temperature series originated from the National Climate Center of the China Meteorological Administration. Areal average series of precipitation and temperature were used instead of point-scale precipitation (e.g., Szolgayova *et al.* 2014). Table 1 shows basic information of discharge, precipitation, and temperature records for the three study areas.

Teleconnections data

We focus on two teleconnections that are relevant for the study area: the PEO and SST (Niño 3.4). The PEO pattern

Table 1 | Basic information for the river basins

River Basin	Weihe	Beijiang	Qingjiang
Hydrological station	Huaxian	Hengshi	Shuibuya
Drainage area (km^2)	106,498	34,097	10,860
Record period	1960–2009	1954–1998	1952–2009
Meteorological stations, number	21	5	6
Mean annual runoff (m^3/s)*	204.5 (0.52)	1,097.6 (0.27)	286.2 (0.26)
Areal average annual precipitation (mm)*	534.7 (0.18)	1,653.3 (0.17)	1,436.2 (0.16)
Areal average annual temperature (°C)*	9.5 (0.06)	20.0 (0.02)	14.5 (0.07)

*The coefficient of variation is given in brackets.

represents a dipole of pressure anomalies with the positive phase associated with above-average geopotential height anomalies over northern China and Mongolia as well as low heights over the polar region (Wilby *et al.* 2004). Monthly data for the PEO and SST (Niño 3.4) originated from the NOAA Climate Prediction Center (http://www.cpc.ncep.noaa.gov/data).

Human impact data

A set of human activity factors were considered: population level (million); cultivated land (million ha); irrigated area (million ha); water supply (million t); grain yield (million t); gross domestic product (GDP; yuan); afforested area (ha); hydroelectricity (billion kWh); reservoir storage (billon m^3); and area of soil-water conservation (ha), which have been frequently used by other researchers (e.g., Wang & Hejazi 2011). The first eight factors that could influence runoff variation in the Weihe, the Beijiang, and the Qingjiang were extracted for the same period as runoff records from statistical yearbooks for the Shaanxi (Yang 2009), Guangdong (Chen & Bu 1999), and Hubei (Li & Xu 2014) provinces, respectively. The records for the Beijiang and the Qingjiang basins have a small gap before 1956. The last two factors originating from yearbook of China water resources (Wu 2010) for all three basins were much shorter (15 years). The runoff data were adjusted accordingly for correlation analysis. Population level, water supply, and GDP are indirect characteristics of urbanization. Cultivated land, irrigated area, grain yield, afforested area, and area of soil-water conservation (e.g., terraces, grasses) are relevant indices for the alterations of land use and land cover of a catchment that might affect water balance and evaporation losses in particular. Grain yield may also serve as an indirect indicator of 'green water,' (Falkenmark 1995) herein water consumed by agricultural crops. River regulation may exert an important effect on regional hydro-cycles, especially in the Weihe, where numerous dams have been built to meet high demands on water, electricity-generation, etc.

Climate scenarios

GCMs remain one of the main tools for climate projections to future (Chen *et al.* 2012). Precipitation scenarios were obtained from both GCMs (http://cmip-pcmdi.llnl.gov/cmip5) and NOAA NCEP reanalysis (http://www.esrl.noaa.gov) datasets. We utilized the latest generation of GCMs developed by the research institutions of the countries participating in the Coupled Model Intercomparison Project Phase 5 (CMIP5) due to its improvement of predictive ability. Seven GCMs under a high greenhouse gas scenario (RCP8.5) were considered, i.e., CanESM2, CCSM4, CNRM-CM5, GFDL-ESM2M, MIROC-ESM, MIROC-ESM-CHEM, and NorESM1-M (Du *et al.* 2015). However, it is beyond the scope of this study to analyze the relative advantages and disadvantages of these GCMs.

METHODS

The basic statistical methods of empirical orthogonal functions (EOF) (Lorenz 1956) and contingency analysis were the main tools for investigating hydrological data series.

When studying high-dimensional data in search for variation patterns, it is advantageous to first reduce the dimension in order to eliminate redundant information and noise. Decomposition into EOF is a convenient tool to accomplish this goal. According to the EOF-method, the original time series are represented by a set of orthogonal (amplitude) functions (AF) with weights equal to the eigenvectors of the covariance function of the original data. While AFs do not change, the weights are different for different observation years. The series decomposition can be truncated to eliminate noise when a sufficiently high level of the explained variance (commonly 90%) is reached. EOF decomposition has been successfully used in hydrology studies for dimensionality reduction and pattern recognition with regard to river flow (Krasovskaia *et al.* 1999; Sauquet *et al.* 2000, 2008; Gottschalk *et al.* 2015). For example, Li *et al.* (2013) utilized EOF when studying the relationship between SST indices and precipitation in China.

We perform EOF decomposition of the monthly runoff series for several purposes. First, we study grouping of the weights during deficit and non-deficit years to discern differences in the runoff variation patterns. Second, we attempt to identify the human impact signal in monthly runoff variation via investigation of the correlation between the weights and the human activity factors.

Contingency tables displaying the frequency distribution of variables are a widely used tool in engineering and scientific research (e.g., Cassou 2008; Stoll *et al.* 2013). They indicate the degree of interrelation between two variables. Li *et al.* (2015) used contingency tables to compare actual land use maps and simulated land use according to different scenarios of water use. We apply contingency tables to study the impact of low-frequency atmospheric oscillations on the occurrence of deficit and non-deficit years. The significance of the interrelationship is assessed via Chi-square test, while the degree of association is estimated using Cramér's V statistic (Cramér 1971). These are both standard methods for the analysis of contingencies.

Downscaling of GCM data to represent the local-scale climate for the three basins is performed by means of the statistical downscaling model (SDSM) for projection of runoff variation. The SDSM operation includes several steps: analyzing the correlation between the NCEP reanalysis predictors and historical precipitation record by a multiple linear regression; running weather generator in the SDSM to simulate precipitation based on the constructed multiple linear regressions; calibrating the SDSM by assessing the predictive performance; and projecting precipitation scenarios from the GCMs data in the calibrated SDSM. More technical details on the structure and application of the SDSM can be found in Wilby *et al.* (2002) and Wilby & Dawson (2007).

RUNOFF VARIATION DURING DEFICIT AND NON-DEFICIT YEARS

Average monthly runoff and precipitation patterns

We begin with a presentation of the average monthly runoff (Qs) and precipitation (Ps) patterns with a focus on the timing of the peak flows for investigation of runoff variation during deficit and non-deficit years (Figure 2). The timing of the peak flows and minimum flows is also used as the discriminating criteria in flow regime classifications (e.g., Tollan 1975; Krasovskaia & Gottschalk 1992; Arnell *et al.* 1993).

In the Weihe basin, Ps has a maximum in July–August in 66% of the years. Ps maxima occur a month later in 20% of the years, and they occur earlier in 12% of the years. Qs are significantly correlated with Ps ($R = 0.92$), with a one month lag. Maximum Qs typically occur in late summer-autumn

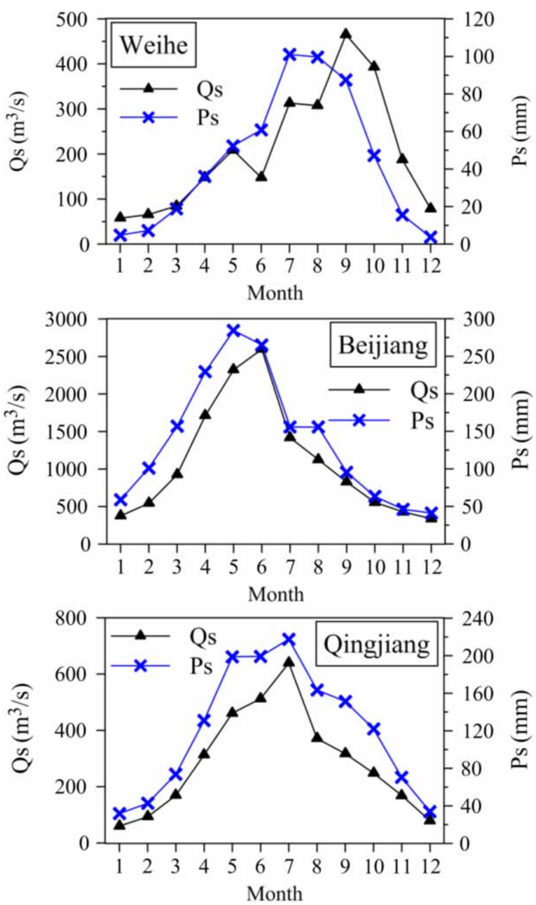

Figure 2 | Average monthly runoff (Qs) and precipitation (Ps).

(68% of the years), less frequently in July (20% of the years), and rarely during April–June (12% of the years).

In the Beijiang basin, maximum Ps typically occurs during May and July, representing 39% and 31% of the years, respectively. Correlation between Qs and Ps is high ($R = 0.98$), with a lag of approximately one month. Maximum Qs are usually observed in June (47% of the years), May (31% of the years), and April (18% of the years).

In the Qingjiang basin, Ps frequently exhibits maxima in July (31% of the years) and during the period of May–June (22% of the years). Qs are highly correlated with Ps ($R = 0.98$). Maximum Qs are typically observed in July (41% of years) or June (20% of years).

Temporal variation of annual runoff deficit

The frequency of deficit precipitation and runoff years is very similar: 60% and 56%, respectively, for the Weihe basin; 57% and 64% for the Beijiang basin; and 49% and 53%, for the Qingjiang basin.

Figure 3 illustrates the percentage of deficit and non-deficit years relative to the mean annual precipitation (P_{ann}), mean annual runoff (Q_{ann}), and mean annual temperature (T_{ann}). In the Weihe (Figure 3(a)), the Mann-Kendall (MK) trend test confirmed a significant increase in T_{ann} and a decrease of Q_{ann}. Only slight changes (non-significant downtrends) were found in P_{ann}. This indicated the possibility of other reasons behind

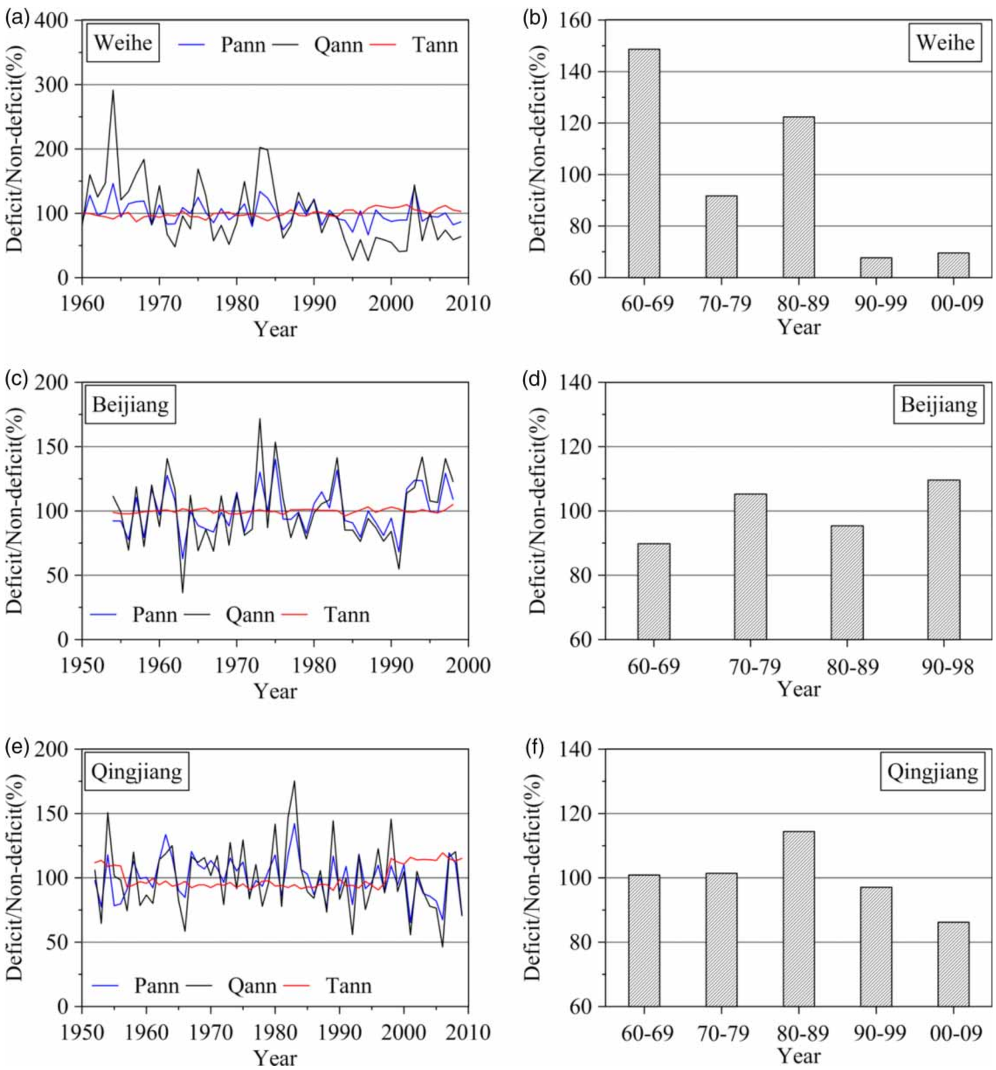

Figure 3 | Deficit/non-deficit (%) of annual runoff (Q_{ann}), precipitation (P_{ann}), and temperature (T_{ann}) (left), and decadal changes in the annual runoff (right).

the large decrease in Q_{ann}. Q_{ann} had three periods associated with deficit (Figure 3(b)): 1970–1979 (approximately 10%) as well as 1990–1999 and 2000–2009 (approximately 30%), showing a tendency towards stronger deficit. It is during these last two decades the large-scale water conservancy constructions in the Weihe basin increased.

In the Beijiang, slight changes in Q_{ann}, T_{ann}, and P_{ann} can be noted between different decades (Figure 3(c) and 3(d)). The magnitudes of deficit in P_{ann} and Q_{ann} are in agreement. Although P_{ann}, Q_{ann}, and T_{ann} were 13%, 8%, and 3%, respectively, higher in the last decade than their long-term means, they showed no significant uptrends for the entire period (MK test).

In the Qingjiang, the deficit in Q_{ann} often appears to be greater than that of P_{ann} (Figure 3(e)). A tendency for decreasing P_{ann} and Q_{ann} during the last two decades can be noticed (Figure 3(f)). During the first and the last decades, T_{ann} was approximately 0.5 °C and 1 °C, respectively, higher than the average, which might have contributed to the runoff deficit. However, no significant trends in Q_{ann}, P_{ann}, and T_{ann} over the studied period were detected (MK test).

Table 2 | Relative explained variance with different number of AFs

	Relative explained variance (%)		
Number of AFs	**Weihe**	**Beijiang**	**Qingjiang**
1	65	70	60
2	11	12	11
3	10	6	9
4	7	4	8
Sum	93	92	88

Flow variation patterns during deficit and non-deficit years

Mean annual runoff proved to be significantly different for deficit and non-deficit years (t-test, at the 5% significance level). We continued to investigate whether the flow variation patterns differ between these years. Grouping the weights of the AFs for different years as obtained by EOF decomposition can be used for discriminating the flow variation patterns in the observation series (Krasovskaia et al. 1999, 2003). Table 2 presents the values of the relative explained variance after a truncation level of approximately 90% and the number of AFs necessary to reach this level. It can be observed that for all three series the first AF represents 60–70% of the variation in monthly runoff. In general, the first AF reflects the average monthly variation pattern, while the second and higher AFs might indicate shifts from this pattern (Krasovskaia et al. 1999).

Possible grouping of the weights can be discerned by plotting them against each other. Figure 4 presents the plots of the 1st weight against the 2nd, where the weights for the deficit and non-deficit years are shown with different symbols. A clear tendency for higher values of the 1st weight in deficit years can be seen, although there is some overlap, especially for the Qingjiang. Similar groupings have been noted for the plots of the 3rd and 4th weights against the 1st (not shown for brevity). We therefore conclude that there are differences in the monthly runoff variation patterns between deficit and non-deficit years.

The timing of monthly flow peaks appeared to be different during deficit and non-deficit years (Figure 5). In the

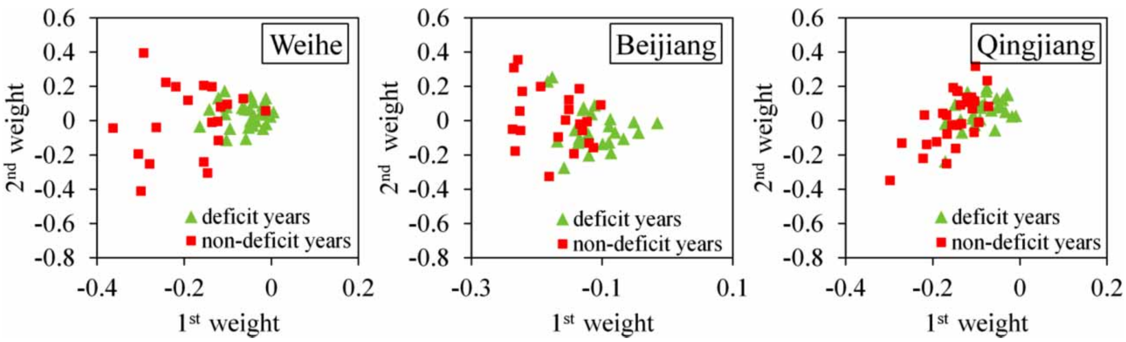

Figure 4 | Plots of the 1st weight against the 2nd.

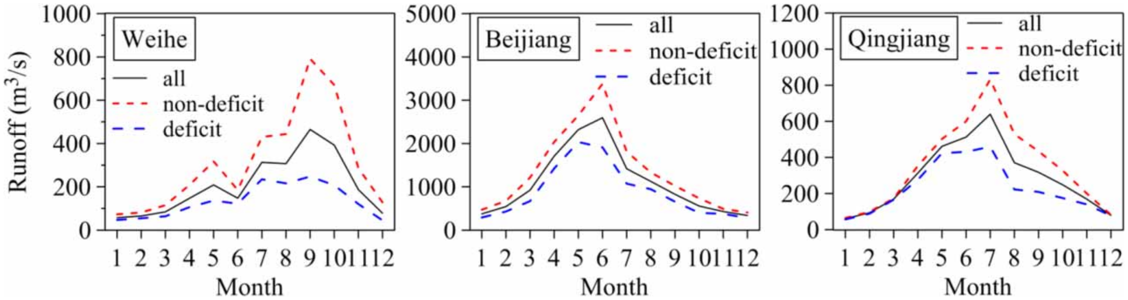

Figure 5 | Average monthly runoff patterns for all years and for years with and without runoff deficit.

Weihe basin, the monthly runoff patterns during non-deficit years resemble the average patterns. Flow maxima mostly occur in autumn (September–October) (70%), and more rarely one month later (20%) or one month earlier (10%), but never earlier than July. Forty-seven percent of the deficit years have maxima earlier than July, and the timing of high flow is more dispersed and occurs during April–October.

In the Beijiang basin, the monthly runoff peaks occur earlier during the deficit years than on the average. A majority (63%) of runoff maxima are observed during April–May, while less than half occur that early on the average. During non-deficit years the percent of years with early maxima decreases to 38%, and 57% of the years have maxima in June. These results indicate that early monthly runoff maxima are often associated with deficit years.

In the Qingjiang basin, there is an obvious connection between the timing of runoff maxima and annual runoff deficit. During runoff deficit years, 50% of runoff maxima occur earlier than July, while the corresponding rate for the average pattern is only 36%. In contrast, during non-deficit years early peaks occur only in 24% of the years, and maxima occur in July or later in the majority of years.

Figure 6 illustrates that the average FDCs differ between the deficit and non-deficit years with the 95% confidence limits constructed under the assumption that the percentiles of the average FDC follow the normal distribution (Cramér 1971).

On the basis of these results, we conclude that monthly runoff variation patterns differ between years with annual runoff deficit and those without a deficit. This difference is reflected in the variations in the timing of monthly flow peaks and FDCs.

CLIMATE AND HUMAN IMPACT SIGNALS IN LONG-TERM RUNOFF VARIABILITY

Impact of quasi-periodical atmospheric circulation patterns

We use contingency tables to investigate the impact of the positive and negative phases of the PEO and SST (Niño 3.4) on the occurrence of the deficit and non-deficit runoff years, respectively. Table 3 shows the six contingency tables (for three rivers and two indices), where the contingency values are shown in percent from the lengths of the phase of the respective index. All the contingencies proved to be significant at the 95% confidence level (Chi-square test), except for the contingency between the occurrence of deficit/non-deficit years and the SST (Niño 3.4) phase in the Beijiang. It can be seen that deficit runoff years are contingent with the negative PEO phase and vice versa. In contrast, deficit runoff years are contingent with the positive phase of SST (Niño 3.4) and vice versa.

The next step was to estimate the degree of association between positive/negative phases of the utilized indices and the occurrence of deficit/non-deficit years, respectively, using Cramér's V statistic (Table 3). We note moderate to high association with PEO ($V = 1$ is obtained only if the series are similar) and lower association with SST (Niño 3.4).

The results in general confirm a significant interrelationship between the phases of PEO and SST (Niño 3.4) and the occurrence of deficit and non-deficit runoff years for the river basins studied, with the exception of the Beijiang. Taking into consideration the changing relationship between precipitation patterns in China and the ENSO (Gao & Wang 2007), the predictive value of the ENSO phase is decreasing.

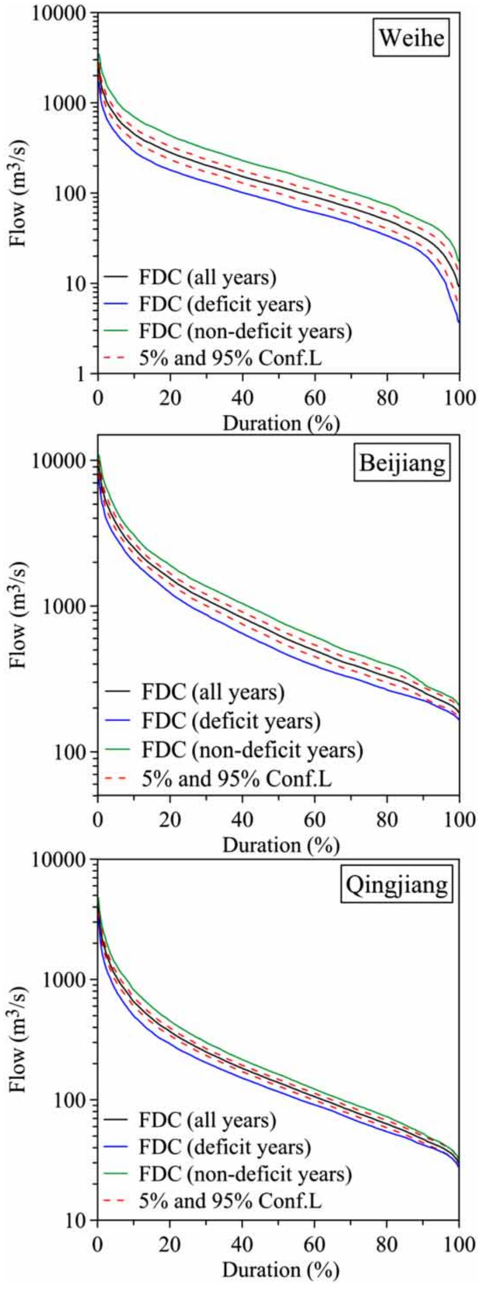

Figure 6 | Average FDCs for all years and for years with and without runoff deficit.

Human impact

We attempt to estimate the human impact on the long-term runoff variability using the correlation between the human activity factors and the weights obtained by decomposing the original runoff series into EOFs. A significant (though low) correlation between the studied factors and the weights are detected (Table 4).

Table 3 | Contingencies (%) between the runoff years (deficit/non-deficit) and the phases (positive/negative) of PEO and SST (Niño 3.4) with Cramér's V statistics (non-significant value shown in italics)

	PEO		SST (Niño 3.4)	
Year/Phase	**Positive**	**Negative**	**Positive**	**Negative**
Weihe				
Deficit	25	75	57	43
Non-deficit	50	50	40	60
Cramér's V	0.52		0.34	
Beijiang				
Deficit	37	63	37	63
Non-deficit	81	19	33	67
Cramér's V	0.94		*0.09*	
Qingjiang				
Deficit	40	60	50	50
Non-deficit	75	25	29	71
Cramér's V	0.66		0.40	

In the Weihe basin, the 1st weight has significant correlations with the population level and water supply. As the first AF represents 65% of the relative explained variance (Table 2), we can estimate the impact of the population level and water supply on the long-term runoff variability via multiplying the contribution of the first AF by the respective correlations to these human activity factors (Table 4). This yield 22% and 25%, respectively. The 2nd weight showed a significant correlation with the reservoir storage and area of soil water conservation (due to a limited record length, the result should be taken with caution), and the 4th weight – with other six factors. The contributions of the 2nd and 4th AFs to the total explained variance are low (11% and 7%, respectively), which yields the negligible impact of 3–6%.

In the Beijiang basin, the afforested area significantly correlates with the 1st weight, which yields an impact of 28% as the 1st AF contributes with 70% to the explained variance. The 2nd and 4th weights significantly correlate with most studied factors. The contributions of the 2nd and 4th AFs to the explained variance are 12% and 4%, respectively, leading to the negligible impact of 1–7%.

For the Qingjiang basin, only the 3rd weight and the irrigated area exhibited a significant correlation. However, the relative contribution of the 3rd AF to the total runoff variation is only 9%, which yields the negligible impact of 3%.

To summarize, we estimate that the human impact on the long-term variation of monthly runoff is 22–25% in the

Table 4 | Correlations between the weights and human activity factors (significant value shown in bold)

Weight	1	2	3	4
Weihe				
Population level	**0.34**	0.02	0.01	**0.35**
Cultivated land	−0.29	0.11	0.02	**−0.38**
Irrigated area	0.17	0.21	0.07	**0.40**
Water supply	**0.39**	0.01	0.05	**0.34**
Grain yield	0.31	0.09	0.11	0.32
GDP	0.21	−0.15	−0.09	0.18
Afforested area	0.01	0.28	0.15	**0.34**
Hydroelectricity	0.18	0.05	0.03	**0.36**
*Reservoir storage**	*−0.36*	***−0.57***	*−0.47*	*0.18*
*Area of soil-water conservation**	*−0.41*	***−0.56***	*−0.33*	*0.35*
Beijiang				
Population level	0.15	**0.40**	−0.03	**0.45**
Cultivated land	−0.04	**−0.56**	0.11	**−0.36**
Irrigated area	0.22	**−0.53**	−0.00	−0.00
Water supply	0.10	**0.55**	−0.07	**0.45**
Grain yield	0.34	0.12	0.06	**0.53**
GDP	−0.10	**0.61**	−0.11	0.33
Afforested area	**0.40**	**−0.47**	0.12	0.10
Hydroelectricity	0.02	**0.55**	−0.13	**0.45**
*Reservoir storage**	*0.09*	***0.56***	*−0.17*	*−0.06*
*Area of soil-water conservation**	*−0.07*	*0.52*	*−0.22*	*0.36*
Qingjiang				
Population level	−0.01	−0.18	0.19	−0.26
Cultivated land	−0.07	0.11	−0.23	0.29
Irrigated area	−0.14	0.05	**−0.31**	0.27
Water supply	0.07	−0.19	0.28	−0.30
Grain yield	−0.11	−0.27	0.07	−0.24
GDP	0.13	−0.11	0.15	−0.20
Afforested area	−0.23	−0.22	0.01	−0.15
Hydroelectricity	0.05	−0.13	0.14	−0.08
*Reservoir storage**	*−0.40*	*−0.24*	*−0.06*	*−0.17*
*Area of soil-water conservation**	*−0.27*	*−0.22*	*−0.10*	*−0.18*

*Results in italics should be taken with caution due to a limited record length.

Weihe, 28% in the Beijiang, and negligible in the Qingjiang. Dong *et al.* (2015) estimated the impact of land use changes on the direct runoff of the Weihe basin at 1.2%. They focused on changes in the different land use types for a much shorter period in contrast to the present study, which may explain differences in the results. Examining the relative contribution of climatic and human impact factors to the 45% decrease of annual runoff in the Weihe basin during 1988–2008 (the end of our study period), Du & Shi (2012) estimated the contribution of the latter at 51%, which yields a 23% contribution to the total runoff variation. This agrees well with the results found in this study. The uncertainties involved in the estimations of the role of human activities in temporal runoff variation highlights the necessity of verification using different methods.

PROJECTION OF FUTURE RUNOFF VARIABILITY

In the context of climate change, estimations of FDCs in terms of probable futures, as well as possible changes in variation patterns of monthly runoff, are extremely important. The precipitation scenarios generated from seven GCMs (Figure 7) offer a sufficient diversity to show how FDCs and average monthly runoff patterns can be projected into the future using the suggested approach. To demonstrate the approach, these scenarios, having a moderate predictive performance by the Nash-Sutcliffe efficiency coefficients (0.69–0.77) between the simulated and observed annual precipitation, are acceptable (e.g., Chen *et al.* 2012; Du *et al.* 2015). We estimated the proportion of deficit/non-deficit precipitation years for the future period 2010–2099 (relative to the average annual precipitation for the observation period) for each scenario (Table 5). Based on a strong correlation between P_{ann} and Q_{ann}, we assume that these proportions are applied as weights for deficit/non-deficit runoff years.

The proportions of deficit/non-deficit precipitation years differ considerably between the models for any of the three basins (Figure 7). For example, all the models indicate more deficit precipitation years for the Weihe but while the NorESM1-M prediction yields proportions of deficit years that are very close to the present values, the other models indicate a much higher percent of years with deficits in P_{ann}. The discrepancy between different models is very large for Beijiang (e.g., CCSM4 and CNRM-CM5). For Qingjiang, five out of seven models have predictions of more deficit years. The large differences in the results originate from the differences in the precipitation simulated by the GCMs and their different predictive performance, as noted by Chen & Frauenfeld (2014).

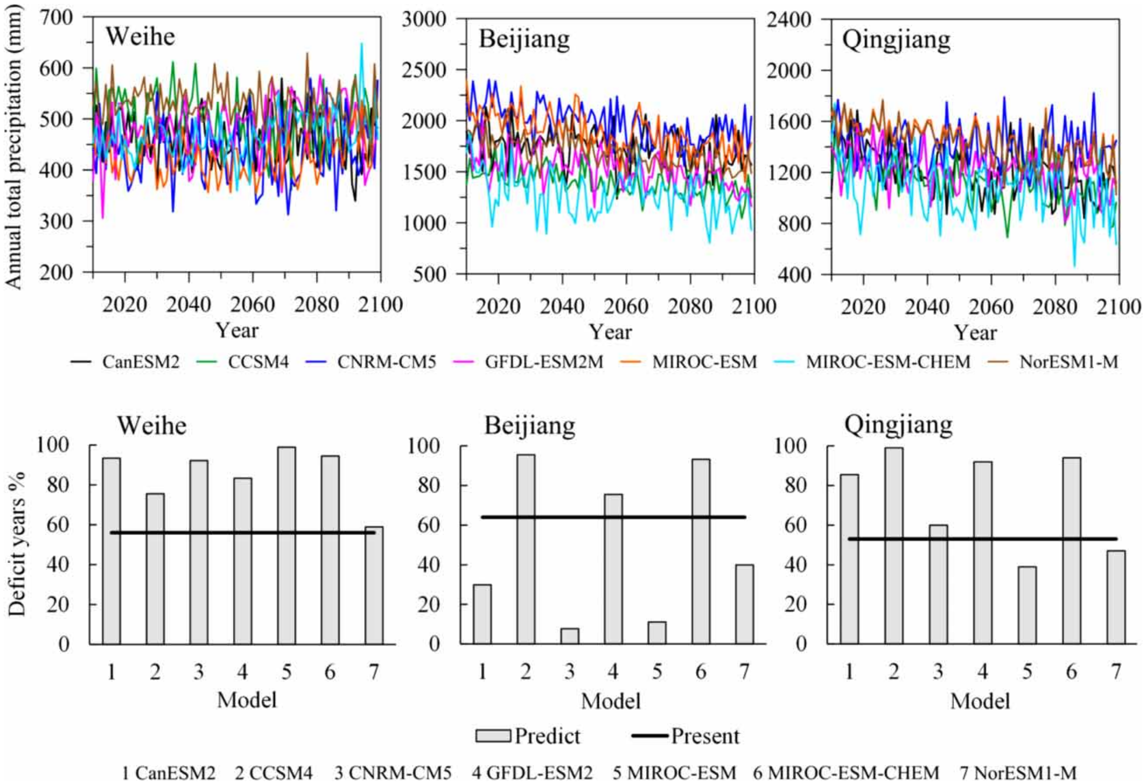

Figure 7 | Precipitation scenarios (upper) and percent of years with annual precipitation deficit at present and under different scenarios (lower).

Projection of average FDCs

Figure 8 shows the weighted average FDCs, where the proportions (Table 5) are applied to the discerned FDCs for deficit and non-deficit years (Figure 6). The discrepancies in the average FDCs for different scenarios are rather large, especially for low durations (Table 6). An example in Figure 9 clearly illustrates the discrepancies for the 10% low duration. As FDC is one of the basic tools for water management, the identified range of uncertainties may be useful for risk assessment studies.

Table 5 | Percent of deficit/non-deficit years for the GCM scenarios

River	Weihe		Beijiang		Qingjiang	
Scenario	**Deficit**	**Non-deficit**	**Deficit**	**Non-deficit**	**Deficit**	**Non-deficit**
CanESM2	93	7	30	70	86	14
CCSM4	76	24	96	4	99	1
CNRM-CM5	92	8	8	92	60	40
GFDL-ESM2M	83	17	76	24	92	8
MIROC-ESM	99	1	11	89	39	61
MIROC-ESM-CHEM	94	6	93	7	94	6
NorESM1-M	59	41	40	60	47	53
Present	**56**	**44**	**64**	**36**	**53**	**47**

Projection of average monthly runoff patterns

The predicted proportions of the deficit/non-deficit precipitation years were also used as weights to construct future average monthly runoff variation patterns (Figure 10). This illustrates the results revealed by the predicted FDCs in a different way. For example, while the scenario from NorESM1-M model indicates higher monthly peaks than at present for the Beijiang, the scenario from MIROC-ESM-CHEM model indicates lower peaks compared to the present. Changes in low flow are very small for all the models. The average patterns

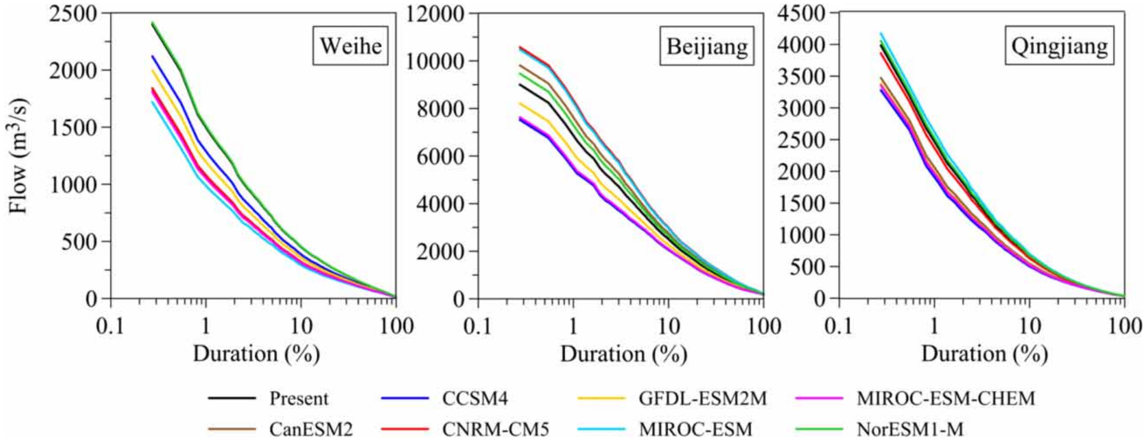

Figure 8 | Average FDCs under different scenarios.

obviously cannot reveal the future changes in the timing of the flow maxima caused by changes in the frequency of deficit and non-deficit years. However, the tendency for earlier and more dispersed peak flows during the deficit years suggests that such patterns might be observed more often if the frequency of the deficit years increases in the future.

CONCLUSIONS AND DISCUSSION

The differences in the variation patterns between deficit and non-deficit runoff years with respect to monthly flow and FDC as well as the influence of low-frequency atmospheric circulation patterns and human impact on this variability were investigated separately for three Chinese river basins.

Table 6 | Runoff (m^3/s) for different durations at present and for the GCM scenarios

		GCMs						
Duration (%)	**Present**	**CanESM2**	**CCSM4**	**CNRM-CM5**	**GFDL-ESM2M**	**MIROC-ESM**	**MIROC-ESM-CHEM**	**NorESM1-M**
Weihe								
90	32.3	23.2	27.9	23.5	26.0	21.6	23.0	32.6
75	59.1	43.3	51.5	43.8	48.1	40.5	42.9	59.6
50	118.5	85.6	102.5	86.6	95.5	79.6	84.6	119.5
25	235.8	167.3	202.6	169.4	188.1	154.8	165.2	237.9
10	445.1	312.1	380.6	316.2	352.4	288.0	308.1	449.1
Beijiang								
90	259.7	276.6	228.8	292.6	243.3	290.4	230.9	269.4
75	362.5	396.2	301.0	427.9	329.9	423.6	305.3	381.8
50	630.2	698.8	504.9	763.4	563.6	754.6	513.7	669.4
25	1,274.6	1,406.8	1,033.0	1,531.4	1,146.3	1,514.4	1,050.0	1,350.1
10	2,468.3	2,709.0	2,028.1	2,935.9	2,234.4	2,905.0	2,059.0	2,605.8
Qingjiang								
90	47.5	44.0	42.7	46.7	43.4	48.8	43.2	48.0
75	72.0	64.8	62.0	70.3	63.5	74.7	63.1	73.0
50	139.2	123.3	117.2	135.3	120.5	145.1	119.6	141.4
25	298.5	257.0	241.2	288.5	249.7	314.0	247.3	304.3
10	643.9	535.0	493.7	617.6	516.0	684.4	509.6	658.9

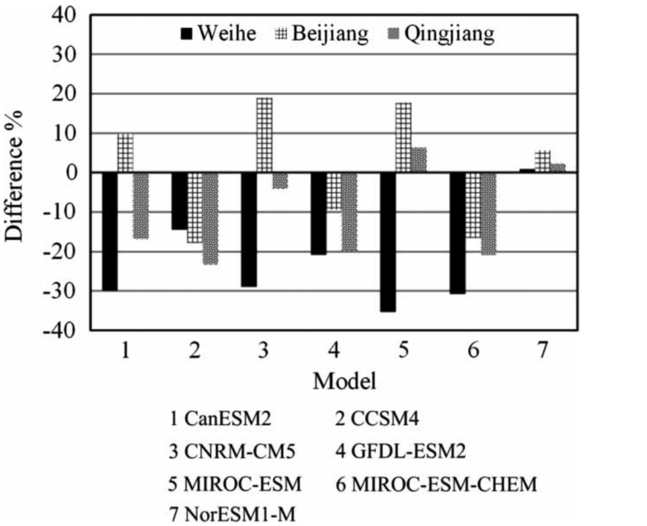

Figure 9 | Differences (%) in the runoff with the 10% duration between the FDCs under different scenarios.

The characteristics of the discerned patterns of variation were used for projecting future runoff variability patterns based on a set of precipitation scenarios. The following conclusions have been made on the basis of the analyses.

Analyses of the frequency and changes in the occurrence of the deficit and non-deficit runoff years indicate the following. (1) In the Weihe basin, significant trends of decrease in runoff and increase in temperature were noted, but there was no similar trend in the precipitation. (2) In the Beijiang basin, very slight increases in the precipitation, runoff, and temperature were found. The variability of deficit/non-deficit precipitation and runoff years exhibited a higher level of agreement. (3) In the Qingjiang basin, there was a non-significant tendency for decreasing precipitation and runoff.

Monthly runoff variation patterns and FDCs differ between deficit and non-deficit years. The deficit years generally demonstrate earlier and more dispersed flow maxima, while the runoff pattern during non-deficit years resembles the average pattern.

The significant contingency between the phase of PEO and the occurrence of deficit and non-deficit runoff years was noted for all three river basins. The association with SST (Niño 3.4) was lower but still significant, except for the Beijiang. Deficit runoff years were associated with the negative phase of PEO and vice versa, while they were contingent with the positive phase of SST (Niño 3.4) and vice versa. The noted contingency may be developed towards probabilistic forecasts of the occurrence of deficit and non-deficit runoff years based on the phases of the studied indices.

The human impact on long-term monthly runoff variation was detectable: 22–25% in the Weihe, 28% in the Beijiang, and negligible in the Qingjiang.

There are considerable differences in the predicted FDCs and monthly runoff variation patterns based on the precipitation scenarios by different GCMs. Earlier and more dispersed monthly flow maxima could be expected if the frequency of deficit precipitation years increases in the future.

We utilized a 'top-down' approach that 'begins with the identification of important regularities at the less fundamental level and defers until later understanding of the underlying, more fundamental mechanisms' (Gell-Mann 1995) and attempted to study runoff variation by letting the data 'speak for themselves.' The suggested approach complements the more common use of hydrological models and avoids more uncertainties incurred by hydrological models

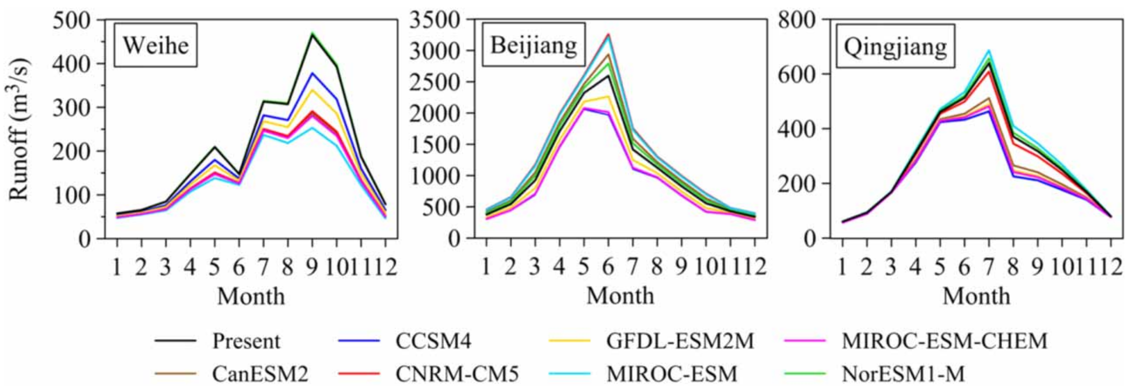

Figure 10 | Average monthly runoff patterns at present and under different scenarios.

for future projection of runoff variation. It shares the dominant part in the uncertainty, i.e., from precipitation scenarios, with the 'modeling approach'. We showed the differences in the future projections of runoff variation to stress the importance of considering the range of uncertainties instead of averaging the results by seven GCMs. A minor source of uncertainty in the suggested approach originates from the statistical errors due to the limited length of the records and the fact that we used only two classes (deficit/non-deficit). The former type of uncertainty is also present in the 'modeling approach' but the model uncertainty is enlarged due to different choices of hydrological models, parameter estimation technique, etc. Using the proportion of the deficit/non-deficit precipitation years based on the scenarios as a proxy for deficit/non-deficit runoff years may also be a source of uncertainty. A comparative study of the uncertainties in both approaches applied to the same precipitation scenarios would be a topic for further investigation. Given a constant increase in the human impact on runoff variation, a further challenge would be introducing 'corrections' stemming from this impact in the future projections of runoff variation.

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REFERENCES

Arnell, N. W., Krasovskaia, I. & Gottschalk, L. 1993 River flow regimes in Europe. In: *Flow Regimes from International Experimental and Network Data (FRIEND9), Hydrological Studies,* Vol. 1 (A. Gustard, ed.). Institute of Hydrology, Wallingford, UK, pp. 112–121.

Barlow, M. A. & Tippett, M. K. 2008 Variability and predictability of Central Asia river flows: antecedent winter precipitation and large-scale teleconnections. *J. Hydrometeorol.* **9**, 1334–1349.

Bower, D., Hannah, D. M. & McGregor, G. R. 2004 Techniques for assessing the climatic sensitivity of river flow regimes. *Hydrol. Process.* **18**, 2515–2543.

Cassou, C. 2008 Intraseasonal interaction between the Madden–Julian oscillation and the North Atlantic oscillation. *Nature* **455**, 523–527.

Chaves, A., Picado, J., Krasovskaia, I. & Gottschalk, L. 2010 Linking annual cycles of ecological indicators with statistical flow descriptors for environmental flow assessment. *IAHS Publ.* **340**, 350–357.

Chen, J. & Bu, X. 1999 *Statistical Yearbook of Guangdong Province.* China Statistics Press, Beijing, China (in Chinese).

Chen, L. & Frauenfeld, O. W. 2014 A comprehensive evaluation of precipitation simulations over China based on CMIP5 multimodel ensemble projections. *J. Geophys. Res. Atmos.* **119**, 5767–5786.

Chen, H., Xiang, T., Zhou, X. & Xu, C.-Y. 2012 Impacts of climate change on the Qingjiang Watershed's runoff change trend in China. *Stochastic Environ. Res. Risk Assess.* **26**, 847–858.

Chen, J., Wu, X., Finlayson, B. L., Webber, M., Wei, T., Li, M. & Chen, Z. 2014 Variability and trend in the hydrology of the Yangtze river, China: annual precipitation and runoff. *J. Hydrol.* **513**, 403–412.

Cramér, H. 1971 *Mathematical Methods of Statistics.* Princeton University Press, Princeton, NJ.

Dibike, Y. B. & Coulibaly, P. 2005 Hydrologic impact of climate change in the Saguenay watershed: comparison of downscaling methods and hydrologic models. *J. Hydrol.* **307**, 145–163.

Dong, L., Xiong, L., Lall, U. & Wang, J. 2015 The effects of land use change and precipitation change on direct runoff in Wei river watershed, China. *Water Sci. Technol.* **71**, 289–295.

Du, J. & Shi, C. 2012 Effects of climatic factors and human activities on runoff of the Weihe River in recent decades. *Quatern. Int.* **282**, 58–65.

Du, T., Xiong, L., Xu, C.-Y., Gippel, C. J., Guo, S. & Liu, P. 2015 Return period and risk analysis of nonstationary low-flow series under climate change. *J. Hydrol.* **527**, 234–250.

Falkenmark, M. 1995 Land-water linkages: a synopsis. Land and Water Integration and River Basin Management. *FAO Land and Water Bull.* **1**, 15–16.

Feng, J., Chen, W., Tam, C. Y. & Zhou, W. 2011 Different impacts of El Niño and El Niño Modoki on China rainfall in the decaying phases. *Int. J. Climatol.* **31**, 2091–2101.

Gao, H. & Wang, Y. 2007 On the weakening relationship between summer precipitation in China and ENSO. *Acta Meteorol. Sin.* **65**, 131–136 (in Chinese).

Gell-Mann, M. 1995 *The Quark and the Jaguar: Adventures in the Simple and the Complex.* Abacus, London.

Gottschalk, L. & Krasovskaia, I. 1997 Climate change and river runoff in Scandinavia, approaches and challenges. *Boreal Environ. Res.* **2**, 145–162.

Gottschalk, L., Krasovskaia, I., Dominguez, E., Caicedo, F. & Velasco, A. 2015 Interpolation of monthly runoff along rivers applying empirical orthogonal functions: application to the Upper Magdalena River, Colombia. *J. Hydrol.* **528**, 177–191.

Hannah, D. M., Kansakar, S. R., Gerrard, A. J. & Rees, G. 2005 Flow regimes of Himalayan rivers of Nepal: nature and spatial patterns. *J. Hydrol.* **308**, 18–32.

Hundecha, Y. & Bárdossy, A. 2004 Modeling of the effect of land use changes on the runoff generation of a river basin through parameter regionalization of a watershed model. *J. Hydrol.* **292**, 281–295.

IPCC 2013 *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, UK and New York, NY, USA.

Jiang, C., Xiong, L., Wang, D., Liu, P., Guo, S. & Xu, C.-Y. 2015 Separating the impacts of climate change and human activities on runoff using the Budyko-type equations with time-varying parameters. *J. Hydrol.* **522**, 326–338.

Krasovskaia, I. 1995 Quantification of the stability of river flow regimes. *Hydrol. Sci. J.* **40**, 587–598.

Krasovskaia, I. & Gottschalk, L. 1992 Stability of river flow regimes. *Nordic Hydrol.* **23**, 137–154.

Krasovskaia, I., Gottschalk, L. & Kundzewicz, Z. W. 1999 Dimensionality of Scandinavian river flow regimes. *Hydrol. Sci. J.* **44**, 705–723.

Krasovskaia, I., Gottschalk, L., Leblois, E. & Sauquet, E. 2003 Dynamics of river flow regimes viewed through attractors. *Nordic Hydrol.* **34**, 461–476.

Li, T. & Xu, X. 2014 *Statistical Yearbook of Hubei Province*. China Statistics Press, Beijing, China (in Chinese).

Li, L., Zhang, L., Wang, H., Wang, J., Yang, J., Jiang, D., Li, J. & Qin, D. 2007 Assessing the impact of climate variability and human activities on streamflow from the Wuding River basin in China. *Hydrol. Process.* **21**, 3485–3491.

Li, Y., Wu, B., Yang, Q. & Huang, S. 2013 Different relationships between spring SST in the Indian and Pacific oceans and summer precipitation in China. *Acta Meteorol. Sin.* **27**, 509–520 (in Chinese).

Li, Z., Deng, X., Wu, F. & Hasan, S. S. 2015 Scenario analysis for water resources in response to land use change in the middle and upper reaches of the Heihe River Basin. *Sustainability* **7**, 3086–3108.

López, J. & Francés, F. 2013 Non-stationary flood frequency analysis in continental Spanish rivers, using climate and reservoir indices as external covariates. *Hydrol. Earth Syst. Sci.* **17**, 3189–3203.

Lorenz, E. N. 1956 *Empirical Orthogonal Functions and Statistical Weather Prediction*. MIT Department of Meteorology, Statistical forecasting project, Scientific Report No. 1, MIT, Cambridge, Massachusetts.

Luo, Y., Liu, S., Fu, S., Liu, J., Wang, G. & Zhou, G. 2008 Trends of precipitation in Beijiang River basin, Guangdong province, China. *Hydrol. Process.* **22**, 2377–2386.

Naik, P. K. & Jay, D. A. 2011 Distinguishing human and climate influences on the Columbia River: changes in the disturbances processes. *IAHS Publ.* **346**.

Sauquet, E., Krasovskaia, I. & Leblois, E. 2000 Mapping mean monthly runoff pattern using EOF analysis. *Hydrol. Earth Syst. Sci.* **4**, 79–93.

Sauquet, E., Gottschalk, L. & Krasovskaia, I. 2008 Estimating mean monthly runoff at ungauged locations: an application to France. *Hydrol. Res.* **39**, 403–423.

Stoll, S., Franssen, H. H., Bárdossy, A. & Kinzelbach, W. 2013 On the relationship between atmospheric circulation patterns, recharge and soil moisture dynamics in Switzerland. *J. Hydrol.* **502**, 1–9.

Szolgayova, E., Parajka, J., Blöschl, G. & Bucher, C. 2014 Long term variability of the Danube River flow and its relation to precipitation and air temperature. *J. Hydrol.* **519**, 871–880.

Tollan, A. 1975 Hydrologiske regioner i Norden (Hydrological regions in Nordic countries), in Norwegian. *Vannet i Norden* **1**, 3–15 (in Norwegian).

Wang, D. & Hejazi, M. 2011 Quantifying the relative contribution of the climate and direct human impacts on mean annual streamflow in the contiguous United States. *Water Resour. Res.* **47**, W00J12.

Wilby, R. L. & Dawson, C. W. 2007 SDSM 4.2 – A Decision Support Tool for the Assessment of Regional Climate Change Impacts. User Manual. http://co-public.lboro.ac.uk/cocwd/SDSM/SDSMManual.pdf.

Wilby, R. L., Dawson, C. W. & Barrow, E. M. 2002 SDSM – a decision support tool for the assessment of regional climate change impacts. *Environ. Modell. Software* **17**, 145–157.

Wilby, R. L., Wedgbrow, C. S. & Fox, H. R. 2004 Seasonal predictability of the summer hydrometeorology of the River Thames, UK. *J. Hydrol.* **295**, 1–16.

Woods, R. 2005 Hydrological Concepts of Variability and Scale. In: *Encyclopedia of Hydrological Sciences* (M. G. Anderson & J. J. McDonnel, eds). John Wiley & Sons, Chichester, p. 24.

Wu, W. 2010 *Yearbook of China Water Resources*. China Water & Power Press, Beijing, China (in Chinese).

Wu, B., Li, T. & Zhou, T. 2010 Relative contributions of the Indian Ocean and local SST anomalies to the maintenance of the Western North Pacific Anomalous Anticyclone during the El Niño decaying summer. *J. Clim.* **23**, 2974–2986.

Xiong, L., Jiang, C. & Du, T. 2014 Statistical attribution analysis of the nonstationarity of the annual runoff series of the Weihe River. *Water Sci. Technol.* **70** (5), 939–946.

Yang, T. 2009 *Statistical Yearbook of Shaanxi Province*. China Statistics Press, Beijing, China (in Chinese).

Yu, K.-X., Xiong, L. & Gottschalk, L. 2014 Derivation of low flow distribution functions using copulas. *J. Hydrol.* **508**, 273–288.

Zhang, X., Zhang, L., Zhao, J., Rustomji, P. & Hairsine, P. 2008 Responses of streamflow to changes in climate and land use/cover in the Loess Plateau, China. *Water Resour. Res.* **44**, W00A07.

Zhang, Q., Xu, C.-Y., Chen, X. & Zhang, Z. 2011 Statistical behaviours of precipitation regimes in China and their links with atmospheric circulation 1960–2005. *Int. J. Climatol.* **31**, 1665–1678.

Zhu, Y., Wang, H., Zhou, W. & Ma, J. 2011 Recent changes in the summer precipitation pattern in East China and the background circulation. *Clim. Dyn.* **36**, 1463–1473.

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