Joint pattern of seasonal hydrological droughts and floods alternation in China's Huai River Basin using the multivariate L-moments

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Under the current condition of climate change, droughts and floods occur more frequently, and events in which flooding occurs after a prolonged drought or a drought occurs after an extreme flood may have a more severe impact on natural systems and human lives. This challenges the traditional approach wherein droughts and floods are considered separately, which may largely underestimate the risk of the disasters. In our study, the sudden alternation of droughts and flood events (ADFEs) between adjacent seasons is studied using the multivariate L-moments theory and the bivariate copula functions in the Huai River Basin (HRB) of China with monthly streamflow data at 32 hydrological stations from 1956 to 2012. The dry and wet conditions are characterized by the standardized streamflow index (SSI) at a 3-month time scale. The results show that: (1) The summer streamflow makes the largest contribution to the annual streamflow, followed by the autumn streamflow and spring streamflow. (2) The entire study area can be divided into five homogeneous sub-regions using the multivariate regional homogeneity test. The generalized logistic distribution (GLO) and log-normal distribution (LN3) are acceptable to be the optimal marginal distributions under most conditions, and the Frank copula is more appropriate for spring-summer and summer-autumn SSI series. Continuous flood events dominate at most sites both in spring-summer and summer-autumn (with an average frequency of 13.78% and 17.06%, respectively), while continuous drought events come second (with an average frequency of 11.27% and 13.79%, respectively). Moreover, seasonal ADFEs most probably occurred near the mainstream of HRB, and drought and flood events are more likely to occur in summer-autumn than in spring-summer.

Keywords. Alternation of droughts and floods (ADFEs); standardized streamflow index (SSI); regional frequency analysis; multivariate L-moments; copula functions; Huai River Basin (HRB).

1. Introduction

A changing climate is intimately linked to changes in the hydrological cycle (Huang *et al.* 2015). There is a consensus that global warming will change

the spatial and temporal patterns of precipitation and thereby result in changes in local dry and wet conditions (Huang *et al.* 2015; She *et al.* 2016a). Particularly, changes in hydrological and meteorological extreme events (e.g., droughts and

floods) may be more significant than changes in the mean conditions (Guhathakurta *et al.* 2011; Su *et al.* 2011; Ivett *et al.* 2013). During the past few decades, droughts and floods have become more intense and frequent, creating widespread concern (Dai *et al.* 1998; Parry *et al.* 2007) and causing huge economic losses. For example, the flooding disasters that have largely affected China have resulted in the economic losses of approximately 100 billion Chinese Yuan every year from 2000 to 2010. Moreover, extreme drought events also occurred more frequently and with longer duration and greater severity. For example, the extreme droughts during December 2009 and April 2010 that occurred in five provinces of southwestern China caused decreased crop production and a serious scarcity of drinking water (Ji *et al.* 2015), and according to the Office of State Flood Control and Drought Relief Headquarters of China, they caused an economic loss of more than 20 billion Chinese Yuan.

The spatio-temporal variability of flood and drought events have attached much attention around the world, as it is of great significance to disaster prevention and regional water resources planning and management (Grimaldi and Serinaldi 2006; Serinaldi *et al.* 2009; Burke and Brown 2010). For example, Shahid (2008) analyzed the spatial and temporal changes of droughts in western Bangladesh; Santos *et al.* (2010) studied the droughts in mainland Portugal; Reihan *et al.* (2012) investigated both the frequency and variation of extreme floods in Baltic States. However, most of the previous studies analyzed droughts and floods separately, and the sudden alternation from drought-to-flood or flood-to-drought event is less studied. In the context of global warming, the prolonged droughts, floods, and alternation of droughts and floods ADFEs between nearby seasons are happening more frequently (Wu *et al.* 2006; Mu *et al.* 2014), which will have tremendous negative effects on industrial and agricultural production, as well as surface water environments (Hrdinka *et al.* 2012; Whitworth *et al.* 2012), ecosystems (Reichstein *et al.* 2002; Zeng *et al.* 2005), economy, food security and human health (Devereux 2007; Bond *et al.* 2008; Pederson *et al.* 2009; Leigh *et al.* 2014). Particularly, the ADFEs, which are characterized by a sudden alternation between floods and droughts, can result in much more serious damage than a separate drought or flood disaster (Wu *et al.* 2006), always with multi-dimensional and multi-level characteristics of adverse impacts (Huang *et al.* 2014). The ADFEs

can be observed in many regions around the world, especially in the Huai River Basin (HRB) and the Yangtze River Basin of China. Due to climate change and fast urbanization in these two areas, the ADFEs have occurred more frequently in recent years (Li and Ye 2015). Hence, separate consideration of droughts and floods cannot fully capture the characteristic changes between droughts and floods and may largely underestimate the hazard risks, which is unbecoming of the hazard management. Therefore, it is crucial to investigate the joint change pattern of continuous dry (wet) conditions and ADFEs between nearby seasons (Huang *et al.* 2014).

Recently, ADFEs have been investigated at different time scales in studies on the single-site estimations. Huang *et al.* (2014) investigated the at-site joint probabilistic characterization of the combination of dry and wet conditions in the Guanzhong Plain of China. However, these previous studies, which were based on single-site estimations of frequency or probability at gauged basins, may not satisfy the requirement on a regional scale. In this way, the regional frequency analysis, which fits distribution and estimates frequency or return period in an entire region, has been proved to be an appropriate approach (She *et al.* 2014).

Many techniques have been proposed to address the regionalization of hydrological variables (Mu *et al.* 2014; She *et al.* 2014), the most widely used method is the univariate L-moments method proposed by Hosking and Wallis (1993, 1997). This method can only identify a homogeneous region by taking only a single variable into consideration, which is insufficient for fully representing multiple hydrological event phenomena, such as the seasonal continuous droughts, continuous floods and ADFEs that are considered in our study. To overcome this limitation, Chebana and Ouarda (2007) further developed the multivariate case using multivariate L-moments and copula functions, which can construct an extended multivariate regional frequency analysis by identifying a homogeneous region based on all the variables considered jointly (Serfling and Xiao 2007).

In this study, we used multivariable L-moments technique to examine the seasonal drought and flood events between nearby seasons in the HRB from 1956 to 2012. HRB is an important agricultural, industrial and commercial region that encompasses one of the fastest growing economic regions in China. However, because it located in the transition zone between the northern and southern

climates in China, this region is also very vulnerable to extreme hydro-meteorological events, and has been affected by severe drought and flood hazards since historical times (Ye *et al.* 2014). In fact, there were 63 extreme floods and 46 extreme droughts recorded in the HRB between 1470 and 2010 (He *et al.* 2015). Thus, it is important to investigate the changing patterns of droughts and floods in this area to guarantee the security of agricultural production and socio-economic development. The hydrological droughts and floods are represented by the standardized streamflow index (SSI) (Vicente-Serrano *et al.* 2014), which is a widely used index for characterizing the hydrological dry and wet conditions.

The major objectives of this study are: (1) to identify the seasonal drought and flood events in space and time in the HRB based on the SSI; (2) to divide the entire HRB into several homogeneous sub-regions using the multivariate L-moments method, which is appropriate for a multivariate regional frequency analysis; and (3) to investigate the joint probabilities of seasonal continuous hydrological droughts, continuous floods and ADFEs by regional frequency methods via multivariate L-moments method.

This study is organized as follows: the methods are described in section 2, a brief introduction to the study area and data description are presented in section 3; section 4 gives the results, and conclusions and discussions follow in section 5.

2. Methodology

2.1 Calculation of the seasonal standardized streamflow index (SSI)

The SSI, principally proposed by Vicente-Serrano *et al.* (2014), is defined as the unit standard normal deviation associated with the percentile of hydrologic streamflow accumulated over a specific duration. The computation of SSI is similar to the standardized precipitation index (SPI) (McKee *et al.* 1993), and contains two steps: (1) choose a suitable probability distribution function (PDF) to fit the aggregated streamflow data over the time scale of interest (e.g., 1, 3, 6, 12, 24 months); (2) obtain the SSI value by inverse normal function, with a mean of zero and a standard deviation of one, of the above cumulative probability functions. In this study, the SSI at the time scale of 3 months is considered, as it is appropriate for capturing the seasonal dry/wet conditions.

The details of the computation of SSI have been previously reported (Vicente-Serrano *et al.* 2014). The classification of SSI is analogous to that of SPI. According to National Standard of the People's Republic of China, the classification of meteorological drought (using SPI) posits: the near normal condition as $(-0.49 \leq \text{SPI} \leq 0.49)$. In the current study, the threshold of the droughts/floods condition is set to 0.49: drought ($\text{SSI} < -0.49$), near normal ($-0.49 \leq \text{SSI} \leq 0.49$) and flood ($\text{SSI} > 0.49$).

2.2 Copula distribution functions

In this paper, the structure and joint distribution of drought and flood variables are simulated with copula theory. Copula is a multivariate distribution function that links joint probability to their corresponding one-dimensional marginal distributions. According to Sklar (1973), in terms of the bivariate case, if H is a bivariate distribution function of two correlated random variables of X and Y , each with a marginal distribution functions F and G , then there exists a copula C such that

$$H(x, y) = C(F(x), G(y)). \quad (1)$$

If F and G are continuous, then the copula C is unique and has the representation:

$$C = H(F^{-1}(x), G^{-1}(y)) \quad (2)$$

where F^{-1} and G^{-1} are the inverse functions of F and G .

Conversely, for any univariate marginal distribution function, F and G , and any copula, the function H defined above is a two-dimensional distribution function with marginal functions F and G . A more detailed treatment of copulas and their properties can be found in Joe (1997) and Nelson (2006).

Copulas can be classified into several families and Archimedean copulas are of particular interests in hydrology. In this study, the Gumbel, Clayton and Frank copula from the Archimedean family are employed to model joint dependence of droughts and floods variables. The expressions for PDF and associated parameter space of bivariate copulas are presented in table 1.

2.3 Multivariate L-moments

The multivariate L-moments were developed by Serfling and Xiao (2007) based on the traditional univariate L-moments (Hosking and Wallis 1993,

Table 1. Expression of PDF, associated parameter and parameter range of applied copulas.

Copulas	$C(u, v)$	Parameter space
Gumbel	$\exp\{ -[(-\ln u)^\theta + (-\ln v)^\theta]^{1/\theta} \}$	$[1, \infty)$
Clayton	$(u^{-\theta} + v^{-\theta} - 1)^{-1/\theta}$	$(0, \infty)$
Frank	$-\frac{1}{\theta} \ln[1 + (e^{-\theta} - 1)^{-1}(e^{-\theta u} - 1)(e^{-\theta v} - 1)]$	$(-\infty, 0) \cup (0, \infty)$

1997). Here, we briefly give the definition and computation of bivariate L-moments method. More detailed information is presented in Serfling and Xiao (2007). In this study, computations were conducted with the MATLAB program provided by Chebana *et al.* (2009) and the R software package ‘lmomco’ by Asquith (2015).

Let $X^{(j)}$ be a random variable with distribution F_j , for $j = 1, 2$. Then, the multivariate L-moments are matrices $\Lambda_k (k \geq 1)$ with elements defined by:

$$\lambda_{k[ij]} = \text{Cov} \left(X^{(i)}, P_{k-1}^* \left(F_j \left(X^{(j)} \right) \right) \right), \quad i, j = 1, 2 \text{ and } k = 2, 3, \dots \quad (3)$$

where P_k^* is the so-called shifted Legendre polynomial. Then the L-moment coefficients are given by

$$\tau_{k[12]} = \lambda_{k[12]} / \lambda_2^{(1)}, \quad \text{for } k \geq 3$$

and

$$\tau_{2[12]} = \lambda_{2[12]} / \lambda_1^{(1)} \quad (4)$$

where $\lambda_k^{(j)} = \lambda_{k[jj]}$ is the classical k th L-moment of the variable $X^{(j)}$, $j = 1, 2$ as defined by Hosking and Wallis (1993, 1997). Then, the matrix of the L-moment coefficients can be written as:

$$\Lambda_k = (\tau_{k[ij]})_{i,j=1,2} = \begin{pmatrix} \tau_{k[11]} & \tau_{k[12]} \\ \tau_{k[21]} & \tau_{k[22]} \end{pmatrix}, \quad k = 2, 3, \dots \quad (5)$$

and for $k = 1$, the first order bivariate L-moment corresponds to the vector $\lambda_1 = E(X^{(1)}, X^{(2)})^t$.

2.4 Discordance test

The discordance test is useful for determining in advance whether the stations in a divided region are conspicuously discordant with the entire group (She *et al.* 2016b). Hosking and Wallis (1993) give the definition of discordancy of sites on the basis of L-moments, and Chebana and Ouarda (2007) extended it to the multivariate case.

Considering a matrix $U_i = (\Lambda_2^i, \Lambda_3^i, \Lambda_4^i)^t$ for each site i , that contains three matrices $\Lambda_2^i, \Lambda_3^i, \Lambda_4^i$

defined in equation (5). Then the following matrix D_i is defined as:

$$D_i = (U_i - \bar{U})^t S^{-1} (U_i - \bar{U}) / 3 \quad (6)$$

where $\bar{U} = \sum_{i=1}^N U_i / N$, $S = \sum_{i=1}^N (U_i - \bar{U})(U_i - \bar{U})^t / (N - 1)$. In order to evaluate the discordancy of site i , it is possible to use the norm of the matrix. In this study, we employed the spectral norm $\|A\|_2$ to quantify the variability, Chebana and Ouarda (2007) suggested the constant $c = \chi_{1-0.05}(3) / 3 = 2.60$ as a critical value for $\|D_i\|$ considered for large regions.

2.5 Homogeneity test

The bivariate heterogeneity statistic $H_{\|\bullet\|}$, which measures a set of sites, is calculated as follows (Chebana and Ouarda 2007):

$$H_{\|\bullet\|} = \frac{V_{\|\bullet\|} - \mu_{V_{\text{sim}}}}{\sigma_{V_{\text{sim}}}} \quad (7)$$

where $\|\bullet\|$ is the spectral norm, $V_{\|\bullet\|} = \sqrt{\sum_{i=1}^N n_i \|A_2^i - \Lambda_2^R\|^2 / \sum_{i=1}^N n_i}$, and A_2^i is the L-covariance matrix for site i with a record length n_i , $i = 1, 2, \dots, N$, $\Lambda_2^R = \sum_{i=1}^N n_i \Lambda_2^i / \sum_{i=1}^N n_i$. $\mu_{V_{\text{sim}}}$ and $\sigma_{V_{\text{sim}}}$ are the mean and standard deviation of the N_{sim} value of $V_{\|\bullet\|}$ in the simulated regions, respectively.

The simulated regions are homogeneous with sites having the same record length as their observed counterparts. To avoid any subjective choice of the bivariate distribution with which simulations are carried out to compute $\mu_{V_{\text{sim}}}$ and $\sigma_{V_{\text{sim}}}$, this bivariate distribution should be as general as possible and include most distributions commonly used in hydrology. Chebana and Ouarda (2007) suggested using the Gumbel–Hougaard (Gumbel) bivariate copula to produce the joint distribution and the Kappa distribution to simulate the marginal distributions. For this occasion, 1000 simulations were performed to validate the result (Hosking and Wallis 1993, 1997). In the present

study, a region of sites was declared to be homogeneous if $H_{||\bullet||} < 1$, acceptably homogeneous if $1 < H_{||\bullet||} \leq 2$ and definitely heterogenous if $H_{||\bullet||} > 2$.

2.6 Copula estimation for homogeneity regions and the regional risk assessment of the ADFEs

In this study, the regional marginal distributions were fitted the traditional univariate L-moments method proposed by Hosking and Wallis (1993, 1997), meanwhile, and the bivariate copula functions for a homogeneous region were fitted using observations from all sites in the region. As the streamflow records in a single site are not large enough, this method can improve the reliability of statistical estimates.

Let D and F denote the variables of droughts and floods, respectively. From the definition of SSI, the value of 0.49 and -0.49 is the truncation level for the flood and drought, respectively. Then the following four joint probabilities of seasonal drought and flood events are considered in this study (Huang et al. 2014):

- (1) Continuous droughts in spring-summer/summer-autumn (DD):

$$P_{DD} = P(X < -0.49, Y < -0.49);$$

- (2) Continuous floods in spring-summer/summer-autumn (FF):

$$P_{FF} = P(X > 0.49, Y > 0.49);$$

- (3) Spring droughts and summer floods/summer droughts and autumn floods (DF):

$$P_{DF} = P(X < -0.49, Y > 0.49);$$

- (4) Spring floods and summer droughts/summer floods and autumn droughts (FD):

$$P_{FD} = P(X > 0.49, Y < -0.49).$$

3. Study area and materials

HRB is located in the eastern China between the Yangtze River Basin and the Yellow River Basin covering a total of approximately 270,000 km² (Wu et al. 2017). The long-term average annual precipitation in the basin is approximately 880 mm, with more than 50% occurring during the flooding

Figure 1. Location of HRB and the hydrological stations used in the study area.

Table 2. Some detailed information of the hydrological stations in the study area.

#	Name	Long. (°E)	Lat. (°S)	Ele (m)	Area (km ²)	MAP (mm)	MASF (10 ⁶ m ³)	RL (a)
1	Dapoling	113.75	32.42	104	1640	993	601	57
2	Xixian	114.73	32.33	43	10190	993	3651	57
3	Huaibin	115.42	32.43	34	16005	951	5444	55
4	Wangjiaba	115.60	32.43	28	30630	998	9037	57
5	Lutaizi	116.63	32.57	21	88630	949	21387	55
6	Bengbu	117.38	32.93	26	121330	976	26372	57
7	Nanwan	114.00	32.12	98	1090	1147	430	53
8	Suiping	113.97	33.13	68	1760	915	529	55
9	Suyahu	114.30	33.03	56	4715	933	1156	53
10	Boshan	113.95	32.65	143	578	930	155	55
11	Miaowan	114.68	33.08	44	2660	892	603	55
12	Bantai	115.07	32.72	36	11280	951	2607	57
13	Meishan	115.88	31.68	215	1970	1394	1375	45
14	Jiangjiaji	115.73	32.30	30	5930	1093	2034	55
15	Dachen	113.57	33.82	80	5550	755	770	55
16	Baiguishan	113.23	33.70	96	2730	747	528	57
17	Luohe	114.03	33.58	63	12150	775	2116	57
18	Gushitan	113.10	33.50	165	286	977	78	48
19	Baisha	113.25	34.33	207	962	686	56	57
20	Zhoukou	114.65	33.63	51	25800	782	3121	57
21	Shenqiu	115.12	33.17	40	3094	889	585	49
22	Fugou	114.40	34.07	58	5710	722	547	57
23	Fuyang	115.83	32.90	28	35246	915	4452	51
24	Bailianya	116.17	31.27	242	747	1413	596	54
25	Hengpaitou	116.37	31.60	55	4370	1251	3372	57
26	Boxian	115.78	33.88	38	10573	801	768	45
27	Mengcheng	116.55	33.28	30	15475	873	1320	45
28	Guzhen	116.32	32.02	27	4541	867	865	45
29	Mingguang	117.98	32.78	33	3501	989	662	57
30	Zhaopingtai	112.77	33.72	178	1416	854	478	57
31	Nianyushan	115.37	31.73	101	924	1245	559	30
32	Xianghongdian	116.15	31.55	271	1430	1412	1074	45

Note. MAP: mean annual precipitation, MASF: mean annual streamflow, and RL: record lengths of precipitation and streamflow.

season (June–September)(Liu *et al.* 2016). The HRB is located in the north-south climate transitional zone in China, with the southern HRB belonging to the subtropical zone and the northern area belonging to the warm temperate zone. The annual precipitation exhibits a large decadal variability. The maximum and minimum annual precipitation differ by four to five-fold in some regions. Annual precipitation is more than 1400 mm in the southern mountainous region, compared to 1000–1200 mm in the western mountainous region and 600–700 mm in the northern region. Droughts and floods occur frequently in this basin, and largely influence the natural systems and human lives (She *et al.* 2016a).

The HRB contains two water systems, i.e., the Huai River system and the Yi-Shu-Si River system.

In our study, special consideration is given to the area above the Zhongdu hydrological station on the upper-middle reach region. The monthly streamflow data at 32 hydrological stations from 1956 to 2012 in this region (figure 1) are provided by the Bureau of Hydrology of HRC, and some detailed information is presented in table 2.

4. Results

4.1 Intra-annual distribution of streamflow

Figure 2 shows the intra-annual distribution of streamflow at each hydrological station in our study area. The summer streamflow (June–August) makes the largest contribution to the annual streamflow, with a proportional contribution

Figure 2. Intra-annual distribution of streamflow in each station.

ranging from 36.65 to 62.09% (with an average of more than 51%) The autumn (September–November) streamflow and spring (March–May) streamflow contribute approximately 22 and 18% to the annual streamflow. Finally, winter (December–February) streamflow contribute <8% to the annual streamflow, the smallest among the four seasons. The intra-year distribution of the streamflow is similar to the distribution of precipitation in the HRB, which can be seen in [He et al. \(2015\)](#). Considering that winter streamflow is almost always the smallest streamflow in any given year, our attention will mainly be focused on the droughts and floods during the remaining three seasons.

The SSI at a 3-month scale are calculated for each station in the HRB according to their definition. Here, the Pearson type III distribution was selected to fit the monthly streamflow time series as it is widely used and quite suitable for streamflow simulations in China ([Hong et al. 2015](#)). The spring, summer and autumn SSIs are characterized by the SSI values in May, August and November, respectively. Figure 3 shows the variations of the

SSI time series at three random stations, Nos. 6, 20 and 28, in the mainstream, the north part of Henan province and the south part of Anhui province, respectively. From figure 3, we can observe distinct seasonal continuous drought events, continuous flood events and ADFEs at all stations.

A continuous drought event can be observed to stretch over spring, summer and autumn in 1994 at the three stations, which was also reported in [Zhang \(2008\)](#). An obvious continuous flood event can be found in No. 6 station in 2003, which is consistent with the results in [Liu \(2012\)](#). According to the Bureau of Hydrology of HRB, the rainfall in 2003 was extremely abundant, and the anomalously high precipitation during the spring of 2003, as well as the southward-shifted subtropical anticyclone in July 2003, directly caused extreme floods throughout the HRB. Finally, a typical ADFE can be observed between spring and summer in 1982 in station No. 20. In April 1982, Henan province underwent a spring drought with high temperature and little precipitation across the entire province. This drought continued to mid-July, and ultimately

Figure 3. SSI time series of three random stations.

led to thorough desiccation of many rivers and weirs in Henan province. After July 12, three consecutive heavy storms struck Henan province, and this caused sudden flood events in the region. Moreover, a similar but even more severe ADFE between spring and summer also occurred in 2000 at the same station, which was caused by the strengthened pattern of the winter El Nino in the equatorial east Pacific (Bu and Jia 2004).

4.2 Regionalization of SSI series based on the multivariate L-moments

The homogeneous regions were initially divided into five sub-regions by the fuzzy c-means cluster method with six indicators, including longitude, latitude, elevation, drainage area, mean annual precipitation and mean annual streamflow (table 2). Then, both the univariate and multivariate discordancy tests were performed in all of the above five regions using the seasonal SSI time series obtained in section 4.1. Some subjective adjustments were also used to make the division more appropriate and guarantee the homogeneity of the sub-regions. The final identified regions are given in tables 3 and 4. Notably, the station No. 32 could not be grouped into any of the above sub-regions, therefore, it was excluded from the following analysis.

As shown in table 3, both the univariate and bivariate discordancy value of each site in each sub-region were less than the related critical value. Both the univariate homogeneity statistics described in Hosking and Wallis (1993, 1997) and the bivariate homogeneity statistics described in section 2.5 illustrated in table 4 were <1 , the above results indicated that all the identified sub-regions were statistically corroborated to be homogeneous.

4.3 Choice of optimal regional frequency distribution

After identifying the homogeneity of the obtained sub-regions, we should choose the optimal regional distributions of both the marginal and bivariate joint distributions. An appropriate marginal distribution should be selected first in each homogeneous sub-region. In this study, three statistical probability distributions with two parameters (exponential (EXP), Gumbel (GUM) and normal (NORM)), and five statistical probability distributions with three parameters (Pearson type III (P-III), log-normal (LN3), generalized Pareto distribution (GPA), generalized logistic distribution (GLO) and generalized extreme value distribution (GEV)), were selected as the candidate distributions to fit the spring, summer and autumn SSI time series in all homogeneous sub-regions.

Table 3. Results of regional discordancy D for the seasonal SSI in each sub-region.

Region	Site no.	Univariate statistics			Bivariate statistics	
		D5	D8	D11	D5, 8	D8, 11
I (1.65)	1	1.36	0.97	1.49	0.99	1.22
	2	0.93	1.39	0.23	0.99	1.16
	3	0.11	0.88	0.27	0.87	1.13
	4	0.57	0.93	1.62	1.19	1.38
	5	1.63	0.59	0.78	1.31	0.93
	6	1.4	1.23	1.61	1.16	0.98
II (1.92)	7	1.28	1.33	1.66	1.19	1.45
	8	1.12	0.19	1.01	1.01	1.3
	14	0.54	0.57	0.76	0.88	1.68
	15	0.67	1.42	0.99	1.43	1.17
	16	1.13	1.01	1.78	1.28	1.55
	17	0.64	1.08	0.24	0.98	0.76
	20	1.62	1.38	0.57	1.1	1.33
III (2.14)	9	0.32	1.3	1.96	1	1.65
	11	1.28	0.42	1	0.87	0.73
	18	0.59	0.41	1.04	1.21	1.19
	21	0.54	1.14	0.35	1.08	0.22
	22	1.85	1.02	1.95	1.77	1.57
	24	0.92	1.73	0.7	1.72	1.87
	25	1.24	0.79	0.21	1.29	0.98
	26	1.27	1.19	0.8	1.14	1.84
IV (1.33)	10	1.08	1.28	1.25	1.04	0.98
	12	1.22	1.15	1.31	0.83	1.07
	13	1.08	0.71	0.86	0.93	0.82
	30	1.24	1.01	1.33	1.02	1.03
	31	0.38	0.86	0.25	0.87	0.98
V (1.33)	19	1.25	0.19	1.22	0.64	1.06
	23	1.33	1.21	1.21	1.06	0.92
	27	1.13	1.32	0.7	0.98	0.63
	28	1.16	1.26	1.32	1.02	1.07
	29	0.13	1.02	0.56	1.04	1.04

Note: Numbers 5, 8 and 11 represent spring, summer and autumn, respectively; the univariate discordancy critical values are displayed in parenthesis while the bivariate discordancy critical values are all 2.60.

Table 4. Results of regional heterogeneity H for the seasonal SSI in each sub-region.

Region	Univariate statistics			Bivariate statistics	
	H5	H8	H11	H5, 8	H8, 11
I	0.018	-0.149	0.249	0.04	0.008
II	-0.084	0.007	0.015	0.236	0.002
III	0.520	-0.056	0.117	0.009	0.126
IV	0.224	0.104	-0.122	0.107	0.271
V	0.039	-0.023	-0.032	-0.056	-0.032

Selection of an optimal distribution is considered to be an important procedure in the regional frequency analysis. In the present study, both the

Hosking and Wallis (1993, 1997) statistic Z_{DIST} and the L-kurtosis criterion L-K developed by Pandey *et al.* (2001) were considered and the

Table 5. Results of goodness-of-fit test for the candidate distributions in different regions and different seasons.

Season	Region	Acceptable distributions in ascending order ($ Z_{DIST} \leq 1.64$)	Best distribution ($\min Z $)	Min(L-K)	Selected DIST
Spring	I	LN3, GLO	LN3 (0.904)	0.0163	LN3
	II	GLO	GLO (0.665)	0.0126	GLO
	III	LN3, NORM	LN3 (0.802)	0.0126	LN3
	IV	GLO, P-III, NORM	GLO (0.925)	0.0209	GLO
	V	GLO, LN3, NORM	GLO (0.741)	0.0174	GLO
Summer	I	*	GEV (2.510)	0.0374	GEV
	II	GLO, LN3, NORM	GLO (0.960)	0.0185	GLO
	III	GLO	GLO (0.654)	0.0118	GLO
	IV	LN3, NORM, GEV, GLO	LN3 (0.167)	0.0035	LN3
	V	GLO, NORM, LN3	GLO (0.904)	0.0205	NORM
Autumn	I	GLO	GLO (0.569)	0.0114	GLO
	II	GLO	GLO (1.329)	0.0248	GLO
	III	GLO	GLO (0.371)	0.0071	GLO
	IV	LN3, GEV, GLO	LN3 (0.359)	0.0074	LN3
	V	LN3, NORM, GLO, GEV	LN3 (0.589)	0.0121	LN3

Note: * represents that there is no distribution with the statistics $|Z_{DIST}| < 1.64$.

results of the goodness-of-fit test were presented in table 5. According to Hosking and Wallis (1993, 1997), the fit of a candidate statistical probability distribution can be treated as the true underlying frequency distribution if the absolute value of goodness-of-fit measure of Z_{DIST} statistic is no more than 1.64, corresponding to a confidence level of 90%, under the hypothesis that the sites in the region are independent with each other; if serial dependence exists in the dataset, the statistic Z_{DIST} could be overestimated, if more than one statistical probability distribution satisfies the measure of $|Z_{DIST}| \leq 1.64$, then the one with the smallest $|Z_{DIST}|$ should be chosen as the optimal distribution. Meanwhile, according to Pandey *et al.* (2001), the optimal distribution should be the one who has the smallest L-K statistic.

From table 5, we can find that two or more candidate distributions ($|Z_{DIST}| \leq 1.64$) could fit the SSI series in each season very well, but the best fit distribution is the one with the smallest $|Z_{DIST}|$, and will ultimately be adopted. Therefore, such procedure indicates that it is a very important step to undertake thorough distribution selection processes rather than only subjectively fit one single distribution for all SSI series so as to reduce the uncertainty originated from the choice of the 'best-fit' distribution for the considered SSI series (She *et al.* 2016b).

In particular, GLO and LN3 perform very well in fitting the regional SSI series in the study region. GLO is found to be acceptable 13 times over all five homogeneous regions from spring to autumn, while LN3, NORM, GEV and P-III are acceptable 8, 7, 3 and 1 times, respectively. GPA, EXP and GAM, are not acceptable for any of the circumstances because the absolute value of Z_{DIST} statistic are more than 1.64. None of the candidate distributions should be employed as the regional distribution of summer SSI series in Region I; however, if there exists serial dependence in the datasets, the statistic Z_{DIST} will often be overestimated (Hosking and Wallis 1993, 1997). Furthermore, the results from the L-K statistic are basically consistent with those from the $|Z_{DIST}|$ statistics measure except for the summer SSI series in Region V, where the best fit distribution is GLO and NORM suggested by the $|Z_{DIST}|$ statistic and L-K statistics, respectively. However, because GLO is widely accepted under most occasions in our study area, we finally chose this distribution to fit the summer SSI series in Region V.

Then, the parameters of the optimal distributions are estimated for each site using the L-moments method, which is shown in table 6. The K-S test shows that all the distributions are acceptable under the significance level of 0.05.

Table 6. Parameter (para.) estimates of the optimal distribution and the corresponding $K-S$ statistic (stat.) p -value for SSI series in spring, summer and autumn in each station.

Region	Site	Spring			Summer			Autumn		
		LN3			GEV			GLO		
	Para./Stat.	Location	Scale	Shape	P-value	Location	Scale	Shape	P-value	P-value
I	1	0.0356	1.0161	0.0832	0.5001	-0.3601	0.8959	0.1677	0.9716	0.7669
	2	0.0356	0.9997	0.0628	0.9818	-0.3552	0.9228	0.1991	0.9467	0.9817
	3	0.0303	0.9863	0.0345	0.9959	-0.3577	0.9292	0.2023	0.8844	0.9882
	4	0.0194	0.9845	0.0164	0.9926	-0.3599	0.8958	0.1676	0.9260	0.9978
	5	0.0283	1.0112	0.0582	0.9767	-0.3511	0.9562	0.2388	0.9909	0.8367
	6	0.0018	0.9737	-0.0387	0.9984	-0.3523	0.9618	0.2423	0.9700	0.9717
II		GLO				GLO				
	Para./Stat.	Location	Scale	Shape	P-value	Location	Scale	Shape	P-value	P-value
	7	0.0276	0.5446	0.01	0.8741	-0.0062	0.5680	-0.0094	0.378	0.8765
	8	0.0413	0.5753	0.0582	0.9439	0.0140	0.5674	0.0078	0.6428	0.2538
	14	0.0199	0.5572	-0.0006	0.9628	0.0088	0.5594	-0.0095	0.9731	0.9041
	15	0.0750	0.6014	0.1282	0.4600	0.0262	0.5796	0.0316	0.9708	0.6252
III	16	0.0759	0.5395	0.0046	0.6292	0.0919	0.5317	0.0095	0.9929	0.9194
	17	0.1061	0.5755	0.1322	0.8607	0.0058	0.5550	-0.0157	0.6286	0.8546
	20	0.1291	0.5565	0.1192	0.5660	0.0200	0.5727	0.0159	0.9783	0.5748
		LN3				GLO				
	Para./Stat.	Location	Scale	Shape	P-value	Location	Scale	Shape	P-value	P-value
	9	0.0514	0.9566	-0.0435	0.9256	0.0045	0.5356	-0.0568	0.8316	0.8648
	11	0.0744	1.0511	0.1951	0.6828	-0.0169	0.5361	-0.0614	0.8967	0.6659
	18	0.1904	0.8601	-0.0704	0.9466	0.1032	0.5067	-0.0306	0.9259	0.3771
	21	0.0142	0.9903	0.0030	0.9194	0.0352	0.5275	-0.0454	0.9358	0.9876
	22	0.0244	1.0096	0.0513	0.7300	0.0747	0.5857	0.1103	0.5332	0.4349
	24	0.0097	1.0075	0.0143	0.9965	0.0342	0.5779	0.0474	0.8687	0.9312
	25	0.0150	0.9434	-0.0717	0.8788	0.0532	0.5773	0.0870	0.4892	0.8857
	26	-0.0292	0.8930	-0.2174	0.9577	0.0299	0.5603	0.0124	0.6257	0.6235

Table 7. Results of the copula parameters and goodness-of-fit test of regional joint distribution.

Copulas	Region I		Region II		Region III		Region IV		Region V	
	Para.	p-val.	Para.	p-val.	Para.	p-val.	Para.	p-val.	Para.	p-val.
Spring-summer										
Gumbel	1.213	0.455	1.234	0.023	1.199	0.238	1.224	0.013	1.172	0.165
Clayton	0.426	0.499	0.467	0.019	0.398	0.292	0.447	0.005	0.345	0.158
Frank	1.620	0.487	1.755	0.024	1.529	0.340	1.690	0.013	1.347	0.155
Summer-autumn										
Gumbel	1.691	0.519	1.379	0.025	1.489	0.038	1.374	0.237	1.353	0.261
Clayton	1.382	0.612	0.757	0.025	0.977	0.055	0.748	0.280	0.706	0.343
Frank	4.282	0.612	2.635	0.028	3.244	0.067	2.610	0.283	2.486	0.345

Table 8. Frank copula parameter (para.) and the results of joint probability (percentage, %) of ADFE in each station.

Region	Site	Spring-summer						Summer-autumn					
		Para.	DD	FF	DF	FD	ADFE	Para.	DD	FF	DF	FD	ADFE
I	1	1.5776	13.30	13.36	5.90	6.73	39.29	2.4174	14.21	14.64	4.86	4.04	37.75
	2	1.9427	13.96	14.32	5.29	5.97	39.53	3.9806	17.39	17.42	2.63	2.36	39.80
	3	1.1432	12.12	12.40	6.77	7.54	38.83	3.9089	17.36	17.43	2.76	2.45	40.00
	4	1.8172	13.71	13.58	5.40	6.05	38.75	4.7080	18.47	18.59	2.04	1.68	40.79
	5	1.4736	13.09	13.47	6.39	6.88	39.84	5.7181	20.05	20.01	1.26	1.20	42.52
	6	1.7610	13.70	13.71	5.82	6.04	39.27	5.6461	19.15	20.13	1.34	1.11	41.74
II	7	2.0547	12.71	13.32	4.43	4.88	35.33	0.4727	8.64	10.55	8.51	6.68	34.37
	8	1.8380	12.39	13.50	5.09	5.36	36.35	3.0674	14.31	16.58	3.71	3.09	37.68
	14	1.3838	11.25	12.05	5.75	5.91	34.96	2.4481	13.59	14.63	4.29	4.09	36.60
	15	1.3173	11.43	13.17	6.24	6.75	37.58	3.3947	15.22	17.29	3.24	2.90	38.65
	16	1.3353	9.03	13.32	5.70	5.42	33.48	2.6277	10.25	15.58	3.22	3.11	32.16
	17	2.1485	12.38	14.76	4.20	5.21	36.55	3.1104	14.37	16.36	3.57	2.99	37.29
	20	2.2279	12.08	15.48	3.95	5.26	36.77	3.6024	15.30	17.93	3.12	2.55	38.90
III	9	0.9037	9.79	11.57	6.45	7.14	34.96	3.8615	15.39	17.65	2.57	2.21	37.82
	11	2.2175	13.58	14.73	4.46	5.22	37.99	4.0776	16.84	17.63	2.47	2.15	39.09
	18	1.2833	6.81	14.92	4.50	5.99	32.22	1.7197	5.80	16.45	5.46	2.81	30.53
	21	1.1040	10.43	12.00	6.82	6.15	35.40	5.6034	15.67	20.53	1.12	0.86	38.18
	22	1.5708	12.24	14.11	6.52	5.91	38.78	3.2767	14.08	18.16	3.41	3.03	38.69
	24	0.6708	10.55	11.34	8.10	7.75	37.75	1.7600	12.34	12.92	5.07	5.49	35.82
	25	0.9794	10.54	12.02	7.08	6.88	36.52	1.3268	11.26	12.31	5.87	6.37	35.81
	26	4.3472	16.74	17.60	2.04	1.81	38.19	7.0536	18.52	23.46	0.82	0.49	43.29
IV	10	1.5602	12.21	13.51	6.10	5.99	37.81	3.4228	13.16	19.01	3.76	2.28	38.21
	12	2.1373	14.01	14.26	4.75	5.33	38.35	4.0926	18.01	18.49	2.83	2.37	41.71
	13	2.2082	13.66	14.66	4.65	5.05	38.02	1.4286	12.23	13.21	6.66	6.16	38.25
	30	1.3277	8.84	13.55	5.77	5.39	33.55	1.8222	9.89	16.17	5.28	5.02	36.36
	31	1.0909	11.34	12.06	7.08	6.71	37.19	2.2455	11.59	16.7	5.75	3.79	37.84
V	19	1.0063	4.69	16.22	4.78	5.55	31.24	1.0872	2.96	20.3	7.25	2.72	33.24
	23	2.0648	11.66	14.85	4.07	5.49	36.08	3.5138	13.87	17.98	3.41	2.19	37.45
	27	1.9859	5.68	18.29	2.16	6.09	32.22	3.7499	12.61	20.18	2.70	2.20	37.69
	28	0.5407	8.61	11.24	7.72	7.32	34.90	1.5438	11.86	13.98	5.63	6.67	38.14
	29	1.2587	6.95	13.84	3.41	7.66	31.85	3.0616	13.12	16.68	3.81	2.64	36.25

Figure 4. Spatial distribution of the probability of seasonal ADFEs on the HRB.

5. Conclusions and discussion

Extreme hydrological events, such as droughts and floods, are proven to be affected by many aspects and the multivariable tool is demonstrated to be an efficient way in modelling their statistical characteristics (Grimaldi and Serinaldi 2006; She *et al.* 2016a). In particular, under the current condition of global climate change, there will be more prolonged droughts or floods that will have a more severe impact on nature and also humanity.

In many regions of the world, events in which floods occur after a prolonged extreme drought or droughts occur after an extreme flood are found to occur more frequently. In this study, we define the sudden alternations between droughts and floods as ADFEs. However, the traditional univariate regional L-moment technique, which identifies the homogeneous region by taking only a single variable into consideration, is insufficient to fully characterize hydrological events with multivariate variables. Therefore, in this study, we concentrated

on the joint probability characteristics of seasonal ADFEs using multivariate L-moments theory and bivariate copula functions. The HRB was chosen as the study area, and the droughts and floods from 1956 to 2012 at 32 meteorological stations were analyzed. The results are as follows:

- (1) Summer streamflow makes the largest contribution to the annual streamflow, with an average of more than 51%. The autumn streamflow and spring streamflow, contribute 22 and 18%, respectively, and winter streamflow contribute <8%. Therefore, only droughts and floods in the spring, summer and autumn are discussed in this study.
- (2) The entire study area was divided into five sub-regions using the fuzzy c-means cluster method. After the combined consideration of the univariate and multivariate discordancy and homogeneity test, some adjustments were adopted to make the division of the sub-regions homogeneous. Finally, we obtain five homogeneous sub-regions in the entire study area, which is appropriate for regional studies of floods and droughts.
- (3) The GLO and LN3 are proven to be the optimal marginal distributions in modelling the SSI series in the spring, summer and autumn in most sub-regions. Our results also demonstrate the importance of considering a sufficient number of candidate distributions rather than one single distribution to reduce the uncertainty caused by the choice of optimal distribution. For the multivariable functions, the Frank copula is the most suitable choice, although the Gumbel, Clayton and Frank copulas were all capable of modelling the joint distribution for the spring-summer and summer-autumn SSI series in the study area.
- (4) In both spring-summer and summer-autumn, FF events show the highest frequency, followed by DD events. The average probability of FF events are 13.78 and 17.06% during the spring-summer and summer-autumn, while they are 11.27 and 13.79% for DD events, respectively. Additionally, the seasonal ADFEs are found to occur most likely near the mainstream of HRB, and seasonally, the summer-autumn droughts and floods occur more frequently than that in spring-summer.

In this study, the multivariate L-moments techniques are used to model seasonal hydrological droughts and floods alternation. However, a basic

assumption of the multivariate regional frequency analysis is that the hydrological series are stationary, and therefore further investigations are needed on the consideration of non-stationarity in the streamflow series. The SSI is chosen to represent the dry/wet conditions in our study area; however, droughts and floods are influenced by many meteorological and hydrological factors, such as precipitation and evapo-transpiration. Hence, further studies can focus on the drought and flood descriptions with comprehensive consideration of other variables. The tail dependence is also very important in estimating the risk of multivariate hydrological extremes (Poulin *et al.* 2007). It is well known that different copula functions do have different abilities in capturing the tail dependence structure (Nelson 2006). For example, the Clayton copula is more suitable for modelling the dependence between the series with lower-tail dependence, while the Gumbel copula has a stronger ability in characterizing the dependence between the series with upper-tail dependence. More detailed consideration of the impact of different types of copula functions, more in terms of different tail dependence structures between the hydrological time series should be taken in subsequent studies.

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