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Hydrological response to large-scale climate variability across the Pearl River basin, China: spatiotemporal patterns and sensitivity

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Abstract: The aim of this study is to examine whether the climatic driving forces can describe the observed variability in available water resources and the magnitude of flooding over the Pearl River basin. 62 stations with 41 years of monthly streamflow records and 28 stations with 60 years of annual maximum streamflow records were used in this study. Four climate indices related to the Atlantic, Pacific and Indian Oceans were used to analyze their influence on annual mean discharge (Qann) and annual maximum daily discharge (Qmax) of the Pearl River basin, and the indices are El Niño/Southern Oscillation (ENSO), North Atlantic Oscillation

(NAO), Indian Ocean Dipole (IOD), and Pacific Decadal Oscillation (PDO). We found that the variations in available water resources and the magnitudes of floods across Pearl River can be explained by climate variability, potentially. The Qann and Qmax in different regions of the domain were significantly related to different climate indices at the same year or at the last year. In addition, in many regions the strengths of the relationships between climate indices and Qann and Qmax have been non-stationary, with either strengthening or weakening trends during the study period. Furthermore, the quantifications of climate indices impacts on Qann and Qmax (i.e. sensitive) were also assessed. The results showed that Qmax was more sensitive to the variability of atmospheric circulation than Qann. In addition, Qann varied on average between 0.3-24%, while Qmax varied between 0.5-31% per unit climate index change. The above relationships between climate indices and Qann and Qmax provided relevant information for water resources management in Pearl River basin, allowing the identification of regions with higher flood risk and enhancement of human mitigation to floods.

Key words: Low-frequency climate indices; Annual mean discharge; Annual maximum daily discharge; Sensitivity analysis

1. Introduction

The Pearl River basin (102°14'E-115°53'E; 21°31'N-26°49'N) (Fig. 1) is 4.573×10^5 km² in drainage area, being the second largest river in China with respect to discharge volume and the third largest river in terms of drainage basin area (Zhang et al., 2010).

The Pearl River basin is located in the tropical and sub-tropical climate zones with annual mean temperature between 14°C and 22°C and long-term annual average precipitation of about 1525 mm (Zhang et al., 2010). Precipitation during wet season (April-September) accounts for 80% of the annual total precipitation amount (Zhang et al., 2010). In addition, the Pearl River basin is in a region of the country plagued by frequent disastrous flood events (e.g., 1915, 1949, 1994 and 1998), which cause large economic and social losses. For example, Guangzhou city was submersed for 7 days with the deaths of more than 80 thousand people due to the 1915 flood (Wen and Song, 2006). During the June 1998 flood, 94 people lost their lives, 93 thousand houses were injured, and the total economic damages were more than \$5.1 billion in Chinese dollar (Wen and Song, 2006).

Moreover, from the viewpoint of regional economic development and water supply, the Pearl River basin is an important region in south China, being the main source of water supply for Shenzhen and Hong Kong, satisfying about 80% of Hong Kong's annual water demand. Because of all these catastrophic flood events over the Pearl River and the importance of available water resources to large urban agglomerations located in Pearl River Delta (PRD), there have been many studies for analyzing the discharge records to detect variability in flood magnitude of annual or seasonal mean streamflow (e.g., Yang et al., 2010; Chen et al., 2012; Niu et al., 2014; Zhang et al., 2009, 2014a, 2014b, 2015a, 2015b; Tang et al., 2016; Yuan et al., 2016). Recently, Zhang et al (2009, 2014a, 2014b, 2015a, 2015b) indicated that over the past 50+ years, high flood risk can be found in the upper and middle West River basin and

the North River basin (Fig. 1) with an increasing magnitude of 0-40% and 10-30%, respectively. They also found that streamflow largely increased due to enlarged streamflow allocation from the West River to the North River (Fig. 1). Changes in precipitation were attributed to the changes in floods and available water resources. The next question to address is why the magnitude of floods and available water resources has been changed? Our hypothesis is that the variability in the climate system related to the Atlantic, Pacific and Indian Oceans can influence the magnitudes of floods and available water resources over the Pearl River basin.

Sea surface temperature (SST) anomalies can affect the dynamic systems between ocean and atmosphere, which governs the planet's climate, such as bringing moisture to produce streamflow and flooding (e.g., Ward et al., 2014a, 2014b). Coupled oceanic-atmospheric variations with different timescales, such as intra-, inter-annual, decadal and inter-decadal, these variations are defined as low frequency climate or large-scale climate variability (Mallakpour and Villarini, 2016). In this study, we focus on the relationship between the available water resources and flood events and large-scale climate indices over the Pearl River using four indices indicating the SST of Atlantic, Pacific and Indian Oceans, respectively. These indices used in this study are El Niño-Southern Oscillation (ENSO), North Atlantic Oscillation (NAO), Indian Ocean Dipole (IOD) and Pacific Decadal Oscillation (PDO), each of which has the potential to describe certain spatial and temporal aspects of the climate variability.

Many studies have examined the relationship between climate indices and East Asian monsoon which can control precipitation and influence the streamflow to some

extent across Pearl River basin (e.g., Linderholm et al., 2011; Chakravorty et al., 2013; Chen et al., 2013). Chen et al (2013) indicated that the East Asian Monsoon has been significantly influenced by ENSO and East Asian Summer Monsoon is much stronger during positive PDO phases than negative PDO phases. The major patterns of summer climate over China are highly connected with the interannual variation of the NAO, supporting a teleconnection between the North Atlantic region and East Asia (Linderholm et al., 2011). Summer rainfall in China also exhibits different patterns corresponding to different phases of the IOD in the previous year (Yuan et al., 2008). However, few studies have been found regarding the relationship between streamflow and climate variability in the Pearl River basin (e.g., Niu et al., 2014; Zhang et al., 2015a). Niu et al. (2014) found that the dominant variabilities of streamflow obtained from Variable Infiltration Capacity (VIC) model across Pearl River were basically correlated with IOD. Zhang et al. (2015a) built the regression relationship between flood peaks and climate indices in eastern sub-basins of Pearl River and concluded that the climate indices could be valuable for flood peak forecasters.

The past studies focused on the influence of climate indices on simulated runoff data by hydrology models or on flood peaks in sub-basins of Pearl River, however, there is a gap about the relationship between available water resources and flood peaks and climate indices across the whole Pearl River basin. Furthermore, to date no sensitivity analysis has been carried out to assess the magnitude of the impact of large-scale climate fluctuations on river discharge across the Pearl River basin. Therefore, the study aims to examine whether the climatic driving forces can describe

the observed variability in available water resources and flood peaks over the Pearl River basin. The objectives of this study are: (1) to investigate the correlations between annual mean discharge (Q_{ann}) and annual maximum daily discharge (Q_{max}) and climate indices; (2) to examine the stationarity of strength of the correlations through time and the percentage anomalies in median Q_{ann} or Q_{max} between warm episode years compared to the median Q_{ann} or Q_{max} of cold episode years; (3) furthermore, to assess the magnitude of the impact of climate indices fluctuations on Q_{ann} and Q_{max} . If we can identify such a relationship as hypothesized above, then it would contribute to help understanding and predicting future flood conditions, potentially.

2. Data

Monthly streamflow data (with a unit of 10^4 m^3) covering a period of 1960-2000 were collected from 62 hydrological stations across the Pearl River basin, China (Zhang et al., 2011). The dataset was provided by Ministry of Water Resources, China, and the quality of the dataset was firmly controlled before its release based on national standards. Monthly streamflow data were dealt with as Q_{ann} (with a unit of m^3/s) used for analysis during calendar years. Besides, annual maximum daily data (Q_{max}) (with a unit of m^3/s) covering a period of 1951-2010 during calendar years were collected from 28 hydrological stations (Zhang et al., 2014b). Q_{max} were obtained from the Hydraulic Bureau of Guangdong Province and the quality of the data is firmly controlled before their release.

ENSO is the difference of sea surface temperature (SST) in the Niño 3.4 (5°N - 5°S , 120°W - 170°W). Monthly ENSO data covering a period of 1950-2010 were extracted from Climate Prediction Center of National Oceanic and Atmospheric Administration (<http://www.cpc.ncep.noaa.gov/products/analysismonitoring/ensostuff/ensoyears.html>). NAO, being centered near the Azores and Iceland, is defined as a meridional dipole in the atmospheric pressure (Moore et al., 2013). The NAO index can be obtained using rotated principal component analysis (RPCA) technique, and the NAO index data were extracted from the Climate Prediction Center of NOAA at <http://www.cpc.ncep.noaa.gov/products/precip/CWlink/pna/nao.shtml>. Meanwhile, IOD is another ocean-atmosphere coupling phenomenon and is defined by Dipole Mode Index (DMI), i.e. the temperature anomaly between the western equatorial Indian Ocean and the southeastern equatorial Indian Ocean (Yamagata et al., 2003). The IOD data covering a period of 1950-2010 were obtained from JAMSTEC (Japan Agency for Marine-Earth Science and Technology) (http://www.jamstec.go.jp/frsgc/research/d1/iod/iod/dipole_mode_index.html). The PDO is defined as the leading principal component of monthly SST anomalies in the North Pacific Ocean, poleward of 20°N (Xiao et al., 2015). The PDO data covering a period of 1950-2010 were extracted from NOAA (<http://www.esrl.noaa.gov/psd/data/correlation/pdo.data>). The annual mean variations of ENSO, NAO, IOD and PDO with different phases are shown in Fig. 2.

The reason why we chose these four climate indices is that previous studies have proved the strong influences of these four indices on river discharge at global or

regional scales (Bouwer et al., 2008; Ward et al., 2014a; Niu et al., 2014; Ouyang et al., 2014). These four climate indices selected by this study are consistent with those used by previous studies, which provided reference ground for this current study. Specifically for ENSO, there are different sea surface temperature anomalies from different regions, such as Nino1+2, Nino3, Nino4 and Nino3.4. However, Ward et al. (2014a, 2014b) indicated the strong influences of ENSO (Nino 3.4) on the global floods and average streamflow. Ouyang et al. (2014) also provided strong evidences on the links between ENSO (Nino 3.4)/PDO and precipitation, streamflow in China. Therefore, we decided to choose the sea surface temperature anomalies of Nino3.4. It should be pointed out that the sensitivity between different indices of ENSO and river discharge across Pearl River basin should be further investigated.

3. Methodology

3.1. REOF-based spatial decomposition of Q_{ann} and Q_{max}

Q_{ann} and Q_{max} are nonlinear, spatially correlated and highly dimensional. Thus, Q_{ann} and Q_{max} were log-transformed, i.e. $\ln(Q_{ann})$ and $\ln(Q_{max})$, before subsequent analysis (Bouwer et al., 2008; Ward et al., 2010, 2014a). Using the Rotated Empirical Orthogonal Functions (REOFs), spatial patterns of $\ln(Q_{ann})$ and $\ln(Q_{max})$ were decomposed into spatial modes (denoted as EOF) and related temporal modes (denoted as principle components, or simply PC). The advantages of such spatial decomposition include: (1) analysis of the relation between climate indices and decomposed temporal modes and related spatial modes can help capture

the influence of climate variability on hydrological processes (Bouwer et al., 2006; Xiao et al., 2015); and (2) REOFs allow assembling the observations of rare peak discharge events that would be randomly distributed across river basins (Bouwer et al., 2008).

The REOFs technique has been widely used in hydrometeorology (e.g., Hannachi et al., 2006, 2007; Xiao et al., 2015; Zhang et al., 2016). The relation between continuous time-space series $X(t,s)$ and decomposed temporal and spatial modes can be determined as:

$$X(t,s) = \sum_{k=1}^M c_k(t)u_k(s) \quad (1)$$

where t denotes the time, s denotes the space, M denotes the number of modes, $u_k(s)$ denotes the optimal basic space function, and $c_k(t)$ denotes the time extension function. More details of REOFs and related algorithm can be found in Hannachi et al. (2007). In analysis of using REOFs, one problem is how to decide the number of modes of EOFs. Theoretically, all EOF modes should be included in the analysis. However, in so doing it is hard to reduce the dimension. Hannachi et al. (2006) suggested that the number of EOF modes should be decided by elimination of modes with smaller eigenvalues. However, Xiao et al. (2015) preferred to decide the number of modes by the accumulative explained variance. This study considered the aforementioned two methods into consideration in deciding the number of modes.

3.2. Relations between climate indices, Q_{ann} and Q_{max}

Relations between ENSO, NAO, IOD and PDO, and REOFs-based temporal

modes of $\ln(Q_{ann})$ and $\ln(Q_{max})$ were evaluated by analyzing the Pearson coefficients (Zhang et al., 2013) at the significance level of 0.1. Climate indices could influence Q_{ann} and Q_{max} in the same year or in the succeeding year. Therefore, the influence of climate indices on Q_{ann} and Q_{max} was evaluated with 0-year and 1-year time lag. Further, the degree of influence of ENSO, NAO, IOD and PDO on Q_{ann} and Q_{max} varies with time and is different in different parts of the Pearl River basin. For this reason, the stability in the influence of ENSO, NAO, IOD and PDO on Q_{ann} and Q_{max} was evaluated using the moving correlation analysis technique. The time window was defined as 21 years (Räsänen and Kummu, 2013; Ward et al., 2014b) and the correlation coefficient between climate indices and $\ln(Q_{ann})$, $\ln(Q_{max})$ was computed with time lag of 0 and 1 year, respectively. For Q_{ann} , altogether 21 moving windows were obtained from 1960-1980 to 1980-2000 with one step; and for Q_{max} , 40 moving windows were obtained from 1951-1971 to 1990-2010 with one step. Then, the percentage of windows with significant correlation coefficient to the total windows was computed. The Mann-Kendall technique was then used to detect trends in the series of moving correlation coefficient between climate indices and Q_{ann} and Q_{max} at the significance level of 0.1. We also examined the individual and coupled percentage anomalies in median Q_{ann} and Q_{max} between warm episode years compared to the median Q_{ann} and Q_{max} of cold episode years. We used the classification of ENSO events and PDO phases based on Ouyang et al. (2014). In addition, we used the classification of NAO and IOD phases from Bai et al. (2012) and Australian Government Bureau of

Meteorology, respectively. Student t test was used to evaluate the significance of the difference in influences and/or joint influences of warm and cold episodes of climate indices on Qann and Qmax. The significance level of Student t test was 0.1.

3.3. Sensitivity of Qann and Qmax to climate indices

The sensitivity of Qann and Qmax to ENSO, NAO, IOD and PDO was evaluated using simple linear regression (Bouwer et al., 2008; Ward et al., 2010, 2014b):

$$\ln(q_i) = \beta_0 + \beta_1 a_i + \varepsilon_i \quad (2)$$

where q_i is the observed Qann or Qmax in the i th year; a_i is the ENSO, NAO, IOD and PDO with 0 and 1 year earlier than Qann and Qmax; β_0 and β_1 are the regression coefficients; and ε_i is the error term. Parameter β_1 is the sensitivity of influence of ENSO, NAO, IOD and PDO on Qann and Qmax. $\beta_1 \times 100$ shows the change of q_i in percentage due to the change in climate indices. The time series of Qann from 62 stations and of Qmax from 28 stations were 41 years and 60 years long, respectively.

4. Results and discussion

4.1. Impact of climate indices on spatial patterns of Qann and Qmax

Based on REOFs decomposition, five modes of Qann and Qmax were analyzed, and the cumulative explained variances of these five modes were 83.1% and 70.9%, respectively (Fig. 3). For Qann, the eigenvalues exhibited moderate changes after the 5th mode. The explained variances of the leading five modes were 47.8%, 18.2%, 9.2%, 4.5%, and 3.4%, respectively (Fig. 3). For Qmax, the eigenvalues also exhibited moderate changes after the 5th mode and the explained variances of the leading five

modes were 31.2%, 15%, 10.1%, 8.7%, and 5.9% (Fig. 3). Therefore, the selection of the leading five modes was reasonable.

Relations between climate indices and temporal modes of Qann and Qmax were evaluated using Pearson correlation coefficients (Fig. 4). In addition, the spatial patterns of the leading five rotated EOFs for Qann and Qmax corresponding to five temporal models (PCs), respectively, were also displayed (Fig. 5 for Qann and Fig. 6 for Qmax). Let us start with Qann (the first panel in Fig. 4 and Fig. 5). Overall, there are two PCs of Qann with significant correlation to climate indices. The PC2 of Qann was significantly negatively correlated to NAO of the last year and PDO of the same year. Then, the negative NAO phases and cold PDO periods individually or jointly tended to increase available water resources in eastern Pearl River (Fig. 5, EOF2). These results are consistent with Ouyang et al. (2014), where they found an obvious increase in annual streamflow in PDO cool phase than warm phase across Pearl River basin. Summer monsoon rainfall over South China with an interdecadal variation had also been identified that there were more dry (wet) monsoon years during the periods of high (low) PDO index (Chan and Zhou, 2005). There is a significant negative relationship between PC3 of Qann and ENSO of the last year, which indicated that positive ENSO events had a tendency to decrease Qann in northern Pearl River basin (Fig. 5, EOF3). The result is in line with Ouyang et al. (2014), where they found that both annual precipitation and streamflow were higher in La Nina periods than in El Nino periods across Pearl River basin. The influence of ENSO on the following East Asian Summer Monsoon (EASM) has been well studied (e.g., Chen et al., 2013). The variability of the EASM was divided into an ENSO-related part named $EASM_{EN}$ and an ENSO-unrelated part named $EASM_{res}$. Chen et al. (2013) found that a weak $EASM_{EN}$ trended to be followed by a strong EASM and vice versa, which may trigger

more precipitation and lead to more streamflow in the last year of La Nina event.

Now, we pay attention to the relationship between Q_{max} and climate indices (the last panel of Fig. 4 and Fig. 6). Overall, four of five PCs are significantly influenced by climate indices (Fig. 4). The relationship between IOD of the last year (ENSO at the last year) with PC2 of Q_{max} was significantly negative (positive) (the last panel in Fig. 4). Then, positive IOD phase and negative ENSO phase individually or jointly tended to increase Q_{max} in central-north Pear River (Fig. 6, EOF2). The fact that we find significant relationships between IOD and ENSO and Q_{max} is consistent with previous studies (e.g., Niu, 2013; Ward et al., 2014a). Yuan et al. (2008) found that posterior to an IOD year, a positive (negative) IOD tended to induce an enhanced (a weakened) 500-hPa western Pacific subtropical high with a westward-advancing (an eastward-retreating) high ridge, and these would increase (decrease) rainfall in the central-north Pearl River. Besides, there are significant negative correlations between IOD of the same year and PC4 and PC5 of Q_{max} , which indicated the southwestern Pearl River and East River with lower Q_{max} during positive IOD phases in the same year (Fig. 6, EOF4 and EOF5). Niu et al. (2014) also found IOD basically correlated to the dominant variabilities of hydrological process in Pearl River. Qiu et al. (2014) indicated that rainfall anomalies over southern China were found to be asymmetrically influenced by the IOD, with a far stronger influence from positive IOD events. Finally, Q_{max} in upper West River had a significantly positive relationship with PDO of the last year, and higher Q_{max} tended to occur during warm PDO periods (Fig. 6, EOF3). The reason behind the result may be that there tends to be a much stronger EASM during the positive PDO phases than during the negative PDO phases (Chen et al., 2013).

4.2. Temporal stability of the influences of climate indices on Q_{ann} and Q_{max}

In this section, we examined whether we could find any indication of changes in the strength of the correlation between $\ln(Q_{ann})$ and $\ln(Q_{max})$ and climate indices through time.

It can be seen from Fig. 7 (ENSO 1 panel, Fig. 7) that strong correlations between ENSO of the last year and Q_{ann} were persistent in North River, Liu River and You River. The strength of correlation between ENSO of the last year and Q_{ann} was increased significantly in the North River and Liu River. The ENSO of the same year had a persistently increasing influence on Q_{ann} in the middle and northwestern of Pearl River (ENSO 0 panel, Fig. 7). Strong correlation between NAO of the last year and Q_{ann} is persistent, but with significant decreasing strength of correlations in the central and eastern parts of the Pearl River basin (NAO 1 panel, Fig. 7). Both IOD and PDO of the same year had strong correlations with Q_{ann} in the entire West River basin and the East River basin, respectively. In addition, the strength of correlations between IOD and PDO of the same year and Q_{ann} in West River basin and the East River basin, respectively, was significantly increased (the last two panels in Fig. 7).

Similar to Fig. 7, changes in the strength of the correlation between $\ln(Q_{ann})$ and each climate index of the same year and the last year were also evaluated (Fig. 8). In general, ENSO persistently and strongly influenced Q_{max} in the West River (the first panel, Fig. 8). However, significant decreasing correlation coefficients between ENSO of the last year and Q_{max} were identified in the You River and a significant decreasing trend in the correlation coefficients between ENSO of the same year and Q_{max} was also observed in the Liu and Long River basins (ENSO 1 and ENSO 0 in Fig. 8). Persistently strong correlations between NAO and Q_{max} were observed in the lower West River basin. Specifically, the middle and northwestern parts of the West

River basin were dominated by persistently strong correlation between NAO and Q_{max} of the same year and particularly significant correlation coefficients were found between NAO and Q_{max} in the North River basin and in the lower West River basin (NAO 1 and NAO 0 in Fig. 8). Persistently stable correlations were found between IOD and Q_{max} of the next year. Besides, significantly increasing/decreasing trends in the correlation coefficients between IOD and Q_{max} were detected in the central parts/the North River basin, respectively. Moreover, IOD exhibited stable correlation with Q_{max} in the middle and southern parts of the Pearl River basin, and also in the North River basin and the East River basin. Significant decreasing correlation coefficients between IOD and Q_{max} were found in You River basin, the lower West River basin and the East River basin, and significant increasing correlation coefficients in the North River basin (IOD 1 and IOD 0 in Fig. 8). Similarly, PDO showed stable and strong correlations with Q_{max} of the next year across almost the entire Pearl River basin. Specifically, significant decreasing correlation between PDO and Q_{max} were found in the middle West River basin and in the central and western parts of the Pearl River basin. However, significant increasing correlation between PDO and Q_{max} of the next year was found in the North River basin. Persistently strong correlations between PDO and Q_{max} of the next year were found in the middle parts of the West River and in the middle and western parts of the Pearl River basin. Correlations between PDO and Q_{max} of the same year were found in the East River basin and in the west Pearl River basin. Specifically, significant increasing correlation coefficients were found between PDO and Q_{max} of the same year in the East River basin (PDO 1 and PDO 0 in Fig. 8).

4.3. Influence of warm/cold episodes of climate indices on Q_{ann} and Q_{max}

Spatial distribution of difference of responses of Qann (Fig. 9) and Qmax (Fig. 10) to warm and cold episodes of climate indices was evaluated. Compared with warm episodes of ENSO, cold episodes of ENSO tended to decrease Qann in the middle and western parts of the Pearl River basin, but caused higher Qann in the eastern parts of the Pearl River basin and the North River basin (ENSO-/ENSO+ in Fig. 9). But this difference in the influence of warm/cold episodes on Qann was not statistically significant. However, a different picture was found for NAO when compared to ENSO. Compared with warm phases of NAO, cold phases of NAO tended to result in lower Qann in the middle and western parts of the Pearl River basin and lower Qann in the North River basin and this difference was statistically significant at the 0.1 significance level (NAO-/NAO+ in Fig. 9). No significant differences in the influence of different IOD and PDO episodes on Qann were detected across the Pearl River basin. The influence of individual and/or joint influence of warm and cold episodes of climate index, on Qmax are shown in Fig. 10. During cold episodes of ENSO, a higher Qmax was found in the northeastern parts of the West River basin and in the East River basin. However, changes in Qmax during cold and warm episodes of ENSO were not statistically different. During warm PDO periods, cold ENSO tended to cause higher Qmax in the northeastern parts of the West River basin and also in the North River basin, and warm ENSO tended to cause higher Qmax in the entire West River basin and the North River basin. Cold NAO tended to cause lower Qmax in the northeast West River basin and the North River basin, but higher Qmax in the East River basin and the southwestern parts of the West River basin (NAO-/NAO+ in Fig. 10). During warm PDO periods, cold NAO resulted in higher Qmax in most parts of the West River basin, but lower Qmax in the northeastern parts of the West River basin due to warm NAO. Higher Qmax was found during cold IOD than that during

warm IOD (IOD-/IOD+ in Fig. 10). During warm PDO periods, cold IOD tended to result in increased Q_{max} in the northeastern parts of the West River basin and warm IOD led to increased Q_{max} in the entire West River basin and in the North River basin. Meanwhile, cold PDO tended to cause higher Q_{max} in the East River basin (PDO-/PDO+ in Fig. 10).

Relations between Q_{ann} and Q_{max} were investigated by analyzing the anomalies of Q_{ann} , Q_{max} and climate indices and boxplot was used to show the dispersion of climate indices that are related to Q_{ann} and Q_{max} (Fig. 11). Generally, warm or cold phases of ENSO, NAO and PDO had no significantly different impacts on larger-than-average Q_{ann} ; however, cold phases of ENSO, NAO and PDO tended to cause occurrences of lower-than-average Q_{ann} , which implied that cold phases of ENSO, NAO and PDO might trigger a water shortage due to the significant reduction of Q_{ann} . Warm episodes of IOD tended to cause higher Q_{ann} , being two times larger than the average of Q_{ann} (Figs. 11a, 11b, 11c and 11d), implying that abundant precipitation can be expected under the influence of warm IOD events. Relative to Q_{ann} , Q_{max} tended to be more influenced by climate indices. Extreme floods, i.e., Q_{max} being two times larger than the average of Q_{max} , occurred more frequently during warm phases of ENSO, cold phases of NAO, warm phases of IOD and cold phases of PDO (Figs. 11e, 11f, 11g and 11h), implying flooding with higher magnitudes in these periods.

4.4. Sensitivity of Q_{ann} and Q_{max}

Figs. 12 and 13 show spatiotemporal patterns of sensitivity of Q_{ann} and Q_{max} to climate indices. Lower sensitivity of Q_{ann} to ENSO of the last and the same year

was observed in most parts of the Pearl River basin. Besides, Qann in most parts of the Pearl River basin was subject to higher sensitivity to ENSO of the last year. NAO had a more influence on Qann of the next year in the eastern parts of the Pearl River basin, the North River and the Liu River, and an increase of 10-20% due to a unit change of NAO was observed. A unit change of NAO caused a reduction of 10% in Qann in the West River basin and an increase of 10-20% of Qann in the eastern parts of the Pearl River basin. Meanwhile, Qann in the eastern parts of the Pearl River basin and the North River basin seemed to be more sensitive to NAO of the last year. When compared to ENSO, NAO and PDO, IOD had the remarkable influences on Qann of the Pearl River basin. The sensitivity of Qann to IOD of the last year in the East River basin, the North River basin, the Liu River basin and the Long River basin was about 0.1-0.3, indicating that a unit change of IOD could increase Qann by 10-30%. The sensitivity of Qann in the West River basin to IOD of the same year ranged between 0.1-0.4, and was -0.3--0.1 in the eastern parts of the Pearl River basin. Qann was sensitive to IOD of the last year, and had lower sensitivity to PDO changes of the last and the same year, and the related sensitivity was lower than 0.1.

Fig. 13 shows the spatiotemporal distribution of sensitivity of Qmax to climate indices. It can be seen that in most parts of the Pearl River basin, a unit change of ENSO of the last year caused an increase of 0-10% of Qmax; however, the change of ENSO resulted in an increase of 0-10% of Qmax in major parts of the Pearl River basin. The sensitivity of Qmax in the middle Pearl River basin to ENSO of the last year was higher than that of the same year. A unit change of NAO of the last year

caused an increase of 10-20% in Q_{max} and NAO had no influence on Q_{max} of the same year, without any confirmative spatial pattern of sensitivity. When compared to other climate indices, IOD had more impacts on Q_{max} , or in other words, Q_{max} was subject to higher sensitivity to IOD. A unit change of IOD of the last year caused an increase of 20-50% of Q_{max} in the northwestern parts of the West River basin, and a decrease of 10-40% of Q_{max} in the southwestern parts of the West River basin and in the East River basin. The IOD changes caused a decrease of 10-40% of Q_{max} in the You River and the East River basins. The sensitivity of Q_{max} to IOD of the last year was higher than that to IOD of the same year. Besides, a unit change of PDO of the last and the same year caused an increase of 0-10% of Q_{max} over most parts of the Pearl River basin.

To further compare the sensitivity of Q_{ann} and Q_{max} to climate indices, areas with higher sensitivity in Q_{max} than in Q_{ann} were computed and spatial interpolation was done with a resolution of $0.05^{\circ} \times 0.05^{\circ}$ grid. Fig. 14 indicates that obvious regional patterns in the sensitivity of Q_{max} and Q_{ann} changes to climate indices were observed. The percentage of grids with higher sensitivity of Q_{max} than Q_{ann} to ENSO of the last and the same years, and to PDO of the last and the same years was, respectively, 59%, 71%, 43% and 14%. The sensitivity of Q_{max} to NAO of the last year in the major parts of the West River basin was larger than Q_{ann} , with 56% of the grids exhibiting higher sensitivity. Furthermore, a larger sensitivity of Q_{max} to NAO of the same year was observed in the lower West River basin. However, the sensitivity of Q_{max} to NAO of the same year was smaller than that of

Qann in the eastern parts of the Pearl River basin and in the Nanpan River basin. IOD had a distinctly different influence on $Q_{\max}$ and Qann, when compared to other climate indices. About 71% of the Pearl River basin showed higher sensitivity of $Q_{\max}$ than Qann to IOD of the last year in the upper basin, the Liu River basin and the East River basin. About 36% of the Pearl River basin showed higher sensitivity of $Q_{\max}$ than Qann to IOD of the same year in the You River basin, the North River basin and the East River basin.

5. Discussion and conclusions

The goal of our study was to examine whether there is any relationship between large-scale climate variability and available water resources and flood events in Pearl River. If the relations are obtained as hypothesized above, we will have the potential to improve future water resources management and flood defense. Most studies on evaluating the potential in developing seasonal to interannual hydroclimatic forecasts were focused on associating low-frequency climatic conditions with basin-level precipitation/streamflow (e.g., Lü et al., 2011; Risko and Martinez et al., 2014; Wang et al., 2015; Zhang et al., 2015a). Lü et al. (2011) found that monthly streamflow and monthly ENSO indicators were significantly correlated during three periods: from January to March, June, and from October to December (OND), with lag periods between one and twelve months in the headwaters region of the Yellow River, China. Zhang et al. (2015a) used four climate indices to model flood peaks in East River and analyzed the performance of probability forecasting by climate indices. Kwon et al. (2008) built the Hierarchical Bayesian Analysis model for exploiting the link between

climate scale indicators and annual maximum flood, providing impetus for developing seasonal forecasting of flood risk applications and dynamic flood risk management strategies. Though our study showed the relationships between annual average streamflow and annual floods and climate indices of the same year and the last year, some studies indicate that climate indices, such as ENSO events, can be accurately predicted one to two years in advance using a physical model of the coupled ocean-atmosphere system (e.g., Whitaker et al., 2011; Gutierrez and Dracup, 2001). Therefore, identifying the relationships holds potential as a powerful forecasting tool for water resources and floods. However, we should know that the reliability of water resources and flood predictions is heavily dependent on the accuracy of the predictions of climate indices.

We also assessed the sensitivity of Q_{ann} and Q_{max} to climate indices using simple linear regression in Pearl River, because there are to date very few locations where the influence of climate on extreme discharge has been specifically examined, suggesting an opportunity for climate indices-sensitive studies at more local scales (Ward et al., 2014b). We are only interested in detecting a climate signal in the discharge records. Therefore, only the influence of climate indices, rather than other factors such as land use and land cover changes, and water reservoirs, on Q_{ann} and Q_{max} was taken into account. Human activities, such as land use, regulation, reservoir, may lead to monotonic change or trends in river discharge, however, we can still detect the climatic driving forces on interannual discharge variations. It is assumed that climate plays a major role in determining discharge as other factors, at

least at the basin scale (Bouwer et al., 2008; Zhang et al., 2015a; Mallakpour and Villarini, 2016). However, the potential future states and influences of climate indices could be further assessed by considering as far as possible the aforementioned factors by coupling atmospheric/oceanic/land surface models with a proper distributed physical-based hydrological model.

Finally, in this study we have examined the relationship between climate variability and the available water resources and magnitude of floods in the Pearl River. The following conclusions are drawn from this study:

(1) The decrease of Q_{ann} and Q_{max} in central and northern parts of the Pearl River basin can be attributed to the warm phase of ENSO of the last year. The warm phase of IOD tends to increase Q_{ann} in the Beipan River basin and decrease Q_{max} in the East River basin. The warm episode of NAO of the same year and warm episode of PDO of the same year tend to increase Q_{ann} in the eastern parts of the Pearl River basin and the North River basin, and the warm phase of PDO of the last year tends to increase Q_{max} in the western parts of the Pearl River basin. (2) There are high regional differences of changes in strength of the correlation between Q_{ann} and Q_{max} and climate indices through time. Persistently strong correlations can be observed between ENSO, IOD and Q_{ann} of the same year in the major parts of the West River basin, and between PDO and Q_{ann} of the same year in the eastern parts of the Pearl River basin and in the North River basin. Thus, ENSO, IOD and PDO can be taken as appropriate predictors for Q_{ann} . Q_{max} is persistently strongly correlated with NAO and IOD of the last year and NAO of the same year in the central parts of the Pearl

River basin, implying that they can be regarded as appropriate predictors for Q_{max} .

These results are useful for developing models for forecasting Q_{ann} and Q_{max} .

(3) Q_{ann} and Q_{max} behave differently in different parts of the Pearl River basin due to warm/cold phases of climate indices. Cold phases of ENSO tend to increase Q_{ann} in the eastern parts of the Pearl River basin and in the North River basin. A larger decrease of Q_{ann} due to cold phases of IOD and PDO than during warm episodes of IOD and PDO is found in major parts of the Pearl River basin. More differences are observed in the spatial distribution of Q_{max} changes than Q_{ann} under the influence of climate indices. PDO complicates the spatial pattern of Q_{max} changes as a result of the influence of ENSO, NAO and IOD. For the entire Pearl River basin, cold episodes of ENSO, NAO and PDO tend to decrease Q_{ann} and hence higher possibility of droughts; however, warm episodes of ENSO, IOD and cold episodes of NAO and PDO tend to increase Q_{max} and hence higher magnitude of flooding. These results can help to better understand the occurrences floods and droughts due to warm/cold episodes of climate indices across the Pearl River basin and hence develop measures for mitigation of natural hazards.

(4) Q_{max} is more sensitive to climate indices than Q_{ann} . A unit change of climate indices can cause a 0.3-24% and 0.5-31% change in Q_{ann} and Q_{max} , respectively. Also, NAO- and IOD-induced changes in Q_{ann} and Q_{max} are different. There are obvious differences of sensitivity between Q_{ann} and Q_{max} induced by NAO and IOD of the last year and the same year with percentages of higher sensitivity of Q_{max} than of Q_{ann} of 56%, 59%, 71% and 36%, respectively. Further, Q_{ann} is more sensitive to

NAO and IOD in the large parts of the Pearl River basin; and Qmax is more sensitive to ENSO, IOD and NAO of the same year over large parts of the Pearl River basin.

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Fig. 1 Locations of hydrological stations, tributaries and provinces within the Pearl River basin. The Qann stations denote stations with monthly streamflow data covering a period of 1960-2000; the Qmax stations denote stations with annual maximum streamflow data covering a period of 1951-2010.

Fig. 2 Temporal changes in different phases of ENSO, NAO, IOD and PDO

Fig. 3 Eigenvalues and accumulated explained variance of REOF for Qann and Qmax. The numbers denote the accumulated explained variance and the error bars denote the 95% confidence interval.

Fig. 4 Pearson correlation coefficients between temporal modes of REOFs for Qann and Qmax and climate indices considered in this study, i.e. PDO, ENSO, NAO, IOD. ‘_0’ and ‘_1’ immediately after the climate indices denote 0-year and 1-year earlier than Qann and Qmax. The significance threshold for Qann and Qmax at 0.1 significance level is 0.26 and 0.21, respectively.

Fig. 5 Spatial patterns of REOFs for Qann

Fig. 6 Spatial patterns of REOFs for Qmax

Fig. 7 Changes in strength of the correlation between $\ln(Qann)$ and each climate index of the same year and the last year using a 21 year moving window, ranging from 1960-1980 to 1980-2000. The colorful dots indicate the trend of the time series formed from the correlation coefficient of each window. The colorful regions and color bar indicate the percentage of windows which the correlation is statistically significant at the confidence interval of 0.1.

Fig. 8 Changes in strength of the correlation between $\ln(Q_{\max})$ and each climate index of the same year and the last year using a 21 year moving window, ranging from 1951-1971 to 1990-2010. The colorful dots indicate the trend of the time series formed from the correlation coefficient of each window. The colorful regions and color bar indicate the percentage of windows which the correlation is statistically significant at the confidence interval of 0.1.

Fig. 9 Percentage differences of Qann between cold and warm climate indices episode years. The percentage differences are calculated using the difference between median Qann during cold episode years and median Qann during warm episode years dividing into median Qann during warm episode years. The colorful dots indicate the difference significance evaluated by Student t test with 0.1 significance level. The colorful regions and color bar indicate the percentage differences.

Fig. 10 Percentage differences of Qmax between cold and warm of individual and coupled climate indices episode years. For individual differences, the percentage differences are calculated using the difference between median Qann during cold episode years and median Qann during warm episode years dividing into median Qann during warm episode years. For coupled differences, taken ENSO for example, the percentage differences of Qmax between El Nino (warm episode) and La Nina (cool episode) during PDO warm phase and during PDO cold phase are evaluated similar as individual differences, respectively. The colorful dots indicate the difference significance evaluated by Student t test with 0.1 significance level. The colorful regions and color bar indicate the percentage differences.

Fig. 11 Relations between departure of Qann and Qmax and climate indices across the entire Pearl River basin. The departure in this study is defined as $Q_{ann}/\text{mean of } Q_{ann}$ and $Q_{max}/\text{mean of } Q_{max}$, respectively.

Fig. 12 Spatial distributions of sensitivity of Qann to climate indices. CI_1 and CI_0 denote that 1-year and 0-year earlier of climate indices than Qann series. The colorful dots indicate the comparison of sensitivity related to CI_1 and related to CI_0. The colorful regions and color bar indicate the values of sensitivity of Qann caused by climate indices.

Fig. 13 Spatial distributions of sensitivity of Q_{max} to climate indices. CI_1 and CI_0 denote that 1-year and 0-year earlier of climate indices than Q_{max} series. The colorful dots indicate the comparison of sensitivity related to CI_1 and related to CI_0 . The colorful regions and color bar indicate the values of sensitivity of Q_{max} caused by climate indices.

Fig. 14 Spatial distributions of differences between the sensitivity of Q_{max} to climate indices and the sensitivity of Q_{ann} to climate indices. Sensitivity difference between Q_{max} and Q_{ann} to climate indices is computed as the difference between the absolute sensitivity of Q_{max} and Q_{ann} to climate indices.