Hydrological alteration of the upper Yangtze River and its possible links with large-scale climate indices
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ABSTRACT

The relationship between hydrological alteration and climate variability in the upper Yangtze River is not fully understood. In this paper, the periodicity features and the intercorrelation of annual and seasonal eco-flow metrics at the Yichang gauge station are analyzed for the period 1882 to 2013. Analysis is carried out to explore the formation of the eco-flow metrics and the possible linkages between eco-flow metrics and selected climate indices, using the cross-wavelet and wavelet coherence methods on data from 1948 to 2013. The results show that the variation of eco-flow metrics correlates well with some selected climate indices, but changes in different eco-flow metrics are complex. Most annual and seasonal eco-flow metrics correlate well with the Northern Hemisphere (N.H) and Indian Ocean Dipole (IOD) and have a significant common power in the two to four years band. In addition, most annual eco-flow metrics have an obvious phase relationship with the selected climate indices. However, the seasonal eco-flow metrics have no significant phase relationship with the selected climate indices. These findings provide a better understanding of how hydrological alterations of the streamflow and better water resource management can ensure ecosystem sustainability for the Yangtze River.

Key words | climate indices, eco-flow metrics, hydrological alteration, Three Gorges Dam

INTRODUCTION

River flow regimes are critical components of the ecological integrity of river systems (Poff et al. 1997; Hart & Finelli 1999) and changes in flow regime are commonly observed in a large number of rivers worldwide, as a response to environmental changes (Gao et al. 2012). However, the formation of such changes in flow regime (hydrological alteration) is not fully understood and the connection between hydrological alteration and climate variability is not well clarified, despite the fact that climate variability is increasingly affecting the natural flow regime (Suen 2010; Kim et al. 2011; Dyer et al. 2014).

Human activity is usually considered to be a major contributor to the changes in flow regime via different approaches, e.g., dam construction, land use change and artificial water withdrawal (Gao et al. 2013; Nakayama & Shankman 2013). However, climate change (such as the direct warming effect on air temperature) may cause variation in global atmospheric circulation (IPCC 2014), which could be represented by some climate indices. A large number of studies have shown how the hydrological regime of the Yangtze River basin is inevitably influenced by climate variability, regardless of the historical or current conditions or future scenarios (Cao et al. 2011; Ju et al. 2014; Su et al. 2017). In addition, the streamflow series can reveal a certain level of climate variability-induced hydrological alteration (Suen 2010). Thus, a causal relationship may
exist between climate indices and hydrological alteration in the flow regime. This is because large-scale patterns of atmospheric circulation determine the distribution of surface temperature and precipitation over the land surface which, in turn, controls key components of the hydrological cycle, e.g., streamflow (Mishra et al. 2011).

The linkage between climate indices and streamflow in China has been documented in a large number of studies. For example, Jiang et al. (2007) and Xu et al. (2007) showed a close relation between streamflow and El Niño–Southern Oscillation (ENSO) events in the Yangtze River basin. Ouyang et al. (2014) investigated the linkage between ENSO/PDO (Pacific Decadal Oscillation) signals and precipitation. Their study showed that the variability of streamflow in four main rivers in China (i.e., Yangtze River, Yellow River, Pearl River, and Songhua River) is largely determined by ENSO/PDO at the annual scale. Although these studies have shown a strong linkage between the streamflow and the climate indices within the Yangtze River basin, the causal relationship of the variation of streamflow remains unclear, and the hydrological alteration in the flow regime may also be influenced by large-scale climate indices. In addition, a better understanding of the relationship between climate indices and indicators of hydrological alteration in flow regime can improve river management and river ecosystem protection (Dyer et al. 2014). This is especially the case for multi-objective dams such as the Three Gorges Dam (TGD), which is the world’s largest power station and provides great benefits for flood protection, hydropower generation, navigation, ecological services, and so on.

The main research objectives of this study are: (1) to analyze the intra-annual variability between the annual eco-flow metrics and seasonal eco-flow metrics of streamflow at TGD (i.e., eco-deficit and eco-surplus metrics, which are indices denoting the hydrologic alteration, both annually and seasonally); and (2) to explore the potential phase relations with large-scale climate indices which reflect climate variability. To fulfill this purpose, eco-deficit and eco-surplus metrics were employed because these indicators provide an accurate measurement of the degree of alteration of streamflow time series (Vogel et al. 2007; Gao et al. 2012). Meanwhile, the wavelet transform theory, such as cross-wavelet and wavelet coherency, was used for data analysis.

DATA

Daily discharge data

The Yichang hydrologic gauge was selected as a representative hydrologic gauge of the Yangtze River basin, which controls the upper reach (an area of 1,005,501 km² of the Yangtze River basin). The Yangtze River is the longest river in China and the third longest river in the world, located between 91°E and 122°E and 25°N and 35°N (see Figure 1). The spatial and temporal variability of precipitation in the Yangtze River basin is influenced greatly by monsoon activities, that connect the large-scale circulation and transport of a huge amount of atmospheric moisture from the East and South China Sea to the basin (Jiang et al. 2007; Xu et al. 2007; Gemmer et al. 2008; Xiao et al. 2015).

The Yichang hydrologic gauge is only 44 km downstream of the TGD and the change in streamflow at this gauge provides a direct measurement of the impact of the TGD. This study used daily discharge data from the Yichang gauge station covering the period from 1882 to 2013, which was collected from the China Three Gorges Corporation (http://www.ctg.com.cn).

Climate indices

To identify the linkage between the hydrological alteration and major climate indices influencing the flow regime at TGD, such as ENSO and sea surface temperature (SST), six indices were collected with consideration being paid to previous studies (Jiang et al. 2007; Xu et al. 2007; Ouyang et al. 2014; Xiao et al. 2015). These indices were: the Niño 3.4 index, the Quasi-Biennial Oscillation (QBO), the Indian Ocean Dipole (IOD) index and the Northern Hemisphere temperature (N.H) (which is the average SST over the northern hemisphere). The Niño 3.4 index is one type of ENSO index and is the average SST anomaly in the region between 5°N and 5°S, and 170°W and 120°W. The PDO index is the leading empirical orthogonal function (EOF) of monthly sea surface temperature anomalies (SST-A) over the North Pacific (poleward of 20°N) after the global average SST has been removed. The QBO is a quasiperiodic oscillation of the equatorial zonal wind between easterlies and westerlies in the tropical
stratosphere, with a mean period of 28 to 29 months. The IOD index is represented by an anomalous SST gradient between the western equatorial Indian Ocean (50°E to 70°E and 10°S to 10°N) and the southeastern equatorial Indian Ocean (90°E to 110°E and 10°S to 0°N). The impacts of these climate indices on precipitation changes over the Yangtze River basin have been well elucidated (Jiang et al. 2018; Gemmer et al. 2012; Xiao et al. 2014). QBO data are from 1948 to 2013, PDO data are from 1900 to 2013, and the other climate indices are from 1882 to 2013 and take account of synchronous data from the Yichang hydrologic gauge station. Please refer to Table 1 for more information about the climate indices.

**METHODOLOGY**

**Eco-flow metrics**

A large number of indices have been developed to evaluate the overall impact of streamflow regulation on flow regimes. For example, Vogel et al. (2007) introduced the non-dimensional metrics of eco-deficit and eco-surplus, which are based on a flow duration curve (FDC) and termed ‘eco-flow metrics’ in the current study. The eco-flow metrics provide an effective tool to understand the integrity of flow change (Gao et al. 2009). Gao et al. (2012) suggested that the quantile of 25% and 75% FDCs could be used as a comparative criterion. Lin et al. (2014) analyzed the change in runoff and eco-flow in the Dongjiang River based on the eco-flow metrics where the median FDC was used to evaluate the hydrological alteration. The eco-deficit metrics represent the deficiency that occurs when the observed streamflow cannot satisfy the river environment’s water demand. In contrast, eco-surplus metrics indicate the surplus that occurs when the observed streamflow satisfies water demand for the river environment; this usually applies to at least 10% of the multi-year mean flow from the perspective of the river’s health.

In this study, the annual and seasonal eco-deficit and eco-surplus flow metrics were calculated using the daily streamflow data from the Yichang hydrologic gauge station from 1882 to 2013, the 1882–1960 streamflow regime being chosen as a natural regime because there were no...
large anthropogenic activities, such as dam construction, forest planting, etc. For more details on the calculation of eco-flow metrics, please refer to Gao et al. (2012).

### Cross-wavelet and wavelet coherency

Continuous wavelet transform (CWT) was applied to both eco-flow metrics and selected climate indices in order to examine the dominant modes in their variability; where the modes could demonstrate interesting time series features in the time and frequency domains. To better assess the relationships between these variables, cross-wavelet transform was computed as wavelet transform coherence helps to highlight any significant coherence of common features between them.

The normality of the eco-flow metrics was first tested in this study by applying the Shapiro–Wilk test (Shapiro & Wilk 1965). CWT, cross-wavelet, and wavelet coherence transform was then performed on the annual and seasonal eco-flow metrics and climate indices in order to identify localized time and frequency information from them. In this study, the Morlet wavelet was selected because it provides a good balance between time and frequency localization. The Morlet wavelet is defined as:

$$\psi_0(\eta) = \pi^{-1/4} e^{i\omega_0\eta} e^{-\eta^2/2}$$  \hspace{1cm} (1)

where $\psi_0(\cdot)$ means the wavelet function of Morlet, $\eta$ is the non-dimensional time, and $\omega_0$ is the non-dimensional frequency and is always taken to be 6, to satisfy the admissibility condition (Torrence & Compo 1998). The CWT of a discrete sequence $x_n$ is defined as the convolution of $x_n$ with a scaled and translated version of $\psi_0(\eta)$:

$$W_n(s) = \sum_{n=-\infty}^{\infty} x_n \psi_0^* [(n' - n)\delta t] / s$$  \hspace{1cm} (2)

where $N$ is the length of discrete sequence $x_n$, $n$ is the localized time index, $\psi_0^*(\cdot)$ indicates the complex conjugate of $\psi_0(\cdot)$, $\delta t$ is time step, and $s$ is scale. The subscript 0 indicates the $\psi_0(\cdot)$ has been normalized.

In order to ignore edge effects (because the wavelet is not completely localized in time), the cone of influence (COI) was introduced. In this case, the COI is the area where the wavelet power caused by the discontinuity has dropped to $e^{-2}$ of the value at the edge (Torrence & Compo 1998; Grinsted et al. 2004).

### Cross-wavelet transform

Cross-wavelet transform exposes high common power and relative phase of time series in the time–frequency plane. The cross-wavelet spectrum of two time series, $X_1$ and $X_2$, with wavelet transform $W_{X_1}$ and $W_{X_2}$ is shown as:

$$W_{X_1 X_2}(s, t) = W_{X_1}(s, t)W_{X_2}^*(s, t)$$  \hspace{1cm} (3)

where the asterisk denotes complex conjugation.
Wavelet coherence

Wavelet coherence is a method that analyzes how coherent the cross-wavelet transform is in a time–frequency space. Wavelet coherence provides a localized correlation between the two time series $X_1$ and $X_2$ for each frequency and time scale, the coherence being a measure of the intensity of the covariance of the two time series in time–frequency space. The coherence was defined by the following equation (Torrence & Webster 1999):

$$R^2_n(s) = \frac{|S(s^{-1}W_n^{X_1}(s))|^2}{S(s^{-1}|W_n^{X_1}(s)|^2)S(s^{-1}|W_n^{X_2}(s)|^2)}$$

(4)

where $R^2$ ranges between 0 and 1 and can be conceptualized as a localized correlation coefficient in time and frequency space (Grinsted et al. 2004), $S$ is a smoothing operator. See Jevrejeva et al. (2005) for more details about $S$.

RESULTS

Features of annual and seasonal eco-flow metrics

Intra-annual variation

The intra-annual variation of the eco-flow metrics was analyzed in the first instance. As shown in Figure 2(a), the annual eco-deficit metric is significantly correlated with the summer eco-deficit and autumn eco-deficit metrics and correlation coefficients are larger than 0.78 ($p < 0.001$). Statistically, the annual eco-deficit metric is also significantly correlated with the winter eco-deficit metric, with a correlation coefficient around 0.4. Compared to other seasonal eco-deficit metrics, the spring eco-deficit metric is less significantly correlated with the annual eco-deficit metric. Summer and autumn eco-deficit metrics comprise much of the annual eco-deficit metric. This is arguably due to the regulation of TGD which greatly alters the flow regime by decreasing the summer and autumn discharge and increasing winter discharge (see Table 2). As for the seasonal eco-deficit metric, the summer eco-deficit metric is correlated significantly with the autumn eco-deficit metric but less significantly with the winter eco-deficit metric. The autumn eco-deficit metric is correlated significantly with the summer eco-deficit metric and winter eco-deficit metric.

As shown in Figure 2(b), the summer eco-surplus metric and autumn eco-surplus metric are significantly correlated with the annual eco-surplus metric, with a correlation coefficient larger than 0.58 ($p < 0.001$). However, the spring and winter eco-surplus metrics are less significantly correlated with the annual eco-surplus metric (with significant level <0.01). As for the seasonal eco-surplus metric, statistically, the spring eco-surplus metric is significantly correlated with the winter eco-surplus metric but the relationship is weak (the correlation coefficient is about 0.3).

In short, summer and autumn eco-flow metrics occupy a great proportion of both the annual eco-deficit metric and eco-surplus metric.

Periodicity analysis

The periodicity of eco-flow metrics at the Yichang gauge station is shown in Figure 3 using CWT. There are clearly common features in the wavelet power of the time series of the eco-flow metrics, such as the significant peak in the 8 years and 16 year band (mainly around 1920, except for the winter eco-deficit and eco-surplus metric). As for the annual eco-deficit flow metric, the significant wavelet power spectra is in the 14 to 18 year band during 1950 to 1970. However, for the annual eco-surplus flow metric, the significant wavelet power spectra is mainly in the 10 to 16 year band during 1910 to 1950. For seasonal eco-flow metrics, the changes of significant wavelet power spectra are complex for different seasonal eco-flow metrics and it seems that each seasonal eco-flow metric pair (eco-deficit metric and eco-surplus metric) has common features. For example, the summer eco-flow metric pair has the common significant wavelet power spectra in the 8 to 16 year band during 1940 to 1950. Thus, the periodicity change feature of eco-flow metrics varies according to the time interval.

Linkage between the eco-flow metrics and climate indices

Correlation analysis

The correlation analysis between the eco-flow metrics and the selected climate indices was performed first. The
Figure 2 | (a) Annual eco-deficit index (A.ED) and its correlation with the seasonal eco-deficit indices, such as spring eco-deficit index (Sp.ED), summer eco-deficit index (Su.ED), autumn eco-deficit index (Au.ED), and winter eco-deficit index (Wi.ED). The lower panels show the bivariate scatterplots as circles and the diagonal is the histogram of the bivariate points. The upper panels are the value of the correlation plus the result of the confidence level as stars; more stars are more significant correlation between the pairs. (b) The same as (a) but for eco-surplus metric.
correlation results between annual and seasonal eco-flow metrics and synchronous de-trended climate indices from 1948 to 2013 are shown in Table 3, where the de-trended indices indicate the seasonal variation of indices has been removed. Table 3 also shows the correlation coefficients between two time lags (lags = 0, −1) of climate indices, where 0 means synchronous climate indices and eco-flow metrics, and −1 means antecedent one-year climate indices and eco-flow metrics.

It can be observed from Table 3 that the de-trended and synchronous climate indices have a relatively stronger correlation with eco-flow metrics compared to the trended and antecedent (time lag = −1) climate indices. For annual eco-flow metrics, the annual eco-deficit metric is, statistically, significantly correlated with N.H with the coefficient of 0.34. Similarly, the annual eco-surplus metric is significantly correlated with QBO with the coefficient of −0.28. For seasonal eco-flow metrics, most of them are significantly correlated with N.H, the largest correlation coefficient is 0.48 for the autumn eco-deficit metric with an antecedent one-year N.H, the smallest correlation coefficient is 0.25 between the synchronous de-trended NINO3.4 index and summer eco-surplus metric (p = 0.05), and between the synchronous winter eco-deficit metric and trended N.H index (p = 0.05).

The effects of different time lags and the trend of climate indices on the eco-flow metrics were also explored (not shown). Results showed that considering the time lag (such as time lag = −1) of climate indices does not play a role in significantly improving the correlation between the eco-flow metrics and most climate indices. However, considering de-trended climate indices can improve the relations to a certain degree in most cases. This is arguably because the

| Table 2 | Mean seasonal streamflow variation pre- and post-TGD (unit: m³/s) |
|---------|---------------------|---------------------|---------------------|---------------------|
|         | Spring | Summer | Autumn | Winter |
| Pre-dam | 7,687.76 | 25,666.87 | 18,875.22 | 4,769.21 |
| Post-dam| 7,795.84 | 24,082.95 | 14,707.64 | 5,138.81 |
| Change ratio (%) | 1.39% | −6.58% | −28.34% | 7.19% |

Note: The change ratio is calculated by the difference of streamflow of post-dam from the pre-dam streamflow divided by the post-dam streamflow.

Figure 3 | Continuous wavelet power spectrum for the normalized time series of eco-flow metrics from 1882 to 2013, such as annual eco-deficit index (A.ED), annual eco-surplus index (A.ES), spring eco-deficit index (Sp.ED), spring eco-surplus index (Sp.ES), summer eco-deficit index (Su.ED), summer eco-surplus index (Su.ES), autumn eco-deficit index (Au.ED), autumn eco-surplus index (Au.ES), winter eco-deficit index (Wi.ED), and winter eco-surplus index (Wi.ES). The thick black contour denotes the 95% confidence level against red noise and the cone of influence (COI), where edge effects might distort the picture, is shown as white shade. The AR(1) coefficients of the normalized eco-flow metrics are all less than 0.2 when some eco-flow metrics have been transformed to ensure that they are not too far from being normally distributed.
Table 3  Correlation analysis between annual and seasonal eco-flow metrics and the same period climate indices from 1948 to 2013

| Time lag (year) | De-trended | NINO3.4 | NAO | PDO | QBO | IOD | N.H |
|----------------|------------|---------|-----|-----|-----|-----|-----|
| Annual         | D          | 0       | n   | 0.25* | 0.12 | 0.13 | 0.16 | 0.31* | 0.34* |
|                |            |         | y   | 0.26* | 0.16 | 0.14 | 0.16 | 0.26* | 0.27* |
|                |            |         | −1  | 0.03  | −0.48*| 0.13 | −0.12| −0.13| 0.27* |
|                |            |         | y   | 0.04  | −0.46*| 0.14 | −0.12| −0.19| 0.17  |
| S              | 0          | n       | −0.24| 0.07  | −0.15| −0.28*| 0.21| −0.08|
|                |            |         | y   | −0.25*| 0.05 | −0.16| −0.28*| 0.18| 0.03  |
|                |            |         | −1  | 0.13  | 0.23 | 0.02 | 0.19 | 0.31 | 0.08  |
|                |            |         | y   | 0.12  | 0.22 | 0.02 | 0.17 | 0.34 | 0.22  |
| Spring         | D          | 0       | n   | 0.13  | 0.11 | 0.16 | −0.05| −0.02| 0.26* |
|                |            |         | y   | 0.12  | 0.11 | 0.17 | −0.04| −0.003| 0.29* |
|                |            |         | −1  | 0.05  | 0.006| 0.18 | 0.05 | −0.24| −0.17 |
|                |            |         | y   | 0.04  | 0.006| 0.19 | 0.07 | −0.22| −0.14 |
| S              | 0          | n       | 0.05 | 0.28* | 0.24 | −0.23| −0.12| −0.05|
|                |            |         | y   | 0.04  | 0.28*| 0.24 | −0.23| −0.11| −0.022|
|                |            |         | −1  | −0.14 | −0.05| −0.35*| 0.11| 0.25*| 0.01  |
|                |            |         | y   | −0.14 | −0.052| −0.35*| 0.12| 0.26*| 0.042 |
| Summer         | D          | 0       | n   | 0.18  | −0.08| 0.03 | 0.12 | 0.2  | 0.19  |
|                |            |         | y   | 0.19  | −0.06| 0.03 | 0.13 | 0.18 | 0.14  |
|                |            |         | −1  | −0.02 | −0.04| 0.14 | −0.17| −0.17| 0.12  |
|                |            |         | y   | −0.0081| −0.018| 0.14 | −0.17| −0.18| 0.054 |
| S              | 0          | n       | −0.24| 0.02  | −0.06| −0.2  | −0.08| 0.02 |
|                |            |         | y   | −0.25*| 0.0036| −0.06| −0.2  | −0.07| 0.14  |
|                |            |         | −1  | 0.22  | 0.08 | 0.23 | 0.2  | 0.15 | 0.09  |
|                |            |         | y   | 0.22  | 0.07 | 0.23 | 0.19 | 0.16 | 0.21  |
| Autumn         | D          | 0       | n   | 0.21  | −0.11| 0.12 | 0.13 | 0.28*| 0.42* |
|                |            |         | y   | 0.22  | −0.09| 0.15 | 0.16 | 0.22 | 0.37  |
|                |            |         | −1  | 0.002 | −0.4*| −0.16| −0.12| −0.07| 0.48* |
|                |            |         | y   | 0.011 | −0.32*| −0.13| −0.087| 0.14 | 0.39* |
| S              | 0          | n       | −0.09| 0.01  | 0.02 | −0.07| −0.19| 0.3* |
|                |            |         | y   | −0.1  | −0.003| −0.002| −0.09| −0.15| −0.24 |
|                |            |         | −1  | 0.1   | 0.24 | 0.016| 0.06 | 0.19 | −0.1  |
|                |            |         | y   | 0.097 | 0.23 | −0.004| 0.035| 0.18 | 0.034 |
| Winter         | D          | 0       | n   | 0.16  | −0.09| 0.23 | 0.05 | 0.19 | 0.25* |
|                |            |         | y   | 0.15  | −0.11| 0.21 | 0.07 | 0.24 | −0.18 |
|                |            |         | −1  | 0.12  | −0.18| 0.01 | 0.04 | −0.17| 0.36* |
|                |            |         | y   | 0.11  | −0.19| −0.003| 0.069| −0.13| 0.31* |
| S              | 0          | n       | −0.12| 0.14  | −0.22| 0.02  | 0.05 | 0.34*| 0.41* |
|                |            |         | y   | −0.1  | 0.17 | −0.19| −0.03| 0.03 | 0.18  |
|                |            |         | −1  | −0.18 | 0.05 | −0.08| −0.05| 0.2  | 0.26* |

Note: D, eco-deficit metric; S, eco-surplus metric; n, not de-trended; y, de-trended. The bold font with asterisk and grey shading means significant at 0.05 level.

detrended climate indices reflect natural climate variability much better and climate variability can influence the flow regime changes (van Dam 1999; Zhang et al. 2008). We also conducted the Kendall and Spearman rank correlation between the eco-flow metrics and the climate indices (not shown). However, the Pearson correlation seems to be the most significant among the three correlations. Therefore, this study then focused on the synchronous, de-trended climate indices and eco-flow metrics from 1948 to 2013.

Cross-wavelet and wavelet coherence analysis

To further identify the variability and possible linkages between eco-flow metrics and selected climate indices, the
spectra and phase relationships between these two variables were detected by cross-wavelet transform and wavelet coherence. The cross-wavelet power spectra between the annual and seasonal eco-flow metrics and selected climate indices are shown in Figure 4 and the squared wavelet coherence results are shown in Figure 5. The squared wavelet coherence results can identify both frequency bands and time intervals for the eco-flow metrics and six climate indices (Thiombiano et al. 2016).

As for the annual eco-deficit metric from Figure 4, it has a significant (>95% confidence level) common power with most climate indices in the 2 to 4 year band during 1960 to 1970 and a mainly in-phase relation. There are also other common powers for specific climate indices, but the phase relations have no common features. For the annual eco-surplus metric, most climate indices have significant common power in the 2 to 4 year band during 1960 to 1970, with clear anti-phase relations except for the PDO index. As for seasonal eco-flow metrics (not shown), the significant common power occurred in the 2 to 8 year band during 1960 to 1970, 1980 to 1990, and 1990 to 2000. The changes of phase relations are relatively complex and no obvious change law can be inferred. Thus, the seasonal eco-flow metrics show a similar mode to climate indices, compared to the annual eco-flow metrics. However, as for particular seasonal or annual eco-flow metrics, the changes of phase relation with the same climate indices may be very different.

As shown in Figure 5, a large section stands out as being significant compared with the cross-wavelet transform for eco-flow metrics and climate indices. The relationships in these areas vary significantly. Most climate indices show an in-phase relation to the annual eco-deficit metric except NAO and QBO indices. However, no obvious phase relation to the annual eco-surplus metric can be observed because there is no dominant one. As for the eco-deficit metric, there is one main region with NAO, PDO index, and N.H index with high coherency peaks. For NAO, the region is at the 2 to 4 year band during 1960 to 1970, with no obvious phase relation at 95% confidence level. For PDO index, the region is at the 4 to 8 year band during 1980 to 2000, the phase changes in the region being dominated by in-phase relations and the phase changes slowly from −80° to 0°. For N.H index, the region is at the 6 to 8 year band during 1980 to 2000 and is dominated by in-phase relations. There are two main regions with high coherency peaks for NINO3.4, QBO index, and IOD index. For NINO3.4, the regions are at the 2 to 4 year band during 1960 to 1970 and 4 to 8 year band during 1980 to 2000, respectively. The phase changes in these regions are dominated by in-phase relations that changed slowly in the regions from 0° to 60°. These phase changes are related to the time lag between NINO3.4 and annual eco-deficit metric; for the QBO index, the regions are at the 2 to 4 year band during 1960 to 1970 and during 1980 to 2000, respectively. The phase change has no obvious law; for the IOD index, the regions are at the 2 to 4 year band during 1970 to 1980 and during 1990 to 2000, respectively; the phase changes in these regions are slow from −80° to 30° dominated by in-phase relation. Above all, the changes of phase relation between annual eco-deficit metric and six climate indices are slow, which demonstrate that the time lag varies between them and more than one factor influences the eco-flow metrics in the upper Yangtze Basin (Zhang et al. 2007).

As for the annual eco-surplus metric, there is one main region with PDO index with high coherency peaks in the 4 to 8 year band during 1990 to 2000 and this region is dominated by anti-phase relations. There are two main regions with a NINO3.4, IOD index, and N.H index with high coherency peaks, i.e., for NINO3.4, the regions are at the 2 to 4 year band and 6 to 8 year band during 1990 to 2000. The change of phase is slow and dominated by anti-phase. For IOD index, the regions are at the 2 to 4 year band during 1970 to 1980 and 1990 to 2000 and dominated by anti-phase relations. For N.H index, the regions are at the 2 to 4 year band during 1960 to 1970 and the 6 to 8 year band during 1980 to 2000 and are dominated by in-phase relations. Meanwhile, for NAO index, there are three main regions with high coherency peaks: in the 2 to 4 year band during 1960 to 1970, in the 3 to 4 year band during 1980 to 1990, and in the 6 to 10 year band during 1980 to 2000. The phase change is ambiguous compared to other climate indices (e.g., PDO index, NINO3.4, IOD index, and N.H index). The significant regions of Figure 5 are so extensive that it is very unlikely that this is simply by chance, which may indicate that the annual eco-flow metrics are influenced by the selected climate indices to a certain degree.
Figure 4 | Cross wavelet power spectra of (a) annual eco-deficit metric, (b) annual eco-surplus metric, (c) spring eco-deficit metric, (d) spring eco-surplus metric, (e) summer eco-deficit metric, (f) summer eco-surplus metric, (g) autumn eco-deficit metric, (h) autumn eco-surplus metric, (i) winter eco-deficit metric, (j) winter eco-surplus metric with six climate indices, the 5% significance level against red noise is shown as a thick contour. The relative phase relationship is shown as arrows with in-phase pointing right, anti-phase pointing left. (Continued.)
Figure 4 | Continued.
Figure 4 | Continued.
For the seasonal eco-flow metrics (not shown), most eco-flow metrics have one more region with high coherency peaks (in the 2 to 8 year band during 1960 to 1970 and 1980 to 2000), but the phase changes slowly between the seasonal

Figure 4 | Continued.
eco-flow metrics and six climate indices. The eco-flow metrics vary in a complex manner, therefore factors other than climate variability may also influence the variation of the eco-flow metrics.
Figure 5 | Squared wavelet coherence result for the normalized times series of annual eco-flow metrics for (a) annual eco-deficit metric, (b) annual eco-surplus metric and six climate indices. The 5% significance level against red noise is shown as a thick contour. The relative phase relationship is shown as arrows with in-phase pointing right, anti-phase pointing left.
DISCUSSION

The widely adopted eco-flow metrics (i.e., eco-surplus or eco-deficit) are used in this study to denote the hydrologic alteration of the flow regime for the upper Yangtze River basin. Usually, the eco-flow metrics are mainly related to human activities. However, the hydrological alteration is inherently influenced by the climate variability and the impact of climate variability on the natural flow regime is increasing (Suen 2010; Kim et al. 2011; Dyer et al. 2014). Thus, the relationship between the eco-flow metrics and climate variability may be very important for the ecological and environmental protection of the Yangtze River or for water resource management of TGD, due to limited research on this issue to date.

The streamflow of the upper Yangtze River is well connected to climate variability; convincing evidence has been presented in many research papers (Jiang et al. 2007; Xu et al. 2007; Ouyang et al. 2014). The eco-flow metrics may also be linked to climate variability and the latter is represented by some selected climate indices in the current research. As a seasonal regulation reservoir, TGD has had a great influence on seasonal streamflow because of the flood mitigation function during the summer period, when the peak is cut off and the water level is limited to 145 m, and the refill to the normal water level of 175 m in the early autumn. Thus, the seasonal eco-flow metrics play a different role within the annual eco-flow metrics, and this is understandable from the regulation of TGD. However, the annual and seasonal eco-flow metrics are modified by climate variability to a different degree, which can be seen from the periodicity analysis (Figure 3) and the correlation analysis (Table 3). The periodicity of the annual eco-flow metrics is dominant at low frequency power (16 years) and seasonal eco-flow metrics are dominant at higher frequency power (2 to 4 years and 8 to 16 years) and may be very different for specified seasonal eco-flow metrics. This demonstrates that, from the perspective of longer periods, annual eco-flow metrics are impacted by the selected climate indices and the seasonal eco-flow metrics are influenced by other complex factors besides the selected climate indices. This is consistent with previous studies (Xu et al. 2007; Zhang et al. 2007; Xiao et al. 2015). The coherence power of most annual and seasonal eco-flow metrics is generally high, between 2 and 8 years from the cross-wavelet (Figure 4) and wavelet coherence (Figure 5) analysis. This is an indication that the frequency structure in the eco-flow series of the Yangtze is replicated as intermittent oscillations at different times in the selected climate indices, such as NINO3.4, NAO, and PDO indices in the same frequency bands. The causal relationship between the streamflow and the climate indices has been documented (Hu et al. 2000; Wei 2005). The phase relation between the annual and seasonal eco-flow metrics of the Yangtze River basin changes slowly over shorter periods (e.g., in the 2 to 4 year band and 4 to 8 year band in Figures 4 and 5), indicating that the eco-flow metrics (especially the seasonal eco-flow metrics) are not only impacted by the climate indices but also other factors, like the regulation of TGD which we have mentioned above. This is also consistent with previous research (Zhang et al. 2007; Zhang et al. 2013; Wang et al. 2017).

A major limitation of this study is that the impacts of climate variability and human activity on hydrologic alteration of the flow regime (such as eco-flow metrics) is not quantitatively attributed and is outside the scope of this research. The focus of this study is to explore the potential relationship between the eco-flow metrics and climate variability based on some knowledge of the features of eco-flow metrics. Another limitation is that changes, including spatiotemporal change, of seasonal eco-flow metrics along the Yangtze River are not fully understood because of the complex factors and limited data available. Finally, the post-dam eco-flow series are still short, thus the regulation of TGD on the flow regime based on the eco-flow metrics is not well detailed; however, with the accumulated data and the help of some hydrological models, future study may solve this issue better.

CONCLUSIONS

This paper investigated the variation of eco-flow metrics at the Yichang gauge station and explored the linkages between the eco-flow metrics and the selected climate indices based on linear, non-linear, and phase correlation
analysis. The primary conclusions can be drawn as follows:

(1) The summer and autumn eco-flow metrics have a significantly strong correlation with the annual eco-flow metrics and comprise a large proportion of them. The periodicity of annual and seasonal eco-flow metrics are different but they have common and significant peak features in the 8 and 16 year band (around 1920) except in the winter eco-flow metrics. This is the basis for recognizing the change law of eco-flow metrics.

(2) Correlation between the eco-flow metrics and selected de-trended climate indices is strong, especially for the synchronous N.H and IOD indices. The seasonal eco-flow metrics correlate more with selected climate indices than the annual eco-flow metrics.

(3) Most eco-flow metrics have a significant common power in the 2 to 4 year band, with various changes in the phase relationships between the annual eco-flow metrics and the selected climate indices. For instance, the annual eco-deficit metrics mainly have an in-phase correlation with selected climate indices and the annual eco-surplus metrics mainly have an anti-phase correlation with selected climate indices. Despite the identification of extensive and significant regions between the eco-flow metrics and selected climate indices based on the wavelet coherency method (which means the climate variability may affect the eco-flow metrics), phase changes slowly in these regions and no obvious phase relationship exists between the eco-flow metrics and six climate indices.

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