Multi-scale investigation on streamflow temporal variability and its connection to global climate indices for unregulated rivers in India

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Abstract

With the increasing stress on water resources for a developing country like India, it is pertinent to understand the dominant streamflow patterns for effective planning and management activities. This study investigates the spatiotemporal characterization of streamflow of six unregulated catchments in India. Firstly, Mann Kendall (MK) and Changepoint analysis were carried out to detect the presence of trends and any abrupt changes in hydroclimatic variables in the chosen streamflows. To unravel the relationships between the temporal variability of streamflow and its association with precipitation and global climate indices, namely, Niño 3.4, IOD, PDO, and NAO, continuous wavelet transform is used. Cross-wavelet transform and wavelet coherence analysis were also used to capture the coherent and phase relationships between streamflow and climate indices. The continuous wavelet transforms of streamflow data revealed that intra-annual (0.5 years), annual (1 year), and inter-annual (2–4 year) oscillations are statistically significant. Furthermore, a better understanding of the in-phase relationship between the streamflow and precipitation at intra-annual and annual time scales were well-captured using wavelet coherence analysis compared to cross wavelet transform. Furthermore, our analysis also revealed that streamflow observed an in-phase relationship with IOD and NAO, whereas there was a lag correlation with Niño 3.4 and PDO indices at intra-annual, annual and interannual time scales.

Key words: continuous wavelet transform, cross wavelet spectrum, streamflow, time-frequency characterization, wavelet, wavelet coherence

Highlights

- Unravelled the spatiotemporal characterization of streamflow of six unregulated catchments.
- Cross-wavelet transform and wavelet coherence analysis used to disentangle the coherent and phase relationships between streamflow and climate indices.
- Streamflow observed an in-phase relationship with IOD and NAO, whereas there was a lag correlation with Niño 3.4 and PDO indices at intra-annual, annual and interannual time scale.

1. Introduction

Human-induced global warming is changing the frequency and magnitude of hydrological variables altering the water cycle (Fanta et al. 2001; Adeloye & Montaseri 2002; Burn & Hag Elnur 2002; Cunderlik & Burn 2002; Kahya & Kalayci 2004; Cherinet et al. 2019; Sridhar et al. 2019; Zhong et al. 2019). Due to abrupt changes in the water cycle, water resources’ occurrence and availability are deeply affected. These variations in hydroclimatic processes trigger extreme events, endangering the availability of water resources and affecting socioeconomic conditions (Brutsaert & Parlange 1998; Kiely et al. 1998; Lins & Slack 1999; Khatiwada et al. 2016). Variability of these hydroclimatic variables is pertinent to map the hydrological cycle dynamics (Zhao et al. 2014). Streamflow is an important hydroclimatic parameter that aids in understanding the water cycle dynamics (Tamaddun et al. 2016). Many studies have investigated the variations in streamflow (trends, seasonality, and change-point detection) around the globe, confirming that streamflow is affected by the wide range of local (precipitation) and global (El Niño Southern Oscillation, Indian Ocean Dipole) climatic drivers (Hu et al. 2011; Masih et al. 2011; Panda et al. 2013; Abeyesingha et al. 2016; Fathian et al. 2016). For instance, Burn & Hag Elnur 2002 identified that Pacific

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Decadal Oscillation (PDO), North Atlantic Oscillation (NAO), North Pacific index (NP) affect the timing of runoff in the Mackenzie river basin in northern Canada. Sahu et al. 2012 evaluated IOD and ENSO’s influence on extreme streamflow in the Citarum River in Indonesia. The results indicated that IOD could capture extreme events and a high correlation between seasonal IOD and seasonal streamflow. Nalley et al. (2016) used NAO, PDO, and ENSO to understand the variability of streamflow in Quebec and Ontario. Furthermore, significant water cycle changes lead to extreme drought and floods (Kustu et al. 2010; Miguez-Macho & Fan 2012; Himayoun & Roshni 2019; Sahu et al. 2020).

For a country like India with an extensive river system and streamflow being the primary source of water supply for irrigation, power generation, industrial use, and others, it is crucial to understand the streamflow dynamics. Quantifying the influences of local and global climate drivers on streamflow at basin scale is of utmost importance to develop probabilistic flood and drought forecasting models in assessing hydrologic risk. It would further help in decision-making for disaster management across the basin in India. Maity & Nagesh Kumar 2008 used climate indices to develop forecasting models for the Mahanadi river in India. Their results indicated that climatic indices help improve the predictability of models at the basin scale.

Similarly, Panda et al. (2013) have analyzed using the Mann-Kendall test and climate models to understand climate variability on streamflow in the Mahanadi river basin. The results showed the correlation of ENSO on precipitation and streamflow in the basin. Finally, Sharma et al. (2019) evaluated ENSO and IOD’s influence on streamflow variability for the Tapi river basin, India. They found that the IOD influences streamflow compared to ENSO using trend analysis.

Significant progress has been made in quantifying the impact of global drivers on streamflow. However, there are only a few studies dedicated to the quantification of multi-scale variability in streamflow processes. Further, in conventional approaches to studying hydrological processes, this work focuses on one particular scale. The effects of finer scales are understood through the constitutive relation, and the consequences of coarser scales are neglected by assuming that the system is homogeneous at larger scales (Agarwal et al. 2019). In recent years, wavelet analysis has emerged as an essential tool in spectral analysis owing to its ability to deal with non-stationary data. Lau & Weng (1995) highlighted that wavelet is an effective hydrological time series analysis method. Adamowski et al. (2013) used wavelet analysis for quantifying the spatial-temporal variability of annual streamflow and meteorological changes in eastern Ontario and southwestern Quebec. Taye & Willems (2013) used wavelet analysis for identifying sources of temporal variability in hydrological extremes of the upper Blue Nile basin. Canchala et al. (2020) investigated the relationship of the streamflow variability with ENSO of Colombian Pacific Basins at interannual and decadal timescales and revealed significant coherencies at interannual (2-7 years) and decadal-scale (8-14 years). It is important to note that all the mentioned studies were based on catchments which are regulated. In the regulated catchment, hydropower plant, dams, or any other hydraulic structure might alter the natural flow regime and affect the streamflow variability by increasing annual base flow and decreasing peak flow magnitude (Swain & Patra 2017; Milner et al. 2019). However, for better understanding of the natural streamflow variability, and its relation with other hydrologic variables, unregulated catchments must be considered. Therefore, the main aim of this study is to investigate the streamflow variability of six different unregulated streamflow stations at different time scales and quantifies the influence of precipitation and global climatic indices on them. For this purpose, we have considered six virgin catchments from the Indian subcontinent and analyse the streamflow variability using different statistical methods such as wavelets analysis, wavelet coherence analysis and Mann Kendall Test. The rest of the paper is arranged in the following manner. Section 2 provides information about the study area and the data used. The methods used in the study are described in Section 3. Results and discussion are provided in Section 4 and 5 respectively, whereas Section 6 gives the concluding remarks from the study.

2. STUDY AREA AND DATA USED

2.1. Study area description

India consists of 58 major river basins with varying flows and climatic regimes. Six unregulated streamflow stations from six different major river basins viz Brahmani, Cauvery, Mahanadi, Narmada, Godavari, and Subarnarekha basin are selected (Figure 1). Around 74 gauging stations are operational in the selected six river basins. In addition, one unregulated gauging station is determined based on the availability of long-term continuous data without missing values. All the selected river basins directly influence the water resources in their respective regions in irrigation, power generation and flood risk hazards in their flow regions. Figure 1 represents the geographical location of selected gauging stations in the river basins chosen for analysis, and Table 1 shows the details of chosen river basins.
Figure 1 | Locations of gauging stations and catchments of the chosen river basins.

Table 1 | Details of the six catchments analyzed in this study

| Sno | River   | Station name | Indicated as | Latitude | Longitude | Catchment Area (Km²) | River length (Km) | Annual average discharge (m³/s) |
|-----|---------|--------------|--------------|----------|-----------|----------------------|-------------------|-------------------------------|
| 1   | Brahmani | Anandapur    | BA           | 21.78    | 86.3      | 8,570                | 799               | 678                           |
| 2   | Cauvery  | Kudige       | CK           | 12.45    | 76.24     | 1,934                | 805               | 677                           |
| 3   | Mahanadi | Bamnidhi     | MB           | 22.45    | 83.12     | 9,730                | 1,465             | 3061.8                        |
| 4   | Narmada  | Garudebarhar | NG           | 21.54    | 73.66     | 87,892               | 900               | 2,119                         |
| 5   | Godavari | Tekra        | GT           | 19.28    | 80.38     | 108,780              | 1,312             | 1,447                         |
| 6   | Subarnarekha | Adityapur   | SA           | 22.95    | 86.52     | 6,309                | 395               | 392                           |
2.2. Streamflow data
Streamflow data sets for the six selected stations were obtained from the WRIS India website http://indiawris.gov.in/wris/ for a 41-year period from 1975 to 2015. The daily streamflow data are converted to monthly using the downsample toolbox in MATLAB 2019a.
2.3. Precipitation data
The precipitation data set used a high-resolution of 0.25°x 0.25°daily gridded data available from 1901 to 2019. This data set is developed by Indian Metrological Department (IMD) for the spatial domain of 66.5° to 100°E and 6.5° to 38.5°N covering entire India. The data set used in this study is from 1975 to 2015, 41 years of daily precipitation and was downloaded from http://www.imdpune.gov.in/Clim_Pred_LRF_New/Grided_Data_Download.html
2.4. Global climate indices
Global climate indices influence various hydrological variables, including precipitation and streamflow around the world. Based on previous studies, Indian Ocean Dipole (IOD), North Atlantic Oscillation (NAO), El Niño Southern Oscillation (Niño3.4), and Pacific Decadal Oscillation (PDO) are major indices found to influence the Indian subcontinent. The brief details on these indices are as follows:

(1) IOD index represents sea surface temperature between the western equatorial Indian ocean (50° E - 70°E and 10° S -10° N) and the southeastern Indian ocean (90°E - 110° E and 10° S -10°N). Several studies showed that IOD plays a vital role in the climate of the Indian subcontinent. Hence, it is also referred to as Indian Niño. The IOD data was obtained from the Bureau of Metrology, Australia, from the website https://www.esrl.noaa.gov/psd/gcos_wgsp/Timeseries/Data/dmi.long.data. The data is available at monthly scale from the period of 1948 to 2018.
(2) NAO refers to the North Atlantic Ocean fluctuations, calculated based on the subpolar low and subtropical high. The NOAA climate prediction centre (CPC) prepares data for NAO, and it is available at the monthly level from 1948 to 2018.
(3) Niño 3.4 index represents the anomalies in sea surface temperature at East Central Tropical Pacific in the region bounded between 5° N to 5°S and 170° W to 120° W. Data is available from the period 1870 to 2019 at monthly scale.
(4) PDO is a climate index that occurs at a larger scale with its patterns primarily observed in the North Pacific, and its phases are classified into warm and cool based on temperature changes. The length of the data available is from 1948 to 2018.

Data for NAO, NIÑO 3.4, and PDO were obtained from the NOAA website https://www.esrl.noaa.gov/psd/data/climateindices/list/.
3. METHODS
This section describes trend analysis using the Mann-Kendall test and temporal analysis using continuous wavelet transform. It also describes the cross wavelet analysis and wavelet coherence used for investigating the connection between streamflow, precipitation, and climate indices. The detailed frame of the adopted methodology in this study is represented in Figure 2.
3.1. Mann-Kendall test (MK test)
The Mann-Kendall (MK) test determines the trend for each gauging station considered in this study. The MK test capabilities were robust in detecting trends based on Kendall 1975 and Mann 1945. Some of the studies that used this trend detection test to determine trends in hydroclimatic variables include works by Burn & Hag Elnur 2002; Sayemuzzaman & Jha 2014; and Guntu et al. 2020. In this test, based on the p-value, the presence or absence of a trend is determined. Equations 1 to 3 govern the detection of the trend in a series.

\[
S = \sum_{i=1}^{n-1} \sum_{k=i+1}^{n} \text{sgn}(X_k - X_i)
\]
\[
\text{Var}(S) = \frac{1}{18} \left[ n(n-1)(2n+5) - \sum_{k=1}^{q} t_k(t_k - 1)(2t_k + 5) \right]
\]

If \( S > 0 \), \( Z = \left( \frac{S - 1}{\text{std}(S)} \right) \); \( S = 0 \), \( Z = 0 \); \( S < 0 \), \( Z = \left( \frac{S + 1}{\text{std}(S)} \right) \)
Figure 2 | Framework of the adopted methodology.

- **Collection of Data**
  - **Precipitation Data**: High-resolution of 0.25°x0.25° daily gridded precipitation 41 years' data was downloaded from 1975 to 2015.
  - **Streamflow Data**: Streamflow data sets for the six unregulated stations were obtained from the WRIS India website for a 41-year period from 1975 to 2015.
  - **Climate Indices Data**: Monthly data of four global climate indices, namely, IOD, NAO, Niño 3.4, and PDO was downloaded from National Oceanic and Atmospheric Administration (NOAA).

- **Trend Analysis**
  - For finding gradual or monotonic change in streamflow data.
  - Nonparametric Mann-Kendall trend test.

- **Step Change Analysis**
  - For abrupt or step change in streamflow data.
  - Change point analysis was performed.

- **Association of precipitation and streamflow**
  - XWT and WTC analysis was performed to finding the multi-scale association between these two variables.

- **Hydroclimatonic Teleconnections**
  - XWT and WTC analysis was performed to finding the multi-scale association between streamflow and global climate indices.

- **Temporal Analysis**
  - Continuous wavelet analysis was performed to identify multi-scale variability in streamflow data.
where $S$ represents the value of the test statistic, $n$ represents the length of the time series, $X_k$, $X_t$ represents the sequential data points, $sgn(p)$ is a sign function for which if $p > 0$, $p = 0$ and $p < 0$, then $sgn(p)$ takes the values of $-1$, $0$, $1$. $Z$ represents the standardized statistic value. $t_k$ is the number of ties for $k^{th}$ value and $q$ is the number of tie values.

Based on the value of standardized statistic ($Z$), the $p$-value ($Y$) is calculated, which can be mathematically represented by Equation (3)

$$Y = 2(1 - nmcdf(Z))$$

where $Y$ is the $p$-value, $nmcdf$ denotes the normalized cumulative distribution function of standardized statistics. The level of significance (confidence interval) is denoted by $\alpha$ and if the value of $Z > Z_{1-\alpha/2}(=1.96)$ it determines that the null hypothesis is rejected along with an indication of the presence of a trend. If not, it indicated acceptance of the null hypothesis, in the absence of a trend. In this work, the confidence interval value $\alpha$ is assumed to be 0.05 and, i.e., the probability of the null hypothesis to be wrong is 5% and using this value and the value of test statistic $S$, limits of the $Z$ statistic are determined as $-1.96$ to $1.96$.

In this work the Mann-Kendall test is carried using software MATLAB2019a. Suppose the obtained value for Z statistic lies between $-1.96 < Z < 1.96$, it denotes that there is no significant presence of a trend. If the $p$-value obtained from the MK test is less than alpha (0.05, i.e., 95% probability of null hypothesis being correct), it can be stated that there is a significant presence of a trend. If the value of Z statistic and $P$-value are negative, it represents a negative trend; if the positive side represents a positive trend.

### 3.2. Change point analysis

Change points are abrupt variations in time series data. Such abrupt changes may represent transitions that occur between states. Detection of change points is helpful in modeling and predicting time series. Time series data are sequences of measurements over time, describing the behavior of systems. These behaviors can change over time due to external events and systematic internal distribution changes (Kawahara & Sugiyama 2012). Change point detection (CPD) is the problem of finding abrupt changes in data when a property of the time series changes (Reeves et al. 2007).

In this study, change point analysis is carried out in Matlab 2019a; based on the streamflow values in each river, step changes were observed. Suppose there is a change in trend at a particular period considered in the analysis and observed to be a decreasing trend. In that case, a $-ve$ value is assigned to the change point, whereas if it is observed to be a positive trend, $+ve$ value is assigned.

### 3.3. Wavelet analysis

Mathematical tools used to analyze a time series in both time and frequency domain due to the localization capabilities are referred to as wavelets (Daubechies 1990). Due to wavelets’ multi-resolution and localization capabilities, they are widely applied for time series analysis and prediction (Maheswaran & Khosa 2012; Agarwal et al. 2017). Decomposition of wavelets helps reveal the hidden low frequency and high-frequency components in the observed time series, which helps identify the features helpful for good analysis and predictions. In recent years wavelets have been widely used in domains of hydrology and water resources due to their ability to study non-stationarity in a time series (Grossmann & Morlet 1984; Kim & Valdés 2003; Zhou et al. 2008; Maheswaran & Khosa 2012). Wavelets are broadly classified into continuous wavelet transforms (CWT), and discrete wavelet transforms (DWT).

Continuous wavelet transforms work on all the scales to analyse a time series ((Mallat 1999). Continuous Wavelet Transform (CWT) is defined as the sum overall time of the signal multiplied by scaled, shifted versions of the wavelet function $\psi$. The coefficients of the wavelet transform of continuous signal $f(t)$ are defined by a linear integral operator (Maheswaran & Khosa 2012).

$$W(a, \tau) = \int_{-\infty}^{\infty} f(t)\psi_{a,\tau}(t)\,dt$$

(4)

where

$$\psi_{a,\tau}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-\tau}{a}\right)$$
The function $\psi(t)$, which can be real or complex, plays a convolution kernel called a wavelet. The parameter $a$ can be interpreted as a dilation ($a > 1$) or contraction ($a < 1$) factor of the wavelet function $\psi(t)$ corresponding to different scales of observation. The parameter $\tau$ can be interpreted as a temporal translation or shift of the function $\psi(t)$ which allows the study of the signal $f(t)$ locally around the time $\tau$.

The wavelet function $\psi(t)$ has the following properties.

1. The function integrates to zero:
   \[ \int_{-\infty}^{\infty} \psi(t)dt = 0 \]  
   (5)

2. The function is square integral or, equivalently, has finite energy
   \[ \int_{-\infty}^{\infty} |\psi(t)|^2 dt < \infty \]  
   (6)

The wavelet transform $W(a, \tau)$ are also called wavelet coefficients in which the dilation parameter is equivalent to the window size in the windowed Fourier transform. By changing the dilation parameter, the information contained in different data frequencies can be analyzed independently. A small dilation value may be used to analyze high-frequency information, while a larger value may be used to analyze a process with low-frequency components. The wavelet transform, as defined by Equation (4), is called the continuous wavelet transform (abbreviated CWT) because the scale and time parameters, $a$ and $\tau$, assume continuous values. It provides a redundant representation of a signal as the CWT of a function at scale $a$ and location $\tau$ can be obtained from the continuous wavelet transform of the same function at other scales and locations. Since the CWT behaves like orthonormal basis decomposition, it can be shown that it is also isometric as it preserves the overall energy content of the signal and, thereby, allows recovery of the function $f(t)$ from its transform by using the following reconstruction formula:

\[ f(t) = \frac{1}{C_\psi} \int_{-\infty}^{\infty} a^{-2}W(a, \tau)\psi_a(t)d\tau d\tau \]  
   (7)

where $C_\psi$ is a constant and depends on the choice of the wavelet. Equation (7) suggests that the function $f(t)$ may be seen as a superposition of signals at different scales. It can be obtained by varying the scale parameter $a$. Continuous wavelet transforms are more efficient at analyzing hydro-climatic variables than non-normal distributions.

### 3.4. Cross-wavelet transform

Cross-wavelet transform (XWT) explains the coherent relationships between two different time series and the phase relationships. In XWT, the dominant frequency or the lowest frequency may affect the two different time series' coherency. Suppose two discrete time series $X$ ($n = 1 \ldots N$) and $Y$ ($n = 1 \ldots N$), the XWT can be calculated as

\[ W^{XY}(a) = W^{X}(a) \times W^{Y^*}(a) \]  
   (8)

Here $W^{X}(a)$ is the CWT of the time series $X$ considered. The complex conjugate of $W^{X}(a)$ the CWT of time series $Y$. Cross wavelet constructs the relationship between two CWTs with high common power (covariance) of the two-time series (Grinsted et al. 2004). The significant covariance of these timeseries can be observed as red noise in the wavelet scalograms.

### 3.5. Wavelet coherence

Cross-wavelet transform sometimes may not give precise results in terms of coherency. Wavelet coherence is used to overcome this problem, which provides accurate results about coherent relationships. Wavelet coherence exhibits the correlation of two-time series, which is based on time-frequency analysis. Wavelet coherence aids in understanding the...
relationship between low power frequencies, which cannot be correctly analyzed using a cross wavelet (Agarwal et al., 2016). Consider two-time series \( y \) and \( x \); then the wavelet coherence is given by

\[
R(y, x) = \frac{\sqrt[6]{|W(y, x)|}}{\sqrt[6]{|W(y)||W(x)|}} 
\]

(9)

\[
R^2(y, x) = R(y, x) \cdot R(y, x)^*; 
\]

(10)

In the above equation; \( R(y,x) \) – wavelet coherence between \( y \) and \( x \); \( R^2(y,x) \)-squared wavelet coherence between \( y \) and \( x \); \( W(y,x) \) denotes the corresponding cross-wavelet transforms; \( \phi \) denotes smoothing factor.

Wavelet coherence ranges from 0 to 1. Thus, if the correlation coefficient value is closer to 1, there is more correlation between the two-time series and vice versa.

4. RESULTS

In this section, the long-term trend and step-change analysis of streamflow of six unregulated catchments are presented. Furthermore, the precipitation and global climatic indices are decomposed to investigate the association with streamflow at different timescales.

4.1. Long-term trend and change point detection

Firstly, estimation of the general pattern of a streamflow timeseries over a period between 1975 and 2015 for six ungauged catchments. Table 2 shows the Z value, \( p \)-value, and step-change year obtained through the MK test and step-change detection technique. Our results showed a significant long-term negative trend for station CK and NG at a 5% significance level. However, other stations viz BA, GT, MB, and SA had a significant trend in their respective streamflow data. Figure 3 illustrates the trend lines and change point for each considered streamflow station. In the case of change point analysis, the result indicated a significant abrupt change for all the stations. For instance, significant negative abrupt changes were observed for the station BA, CK, MB, and NG in 2015, 1985, 2007, and 2006, respectively. Whereas stations like GT and SA observed significant positive abrupt changes in their respective streamflow data in 1992 and 1985.

4.2. Wavelet analysis of streamflow

Wavelet transformation (WT) is used to determine the scale-specific dominant parameters that might cause the trend and step change in streamflow. Daily streamflow data of six considered stations are decomposed using continuous wavelet transforms (CWT), and scalograms are plotted (Figure 4(a)–4(f)) for each station. In general, all considered stations (BA, CK, GT, NG, MB, and SA) showed high variability at intra-annual, annual and inter-annual scales (0.5, 1, 2, and 4 years). Interestingly, significant intra-annual oscillations of 0.5 years occurred mostly up to the 1990s for stations BA (Figure 4(a)), MB (Figure 4(d)), NG (Figure 4(e)), and SA (Figure 4(f)). In contrast, such oscillations were absent at station CK (Figure 4(b)) and GT (Figure 4(c)) at this particular scale. Annual oscillations were active for all the stations throughout the study period, except station CK that showed vanishing features from 1985 to 2000. At the inter-annual scale (2 years and 4 years), BA, MB, NG, and SA observed significant oscillations mainly in the 1990s. Scalograms showed the streamflow variability at

| River     | Station       | River/Station | Z value | \( p \)-value | Significance | Step change |
|-----------|---------------|---------------|---------|---------------|--------------|-------------|
| Brahmani  | Anandapur     | BA            | −0.21   | 0.83          | *            | 2015 –      |
| Cauvery   | Kudige        | CK            | −3.95   | 7.69e-05      | **           | 1985 –      |
| Godavari  | Tekra         | GT            | −1.67   | 0.09          | *            | 1992 +      |
| Mahanadi  | Bamnidhi      | MB            | 0.35    | 0.72          | *            | 2007 –      |
| Narmada   | Garudeshwar   | NG            | −2.91   | 0.01          | **           | 2006 –      |
| Subarnarekha | Adityapur   | SA            | 0.86    | 0.38          | *            | 1985 +      |

Note: * * represents no significant trend and ** * represents a significant negative trend. Stepchange denotes the year in which change has occurred and * * indicates a negative change trend, and * * * indicates a positive change trend.
different time scales; however, the causes of variability in its patterns cannot explain using only CWT. In the next section, quantification of correlation between streamflow with precipitation and also global climatic parameters is carried out using wavelet coherence analysis (WCA) and cross-wavelet analysis (XWT).

**Figure 3** | Annual streamflow trend analysis for gauging stations in chosen river basins.
4.3. Association of precipitation and streamflow at multiple timescales

Cross-wavelet analysis (XWT, Figure 5(a)–5(f)) and wavelet coherence analysis (WCA, Figure 6(a)–6(f)) are used to quantify the association between rainfall and streamflow. In general, XWT and WCA plot of streamflow of all the stations (BA, CK,
GT, MB, NG, and SA) showed an in-phase relationship with precipitation; however, stations GT, MB, and NG also observed lag correlation at 0.25, 0.5, and 1 year of scale respectively. Similarly, all stations except the station CK showed similar associations at intra-annual, annual, and inter-annual time scales in both XWT and WCA. For CK station WCA showed a strong

Figure 5 | Cross-wavelet analysis of precipitation & streamflow at all the stations. (a) BA, (b) CK, (c) GT, (d) MB, (e) NG and (f) SA. The sections marked by black color contours are the significant sections indicating a high correlation between precipitation and streamflow. The cone of influence indicates the area affected by the boundary assumption.
feature at 4 years of scale; however, the same is absent in XWT. A significant intra-annual coherence between these two variables can be observed at 0.125, 0.25, and 0.5 years of scale; however, these coherences are short duration and transient in nature. On an annual scale, except for station CK, all other stations observed significant coherence throughout the study.

Figure 6 | Wavelet coherence analysis of precipitation & streamflow at all the stations (a) BA, (b) CK, (c) GT, (d) MB, (e) NG, and (f) SA. The sections marked by black color contours are the significant sections indicating high coherence between precipitation and streamflow. The cone of influence indicates the area affected by the boundary assumptions.
period. In the 1980s and 1990s, some stations like BA, GT, and MB also observed significant inter-annual coherence at 2–4 years of scale. The association between rainfall-runoff at a small time scale may be due to the catchment characteristics and local climate. In contrast, the association at 2–4 and 4–8 years may be deriving the relationship from the global connections characterized by large-scale climate oscillations.

### 4.4. Hydroclimatic teleconnections

Figures 7–14 show the cross-wavelet and wavelet coherence plot for six selected river basins and four chosen climate indices: IOD, NAO, NINO 3.4, and PDO.

XWT plot (Figure 7(a)–7(f)) showed a significant association between IOD and streamflow. All stations viz BA, CK, GT, MB, NG, and SA observed a significant correlation at an annual scale from 1980 to 2010. Interestingly, the annual correlation seems to be vanishing from 2000 to 2005 and nonexistent in recent years. Stations MB and NG observed significant inter-annual correlation at 2–4 years of scale from 1990 to 2000. The analysis based on WTC (Figure 8(a)–8(f)) supports our

![Figure 7](http://iwaponline.com/jwcc/article-pdf/13/2/735/1014241/jwc0130735.pdf)

**Figure 7** | Cross-wavelet analysis of IOD & streamflow at all the stations. (a) BA, (b) CK, (c) GT, (d) MB, (e) NG and (f) SA. The sections marked by black color contours are the significant sections indicating a high correlation between precipitation and streamflow. The cone of influence indicates the area affected by the boundary assumption.
findings and observed coherence at 2–4 years of scale. Indeed, Indian Ocean Dipole plays an essential role as a modulator of Indian monsoon rainfall (Ashok et al. 2001); however, at the regional scale, the influence of IOD on streamflow variability is different (Gouda et al. 2017). Our analysis also unraveled a mixed relationship of IOD with different basins and different scales and periods. There was an in-phase relationship for station BA, GT, MB, and SA. In contrast, station NG observed an anti-phase relationship, and station CK showed an anti-phase, lag, and lead relationship at starting (1977-1982), middle (1985-1995), and end year (2000-2010) of the study period. In-phase association at intra-annual (0.5 years) and annual (1 year) scale were observed between streamflow and North Atlantic Oscillation (NAO) in XWT analysis (Figure 9(a)-9(f)) from 1980 to 2010 with breaks in 1985, 1995, 2000 and 2005. The WTC analysis (Figure 10(a)-10(f)) support obtained similar patterns; however, stations like GT, MB, and NG also observed significant correlation at 2 and 4 years of scale. Compared with other indices, NIÑO 3.4 demonstrates maximum significance association with streamflow at an

Figure 8 | Wavelet coherence analysis of IOD & streamflow at all the stations (a) BA, (b) CK, (c) GT, (d) MB, (e) NG, and (f) SA. The sections marked by black color contours are the significant sections indicating high coherence between precipitation and streamflow. The cone of influence indicates the area affected by the boundary assumptions.
annual scale. In unity with the statement that summer monsoon rainfall and streamflow over the Indian basin is best correlated with temperature anomaly from NIÑO 3.4 (Smith & Reynolds 2003). Analysis based on the XWT plot (Figure 11(a)–11(f)) showed that stations like BA, GT, MB, and SA showed correlation throughout the period (1975–2010), whereas station GT and NG observed some vanishing features 1995–2005. The WTC plot (Figure 12(a)–12(f)) observed periodicities at intra-annual, inter-annual, and intra-decadal scale along with the annual scale. Interestingly, 4–8 years of cycle were observed in the last decade. The arrows in both scalograms are not pointing in one direction, but most of them showed a leading relationship between streamflow and NIÑO 3.4 at an annual scale. Like NIÑO 3.4, PDO indices also showed a leading association with streamflow at 1 year of scale in the XWT plot (Figure 13(a)–13(f)). In the case of the WTC plot (Figure 14(a)–14(f)), along with 1 year of scale, stations GT, MB, and SA also observed these periodicities at 2, 4 and 8 years of scale. These associations can be shown mostly from 1985 to 2000.

**Figure 9** | Cross-wavelet analysis of NAO & streamflow at all the stations. (a) BA, (b) CK, (c) GT, (d) MB, (e) NG and (f) SA. The sections marked by black color contours are the significant sections indicating a high correlation between precipitation and streamflow. The cone of influence indicates the area affected by the boundary assumption.
5. DISCUSSION

The temporal characteristics of six unregulated stations are disentangled by analyzing monotonic and abrupt trends of streamflow and their teleconnections with precipitation and global climate indices. Based on the results of the Mann-Kendall test, only Cauvery and Narmada showed significant flow variability changes. Interestingly, both the rivers indicated a long-term negative trend congruent with findings by Jain et al. (2017). On the contrary, Das (2019), Kuriqi et al. (2020), Murthy et al. (2017), Panda et al. (2013), and Rao (1995) reported significant trends for Mahanadi, Godavari, and Subarnarekha basin; however, these results report that the trends are insignificant. Intriguingly, unlike the gradual change, an abrupt shift in streamflow for all the stations was also observed. The change point detection observed major step changes from 1985 to 2015. Some stations like Anandapur (Brahmini) and Garudeshwar (Narmada) observed a significant drop in

Figure 10 | Wavelet coherence analysis of NAO & streamflow at all the stations (a) BA, (b) CK, (c) GT, (d) MB, (e) NG, and (f) SA. The sections marked by black color contours are the significant sections indicating high coherence between precipitation and streamflow. The cone of influence indicates the area affected by the boundary assumptions.
streamflow of about 55,000 m$^3$/sec and 200,000 m$^3$/sec in 2015 and 2006. Despite unregulated catchments that are not supposed to be influenced by hydropower plants, dams, or other reservoirs, such drastic change in streamflow presents an idea that there may be some other predominating factor for variations streamflow for these basins. Das et al. (2018) reported that urbanization and change in land use land cover could have impacted the streamflow alteration. Besides, they also discussed increasing population density over these basins, causing the transformation of cropland into builds up-lands which reduces the infiltration and increase the runoff. Many other researchers (Islam et al. 2012; Chawla et al. 2018; Vandana et al. 2019) found changes in precipitation and climatic patterns responsible for this streamflow alteration.

Decomposition of streamflow data using Continuous Wavelet Transform (CWT) is done to get further insight into streamflow variability. All the stations observed robust features at intra-annual (0.5 years) and annual (1 year) time scale. In addition, most of the stations showed a vital feature throughout the study period. Cross-wavelet and Wavelet Coherence Analysis plot between streamflow and precipitation showed an in-phase relationship for almost all the stations. Overall, our analysis

**Figure 11** | Cross-wavelet analysis of NiÑO 3.4 & streamflow at all the stations. (a) BA, (b) CK, (c) GT, (d) MB, (e) NG and (f) SA. The sections marked by black color contours are the significant sections indicating a high correlation between precipitation and streamflow. The cone of influence indicates the area affected by the boundary assumption.
observed an in-phase relationship between streamflow and precipitation that is also reported by Jena et al. (2014), Maity et al. (2007), and Panda et al. (2013).

Hydroclimatic teleconnections between streamflow and four climate indices unravel maximum correlation with NIÑO 3.4 followed by PDO index. PDO influences to six basins were similar to NIÑO 3.4, highlighting the possibility of proxy connections as highlighted by Rathinasamy et al. 2019. These reported results are also in line with Agarwal et al. (2020). However, the association of PDO indices to the selected basin is not much explored yet except the research by Krishnamurthy & Krishnamurthy (2014), who reported that the warm and cold phases of PDO influence the condition of ENSO and thus affect the streamflow and precipitation over Indian basins. This may be due to the warm phase of PDO, which increases the sea surface temperature of the Pacific Ocean, affecting the trade winds and strengthening the Walker Circulation and thus amplifying the NIÑO condition (Agarwal 2019). Ashok et al. (2001) also described in their study how the NIÑO

Figure 12 | Wavelet coherence analysis of NIÑO 3.4 & streamflow at all the stations (a) BA, (b) CK, (c) GT, (d) MB, (e) NG, and (f) SA. The sections marked by black color contours are the significant sections indicating high coherence between precipitation and streamflow. The cone of influence indicates the area affected by the boundary assumptions.
condition affects the Indian summer monsoon rainfall. Due to pressure and the temperature difference between oceanic surface and landmass of Indian subcontinent moisture driven current move towards land during the normal condition. However, during NIÑO condition (warm phase of ENSO), sea surface temperature increases. The temperature difference between landmass and sea gets minimized, further hindering the adequate moisture movement towards a landmass. Our analysis, in congruence with other studies (Maity et al. 2007; Panda et al. 2013; Jena et al. 2014), observed a positive association between stream flow and precipitation, concluding PDO (positive phase) and NIÑO 3.4 both negatively impact the summer monsoon rainfall and thus reduced the stream flow in the study area.

The Indian Ocean Dipole plays an essential role in deriving hydrologic variables like stream flow and precipitation and acts as a modulator of the Indian monsoon (Ashok et al. 2001). However, observed results showed little influence in stream flow and precipitation on considered basins, highlighting Indian stream flow teleconnections spatial diversity. This may be due to the fact that IOD alone does not influence the hydrologic variables of the Indian basin as compared with ENSO, which is also

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**Figure 13** | Cross-wavelet analysis of PDO & streamflow at all the stations. (a) BA, (b) CK, (c) GT, (d) MB, (e) NG and (f) SA. The sections marked by black color contours are the significant sections indicating a high correlation between precipitation and streamflow. The cone of influence indicates the area affected by the boundary assumption.
accepted by many researchers like Ashok et al. (2003), Marchant et al. (2007), Saji & Yamagata (2003), Ashok et al. (2003), Saji & Yamagata (2003), and Marchant et al. (2007). Recently Créat et al. (2017) and Rathinasamy et al. (2019) studied the impact of IOD on the Indian Summer Monsoon by removing the influence of ENSO and found that it did not force the monsoon circulation in the absence of ENSO. Pokhrel et al. 2012 also reported the Indian summer monsoon’s better prediction by ENSO and IOD’s combined influence. This indicated the need to examine further the influence of these two indices’ combined effect on the streamflow variability on the Indian peninsular basin.

Like IOD, it is observed that the significant areas of the strong feature in XWT and WTC are less with NAO than other indices, indicating lower NAO dominance in these basins. This is well supported by a previous study by Yadav et al. (2009). During the positive phase of NAO, the pressure at the polar region decreases and mid-latitude (Indian subcontinent) increases. This positive phase of NAO intensifies the westerly jet stream over the Middle East, strengthening the western

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**Figure 14** | Wavelet coherence analysis of PDO & streamflow at all the stations (a) BA, (b) CK, (c) GT, (d) MB, (e) NG and (f) SA. The sections marked by black color contours are the significant sections indicating high coherence between precipitation and streamflow. The cone of influence indicates the area affected by the boundary assumptions.
disturbance (Nageswararao et al. 2016). These disturbances mainly affect the northwest region of the Indian subcontinent by heavy rainfall in the winter season. Our study area is around the peninsular region that observed significantly less effect of western disturbance and hence was not affected by NAO. Kurths et al. (2019) also confirmed a weaker linkage between NAO and hydrometeorologic variables of the southern region of India.

6. CONCLUSIONS
In this study, India’s six different virgin catchments were analyzed in terms of runoff variability and its association with precipitation and climate indices. The Mann-Kendall test and step-change analysis were carried out to detect the gradual long-term changes in the streamflow. Only Narmada and Cauvery showed significant negative gradual changes, whereas a significant step change was observed after 1985 in all basins. Wavelet analysis was used to understand the multi-scale association of basin streamflow with the precipitation and climatic indices. Results revealed the effect of precipitation and climate indices on the streamflow data of the selected river basin. Precipitation showed an in-phase relationship, whereas climate indices NINÑO 3.4 and PDO observed lead, IOD, and NAO showed an in-phase relationship with most stations. Indeed, our preliminary results dispense a better understanding of the interrelationship between the streamflow, precipitation and climate indices. However, the analysis must be further extended on more stations in the basin to strengthen the findings, especially hydroclimatic teleconnections. Similarly, along with precipitation and climate indices, other variables may trigger the river basin changes. For instance, land use and land cover changes or any other anthropogenic changes in the respective regions should be further explored.

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COMPETING INTERESTS
The authors declare that they have no conflict of interest.

DATA AVAILABILITY STATEMENT
All relevant data are available from http://www.imdpune.gov.in/Clim_Pred_LRF_New/Grided_Data_Download.html.

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